Dynamic Linkages of Forest Fires in Indian Himalayan Region: An Empirical Analysis

A thesis is submitted to the

UPES

For the Award of

Doctor of Philosophy

in

Economics

By

Laxita Soontha

July 2025

Supervisor

Dr Mohammad Younus Bhat



Department of Economics

School of Business, UPES

Dehradun-248007; Uttarakhand, India

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DECLARATION

I declare that the thesis entitled **"Dynamic Linkages of Forest Fires in Indian Himalayan Region: An Empirical Analysis"** has been prepared by me under the guidance of **Dr. Mohammad Younus Bhat**, Associate Professor, Department of Economics, School of Business, UPES, Dehradun, Uttarakhand (Supervisor).

No part of this thesis has previously formed the basis for awarding any degree or fellowship.



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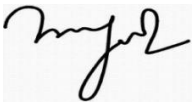
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CERTIFICATE

I Certify that Ms. Laxita Soontha prepared her thesis entitled, **"Dynamic Linkages of Forest Fires in Indian Himalayan Region: An Empirical Analysis"** under my guidance for the award of a Ph.D. degree in Economics from UPES. She has carried out her work at school of Business, UPES, Dehradun, India.

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ABSTRACT

Forests represent one of the most vital and complex ecosystems on Earth, covering approximately 31% of the global land area. They play an indispensable role in maintaining planetary health by acting as critical carbon sinks, conserving biodiversity, and regulating climate systems. Forests contribute to essential ecosystem functions such as water purification, soil conservation, and microclimate regulation, which in turn support agricultural productivity and human well-being. As reservoirs of over 80% of terrestrial species, forests are crucial to global biodiversity conservation efforts. Beyond their ecological value, forests are central to socio-economic development providing food, fuel, medicine, and income to more than a billion people, particularly in rural and indigenous communities. A substantial share of the global economy especially in developing countries is either directly or indirectly reliant on forest-based ecosystem services, including timber and non-timber forest products, tourism, and ecological infrastructure. Consequently, the conservation and sustainable management of forest ecosystems have been recognized as a global priority by numerous international environmental frameworks, including the Convention on Biological Diversity (CBD), the United Nations Framework Convention on Climate Change (UNFCCC), and the Sustainable Development Goals (SDGs).

However, forests are facing increasingly severe threats due to anthropogenic pressures such as climate change, deforestation, land-use transformations, and more recently, a troubling rise in the frequency and intensity of forest fire events. Among these, forest fires have emerged as a primary driver of forest degradation, causing large-scale loss of tree cover, reducing biomass, and triggering cascading ecological imbalances. In India, a country with diverse and ecologically

sensitive forest biomes, the Northern Indian Himalayan Region (NIHR) has become particularly susceptible to frequent forest fires. This region encompasses states such as Uttarakhand, Himachal Pradesh, and Union Territory Jammu & Kashmir is not only a critical biodiversity hotspot but also a vital regulator of hydrological flows, river systems, and climate buffering for the Indo-Gangetic plains. Recurrent fires in these ecologically flammable and topographically complex forest landscapes are resulting in the irreversible depletion of carbon stocks, degradation of water-retention capacity, disruption of soil quality, and intensification of erosion, all of which threaten the long-term resilience of these mountainous ecosystems.

The socio-economic implications of these forest fires are profound and diversified. The destruction of timber and non-timber forest resources undermines regional economies, while biodiversity loss erodes the ecological base for sustainable livelihoods. Agricultural outputs are negatively affected due to altered rainfall patterns, declining soil fertility, and smoke-induced crop damage. The tourism sector, a major economic driver in Himalayan states, also suffers due to reduced forest aesthetics, hazardous air quality, and disrupted access to natural and cultural heritage sites. Local communities, especially those that are economically marginalized and reliant on forests for their daily needs, are disproportionately affected by these disasters. In addition to the economic consequences, forest fires contribute heavily to air pollution by releasing substantial amounts of greenhouse gases, volatile organic compounds, and particulate matter into the atmosphere. This exacerbates global warming and significantly elevates health risks ranging from respiratory diseases to cardiovascular disorders especially in vulnerable populations such as children and the elderly.

Despite these far-reaching impacts, the research landscape surrounding forest fires in India remains underdeveloped. Most existing literature focuses on macro-level deforestation statistics, fire spread modeling, and satellite-based detection systems.

While valuable, these approaches often neglect the granular socio-economic and ecological dimensions of forest fires at the regional and community levels. There exists a critical knowledge gap in terms of understanding how forest fires affect rural economies, disrupt livelihood patterns, contribute to regional inequality, and interact with health and well-being indicators. Addressing this gap necessitates a multidimensional and interdisciplinary approach that incorporates both spatial-temporal environmental analysis and ground-level socio-economic assessments.

To this end, the present study is situated within two robust theoretical frameworks: the Environmental Kuznets Curve (EKC) hypothesis, which examines the relationship between environmental degradation and economic growth, and the Tragedy of the Commons (TOC), which highlights the overexploitation of shared natural resources. Leveraging these perspectives, the study investigates the dynamic interlinkages between forest fire incidences, economic growth trajectories, ecological sustainability, and the social fabric of communities in the Northern Indian Himalayan Region. The research employs a mixed-methods econometric design: an Autoregressive Distributed Lag (ARDL) model is used to explore the short-run and long-run dynamics between forest fire occurrences and key macroeconomic variables at the national level, while Structural Equation Modeling (SEM) is adopted to unpack complex causal pathways and feedback loops between forest fires, environmental stressors, and socio-economic outcomes at the regional and household levels.

Through empirical analysis and model-based simulation, the study reveals the deeply interconnected nature of forest fire impacts demonstrating how ecological degradation, economic instability, and health vulnerabilities reinforce one another, particularly in high-risk regions like the Himalayas. The findings emphasize that forest fires are not merely environmental episodes but developmental challenges that threaten India's progress toward climate resilience, sustainable livelihoods, and inclusive growth. The study concludes with policy recommendations centered on

adaptive forest governance, early warning systems, community-based fire management, and sustainable land-use planning. It calls for an urgent rethinking of fire mitigation strategies that integrate scientific evidence with the lived realities of forest-dependent populations, ensuring that fire management efforts are socially just, economically viable, and ecologically sustainable.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
ARDL	Autoregressive Distributed Lag Model
AVE	Average Variance Extracted
AW	Awareness
CFF	Cost of Forest Fires
CI	Community Impact
CIFFC	Canadian Interagency Forest Fire Centre
CO_2	Carbon Dioxide
CR	Composite Reliability
ED	Evacuation and Displacement
EI	Employment Impact
EKC	Environmental Kuznets Curve
FD	Forest Dependency
FFC	Forest Fire Causality
FFE	Forest Fire Exposure
FH	Forest Habitat
FS	Forest Soil
FSI	Forest Survey of India
GDP	Gross Domestic Product
GHG	Greenhouse Gases
$GtCO_2$-e	Gigatonnes of Carbon Dioxide Equivalent
HP	Health Problem
HP	Himachal Pradesh
HTMT Ratio	Heterotrait-Monotrait Ratio of Correlations
HWI	Heat Wave Impact

IPCC	Intergovernmental Panel on Climate Change
JK	Jammu and Kashmir
NASA	National Aeronautics and Space Administration
NIFC	National Interagency Fire Center
PM2.5	Particulate Matter ≤ 2.5 micrometers
PM10	Particulate Matter ≤ 10 micrometers
PR	Preparedness
SDG	Sustainable Development Goals
SEM	Structural Equation Modeling
TOC	Tragedy of the Commons
UK	Uttarakhand
UNEP	United Nations Environment Programme
VIF	Variance Inflation Factor

CHAPTER I
INTRODUCTION

1.1 Background

Forests are one of the most valuable natural resources on Earth, providing a wide range of environmental, social, and economic goods and services that are fundamental to human well-being and ecological balance (Li and Managi, 2024). They cover about 31% of the land area and host more than half of the world's terrestrial species, providing habitats for 80% of amphibians, 75% of birds, and 68% of mammals (Vié et al., 2009). This remarkable biodiversity is essential for global ecological stability, maintaining food webs and regulating ecosystems, while supporting genetic diversity, which is critical for ensuring resilience to environmental change (Pennekamp et al., 2018). However, the importance of forests goes far beyond their role as reservoirs of biodiversity. Forests also play a very important role in mitigating climate change, ensuring food security, and supporting socio-economic development, and it is impossible to think of sustainable development without their conservation (UNEP,2021). Forests have become a very important element within the global climate regulation in terms of the carbon sequestration process, where CO_2 is taken from the atmosphere and stored in biomass, soil, and forest products. Carbon sequestration is considered the backbone of climate change mitigation based on forests, crucial to reducing GHG concentration in the atmosphere and controlling global warming (Lorenz & Lal, 2009). This role is rendered urgent by recent climate trends: the globally averaged surface temperature was 1.1°C above the pre-industrial level (1850–1900) between 2011 and 2020, a rise attributed largely to human-induced emissions (IPCC, 2021) It is for this reason that forests represent a crucial buffer against the accelerating impacts of climate change. According to estimates, forests

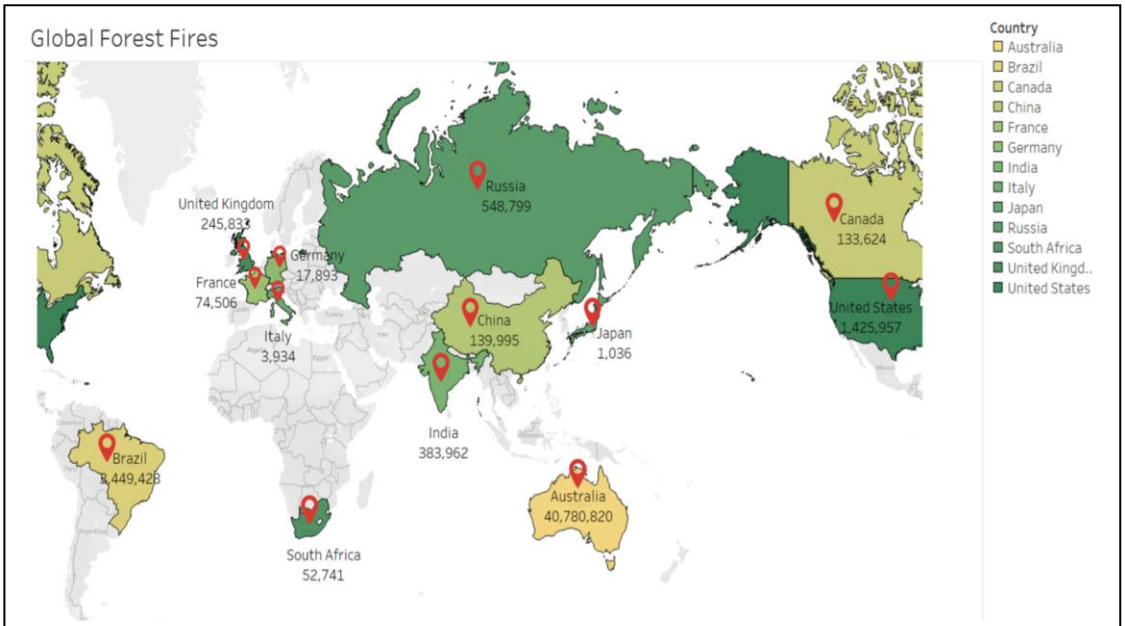
could provide 4.1 to 6.5 $GtCO_2$-e per year by 2030, or about one-third of the mitigation that will be required under international climate objectives as prescribed under the Paris Agreement (IPCC, 2019). This mitigation potential underlines the cost-effectiveness of forest conservation, sustainable management, and reforestation as indispensable strategies in global climate action. Yet, the role of forests far exceeds mere carbon storage.

Forests regulate water cycles, stabilize local climates, and reduce the impacts of extreme weather events such as floods, storms, and droughts, enhancing the adaptive capacity of both ecosystems and human communities (Zhang et al., 2022). Forests contribute to local and regional cooling through the release of water vapor into the atmosphere via evapotranspiration, further mitigating the adverse effects of climate change (Ellison et al., 2017). Therefore, given their dual role for both mitigating and adapting to climate change, forests lie at the heart of the global strategy for resilience building, particularly for the most vulnerable sections, which are the worst sufferers from environmental changes. Many such communities are found living in or around these forests and depend upon them for sustenance in livelihood, food security, and the continuation of culture.

Yet the forests are degrading, with alarming rates of tree cover loss threatening ecological stability and biodiversity. See Figure 1.1 for a visual representation of the rising forest fires from 2000-2019. According to data from Global Forest Watch (2024), approximately 459 million hectares (Mha) of tree cover, representing nearly 12% of the world's total tree canopy as of the year 2000, have been lost globally. This alarming trend reflects a systemic failure to implement sustainable forest management practices, contributing to widespread ecological disruption. Among the multiple drivers of forest degradation, forest fires have emerged as a predominant and escalating factor (Zhao et al., 2021). From 2014 to 2023, the

United States experienced a total of 53,747 forest fires, burning approximately 6.59 million acres, according to data from NIFC (2024). Brazil, another heavily impacted region, lost 10.6 million hectares of tree cover due to fires between 2001 and 2023, with 2016 being the most devastating year, accounting for 2.38 million hectares—44% of that year's total tree cover loss (GFW,2024). Similarly, Russia reported over 12,700 forest fires in 2023, an increase from the previous year. The country has faced catastrophic fire incidents historically, with a peak of 33,400 forest fires recorded in 2010 (Statista, 2023).

Figure 1.1: Global Forest Fires: A Visual Overview (2000-2019)



Source of Data: NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC); Statista

In India, forest fires have been a significant driver of forest degradation. Between 2001 and 2023, the country experienced a loss of 38.1 thousand hectares of tree cover due to forest fires. The highest loss in a single year occurred in 2008, when

3.00 thousand hectares were affected by fire, accounting for 3.5% of the total tree cover loss that year (GFW, 2024). Forest in Northern Indian Himalayan region is highly vulnerable to forest fires due to the climatic conditions, geographical location and anthropogenic activities and leads to unsustainable livelihood of local community, In Uttarakhand only, the year 2021 was one of the worst, with 1778.39 hectares of tree cover lost, reflecting a devastating fire season and environmental stress (FSI,2021). These statistics highlight the pervasive and growing threat of forest fires in different parts of the world, underscoring the urgent need for comprehensive fire management and mitigation strategies. These fires serve as both a symptom and a driver of environmental instability, exacerbating the degradation of forest ecosystems. While natural phenomena such as lightning occasionally ignite fires, human-induced factors such as agricultural expansion, unsustainable logging, and poorly managed fire suppression practices are the primary causes of their increasing frequency and intensity. Climate change further amplifies this crisis by intensifying conditions that make forests more susceptible to fire. Rising global temperatures, prolonged droughts, and unpredictable weather patterns have created a destructive feedback loop that not only accelerates forest degradation but also magnifies climate impacts. The implications of forest fires extend beyond the immediate loss of tree cover. They pose severe threats to biodiversity, disrupt essential ecosystem services, and significantly impact economies and public health. The escalating nature of this issue underscores the urgent need for integrated strategies that address both the prevention of forest fires and the broader drivers of forest degradation.

1.1.2. Forest fires and Sustainable Development Goals (SDGs)

The destructive effects of forest fires extend far beyond ecological degradation, impeding global progress towards multiple Sustainable Development Goals

(SDGs). Affordable and Clean Energy; SDG 7, Forest fires destroy biomass, a critical source of renewable energy for many rural and developing regions. The loss of forest resources undermines energy security, particularly in areas dependent on wood-based fuels. Decent work and economic Growth; SDG 8, the economic consequences of forest fires are severe, including job losses in forestry, agriculture, and tourism sectors. Entire communities reliant on forest ecosystems for their livelihoods face economic displacement and instability. Sustainable Cities and communities; SDG 11, Forest fires contribute to worsening air quality, affecting urban and rural populations alike. Airborne particulates from smoke exacerbate respiratory illnesses and increase healthcare costs, further straining public health infrastructure. Responsible Consumption and Production; SDG 12, unsustainable land management practices, such as slash-and-burn agriculture, become more prevalent in the aftermath of forest fires. These practices reduce land productivity, promote desertification, and compromise long-term food security. Climate Action: SDG 13, Forests act as vital carbon sinks, absorbing atmospheric carbon dioxide. When forests burn, stored carbon is released, contributing significantly to greenhouse gas emissions. Forest fires thus represent a major setback to climate mitigation efforts and international commitments under the Paris Agreement. Life on Land; SDG 15, The ecological damage caused by forest fires disrupts entire ecosystems, leading to loss of biodiversity, habitat destruction, and the destabilization of food webs. These impacts reduce the resilience of ecosystems and threaten the survival of species reliant on forest habitats.

1.2. Business Problem

Forests are a vital natural resource, playing a crucial role in maintaining environmental balance and serving as key indicators of ecological conditions in any

region. The ecological security of a country is intricately linked to the health of its forests (Li et al., 2019). Globally, over 1.6 billion people depend on forests to varying degrees for their survival, utilizing them for food, fuel, grazing lands, and medicine. Among these, approximately 60 million indigenous people are directly reliant on forests, while an additional 350 million individuals living in or near forested regions derive livelihoods and income from forest resources (World Bank, 2006). However, forest degradation has emerged as an urgent issue, signaling the diminishing capacity of forests to provide critical environmental services. Factors such as human intervention, unsustainable exploitation, and forest fires are significant contributors to this decline. Forest fires, largely caused by anthropogenic activities, lead to the destruction of invaluable plant and animal species and can even threaten human settlements. Economically, forests hold immense importance, particularly in regions where they contribute to industries such as pulp and paper. Fires not only disrupt the supply of wood fiber but also reduce the landscape's recreational value, compounding their economic and ecological impacts.

1.2.1. Business Problem Statement

Escalating forest fires in India, especially in the Northern Indian Himalayan Region, are driven by rapid socio-economic changes and infrastructure expansion. These fires are causing widespread biodiversity loss, destabilizing ecosystems, and severely threatening sustainable livelihoods. The lack of effective mitigation strategies exacerbates environmental degradation, endangering regional resilience and long-term development.

1.3. Description of the Study Area

India's extraordinary and multifaceted biodiversity, which encompasses more than one-fifth of the nation's expansive geographical territory, serves as a habitat for approximately 173,000 forest villages, the majority of which are predominantly occupied by indigenous tribal communities that are profoundly dependent on forest resources for their daily sustenance and overall livelihoods, as highlighted by the research conducted by Kishwan et al. in 2009. India has witnessed an alarming escalation in forest fire frequency, intensity, and the area affected over recent years. Annual forest fire incidents surged from 24,817 in 2016 to 37,059 in 2018, marking a 49.3% increase in summer fire incidents over three years. Monthly fire alerts also spiked significantly between November 2018 and March 2019, with over 14,107 alerts reported in March alone. Bandipur faced one of the worst episodes in 2019, with 10,000–20,000 acres incinerated in just five days. The peak fire-prone period remains the summer months, particularly in March, during which most incidents occur. Between January and March 2019, over 2,500 real-time fire alerts were issued nationwide, highlighting the pressing need for effective fire management strategies (FSI, 2021). However, forests are degrading due to forest fires in India, and especially in the Northern Indian Himalayan region, which is a biodiversity hotspot and most vulnerable to forest fires. In this study, Uttarakhand, Jammu & Kashmir, and Himachal Pradesh have been studied due to the increasing trend of forest fires in these regions.

Uttarakhand is a predominantly mountainous state located in the northern part of India, with an area of 53,483 square kilometers (i.e., 1.63% of the total geographical size of India). Geographically, the state is located between latitudes 28°43′N to 31°28′N and longitudes 77°34′E to 81°03′E. It borders Himachal Pradesh in the north, and Uttar Pradesh state in the south, but has international borders with Nepal

and China, thus making its geographical significance enormous. Being partly in the range of the Himalayas, Uttarakhand has a variety of terrains, including hills and high mountains, which contribute to a large elevation difference. Forest fires in Uttarakhand, driven by dry climates, flammable pine forests, and varied terrain, are categorized into fire-prone classes. Extremely fire-prone areas cover 45.56 sq. km (0.17%), while very highly and highly fire-prone regions account for 443.12 sq. km (1.6%) and 2,689.15 sq. km (9.32%). Moderately and less fire-prone areas span 7,316.58 sq. km (21.66%) and 32,275.70 sq. km (67.25%), respectively (FSI, 2021). Forest fire trends in Uttarakhand from 2001 to 2023 reveal significant variability in tree cover loss. The data shows sharp increases in fire incidents, with notable peaks in 2006 (1147.8 hectares), 2008 (1708.56 hectares), 2021 (1778.39 hectares), and 2023 (1977.24 hectares), reflecting the severity of fire seasons. While there were periods of loss reduction, such as in 2003 (269.26 hectares), 2009 (951.23 hectares), and 2013 (468.19 hectares), the overall trend shows an alarming rise in tree cover loss, especially during dry years. Other years, like 2016 and 2020, also saw significant losses (885.09 hectares and 991.96 hectares, respectively), indicating the persistent vulnerability of the region to forest fires (GFW, 2024).

Union Territory Jammu & Kashmir, with an area of 2,22,236 square kilometers, that is about 6.76% of the total geographical area of India. With temperate valleys and forested areas to the north, as well as high-altitude deserts on the southern edge of the Himalayas region in Ladakh, this region has multiple unique ecological zones. Strategically bordered by Pakistan, Afghanistan, and China, this union territory faces challenges in resource management influenced by international policies and ecological disturbances. Forest fire risk in Jammu & Kashmir and Ladakh is relatively low compared to other regions of India, with 85 to 90% of the forest cover classified as less fire-prone. However, significant portions of the forest

(8.38 to 12.38% highly fire-prone, 1.62 to 2.62% very highly fire-prone) still face elevated risk, requiring targeted management strategies for fire prevention and control in vulnerable areas (FSI, 2021). Forest fire trends in Jammu and Kashmir from 2001 to 2023 exhibit significant fluctuations in tree cover loss. The highest recorded loss was 889.57 hectares in 2004, while 2013 saw the lowest at 27.93 hectares. Losses spiked in 2002 (400.41 hectares), 2006 (519.48 hectares), and 2023 (99.59 hectares). Periods of reduced loss were observed in 2011 (80.47 hectares) and between 2014 and 2017, with the lowest at 1.29 hectares in 2015. Despite these reductions, periodic surges highlight the region's vulnerability to forest fire events over the 23 years (GFW, 2024).

Himachal Pradesh, spanning a geographical area of 55,673 square kilometers (1.69% of India's total area), lies between latitudes 30º22'N to 33º12'N and longitudes 75º45'E to 79º04'E. It shares borders with Jammu & Kashmir to the north, Punjab to the west, Haryana to the south, Uttarakhand to the southwest, and an international boundary with China to the east, underscoring its geopolitical significance. Himalayas state is topographically diverse and is categorized into three regions, namely Shiwalkis (up to the altitude of 1500m): dry scrub forest and agriculture land, Middle Himalayan Region (1500 - 3000 m) temperate forests such as pine, oak and deodar trees; Himadris (above the altitude of 3000 m), snow-covered peaks with alpine vegetation. Annual rainfall is 1800 mm, and the climate varies from a near monsoonal sub-tropical in the lowlands (temperatures of up to 35°C) to a harsh sub-alpine zone where sub-zero temperatures can occur. In Himachal Pradesh, forest fire risk is primarily categorized as less fire-prone, moderately fire-prone, and highly/very highly fire-prone zones. A vast majority, 94.20% (35,829.66 sq km), falls under the less fire-prone category, consisting of higher-altitude or moist forest types with cooler temperatures and higher humidity,

reducing fire susceptibility. Moderately fire-prone areas, covering 1,204.52 sq. km. (4.59%), They are typically characterized by dry deciduous and coniferous forests with flammable undergrowth and seasonal dryness. Highly fire-prone zones span 220.4 sq km, while very highly fire-prone areas, though minimal at 4.76 sq km, require intensive monitoring and proactive management to mitigate potential damage (FSI, 2021). Forest fire trends in Himachal Pradesh from 2001 to 2023 exhibit significant fluctuations in tree cover loss. The highest recorded losses occurred in 2004 (716.02 hectares) and 2012 (716.59 hectares), while 2011 and 2015 saw minimal losses of 52.96 and 13.28 hectares, respectively. Periodic increases were observed in years such as 2007, 2009, and 2023 (308.17 hectares), reflecting recurring fire activity. Declines in some years, like 2013 and 2016, indicate relatively stable periods. These trends highlight the varying impact of forest fires on Himachal Pradesh's tree cover over the years (GFW, 2024).

1.4. Objective of the Study

The main objective of the study is to explore the dynamic impacts of rising forest fires in the northern Indian Himalayan region. This study explores the micro and macro aspects of forest fires in three Indian states, viz., Uttarakhand, Himachal Pradesh, and Jammu and Kashmir. Scientific studies are indeed available (Sannigrahi et al., 2020; Kala et al., 2023) which have enriched our understanding about environmental effects and costs of forest fires in India, but these studies need to be supplemented by studies documenting the social, economic, health and environmental impacts of forest fires. Specifying the nature and direction of the causal nexus between forest fires and socio-economic-environmental factors is extremely necessary for formulating effective policy instruments locally as well as globally.

1.5. Overview of Methodology

This research utilizes a mixed-method approach to examine the effects of forest fires in India. To assess both the immediate and long-term impacts, it employs the Auto-Regressive Distributed Lag (ARDL) model, drawing on secondary data related to environmental and socio-economic indicators at the national scale. For a deeper understanding of localized impacts, Structural Equation Modeling (SEM) is conducted using primary data collected from Uttarakhand, Jammu & Kashmir, and Himachal Pradesh in the Northern Indian Himalayan region. This dual approach enables comprehensive analysis by integrating macro-level trends with region-specific insights.

1.6. Operational Definitions

Operating definitions borrowed from literature are presented below to explain the key termsused in this document.

1. Sustainable Livelihood - A livelihood comprises the capabilities, assets, and activities required for a means of living. It is deemed sustainable when it can cope with and recover from stresses and shocks and maintain or enhance its capabilities, assets, and activities both now and in the future, while not undermining the natural resource base (Serrat, O., & Serrat, O., 2017).

2. Forest fires - Forest fires involve the burning of tropical, temperate, or boreal forests, triggered either naturally or by human activities, and are closely linked to deforestation and land clearing. Naturally occurring forest fires are typically caused by events like lightning strikes, whereas human-induced fires often stem from illegal burning practices aimed at converting forested

land into farmland areas (Yadav & Devi, 2018).

3. Dynamics of Forest Fires- According to the Food and Agriculture Organization (FAO), forest fire is a catastrophic occurrence that can destroy the ecological system and be a major factor in both the transition of forestland and ecological devastation (FAO, 2007). Throughout the recent decades, there has been an upward trend in the incidence of forest fires globally, which has increased both public and government awareness of the social, economic, and environmental repercussions of forest fires (Tariq et al., 2021).

4. Environmental Kuznets Curve - Research on development and inequality, notably by Kuznets (1955), introduced the concept of the Kuznets curve, which suggests a causal relationship between income inequality and economic development. Initially, inequality is low but rises as development progresses. However, after surpassing a certain level of development, income inequality begins to decline. Grossman and Kruger (1991)used a similar functional approach in the sphere of ecology, creating the Environmental Kuznets Curve (EKC). Researchers conclude that the amount of ecological deterioration rises in conjunction with economic expansion, but at a specific point, it tends to lag development even while growth proceeds. By graphing the progression of revenue (on the abscissa) and class inequality (on the ordinate), Kuznets predicted that an "inverted U" curve will indeed emerge: the duration of rise in disparities would not only be a "principal" step in the process, preceding a realignment of the inequality of wealth in community (once a definite growth level, or "inflection point," was achieved).

5. Tragedy of Commons- The Tragedy of the Commons (TOC) claimed that the world's population was on a course of unsustainable increase (Hardin, 1968). People only behave in their personal interests, which is increasingly contradictory with sociological research (Van Vugt, 2009). Most commons conceptualizations adhere to an objectivist perspective, according to which a common is a vast ecologic or social system composed of naturally occurring or cultural assets and concepts, the advantages of which are freely reachable to all, making them vulnerable to abuse, disinvestment, and diffusion of responsibility (Olson 1989, Ostrom 1990).

1.7. Significance of Study

The increasing frequency and intensity of forest fires in the Northern Indian Himalayan region highlight an urgent need for comprehensive research and mitigation strategies. This region, a globally recognized biodiversity hotspot, harbors numerous endemic and endangered species, making its conservation critical for maintaining ecological balance and preserving global biodiversity. The forests of the Northern Himalayas play a pivotal role in regulating regional and global climates by serving as carbon sinks and mitigating greenhouse gas emissions. However, recurring forest fires disrupt these functions, exacerbating climate change and undermining efforts to achieve sustainability goals. Furthermore, this region is the source of several major rivers that sustain water security across the Indian subcontinent. Fires degrade forest covers, destabilize watersheds, and compromise hydrological cycles, leading to soil erosion and reduced water availability downstream.

The socio-economic implications of forest fires are equally significant, as millions of local communities depend on forest resources for their livelihoods, including fuelwood, fodder, and non-timber forest products. Fires not only threaten these resources but also disrupt cultural practices tied to the forests, which hold immense spiritual and historical value. Moreover, addressing forest fires aligns directly with achieving Sustainable Development Goals (SDGs), particularly SDG 6 (Clean Water and Sanitation), SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 15 (Life on Land). These goals emphasize the need for ecosystem resilience, biodiversity conservation, and climate adaptation. This study is therefore crucial for informing policies and enhancing forest management practices to ensure ecological sustainability and socio-economic stability in this fragile region.

1.8. Conceptual Framework of the Study

The conceptual framework of this study is built around the interconnections between forest fires and their multidimensional impacts on health, socio-economic conditions, and environmental sustainability in India. The framework integrates various components to analyze these relationships at both the national and regional levels.

At the national level (India), the study examines the long- and short-term effects of forest fires driven by factors such as economic, environmental variables. This segment explores how these macroeconomic drivers contribute to unsustainable economic development, environmental degradation, and health effects. At the regional level, the focus shifts to the Northern Indian Himalayan Region, where primary data is used to capture the localized impacts of forest fires. The framework considers the direct consequences on health (respiratory issues, psychological

stress, heat exhaustion), economic (property damage, business disruptions, loss of timber), social (displacement, evacuation), and environmental benefits (habitat and biodiversity loss).

Overall, this conceptual framework (Figure 1.2) provides a holistic understanding of how forest fires operate within broader socio-economic and environmental systems, allowing for the identification of critical policy interventions for sustainable development and resilience building.

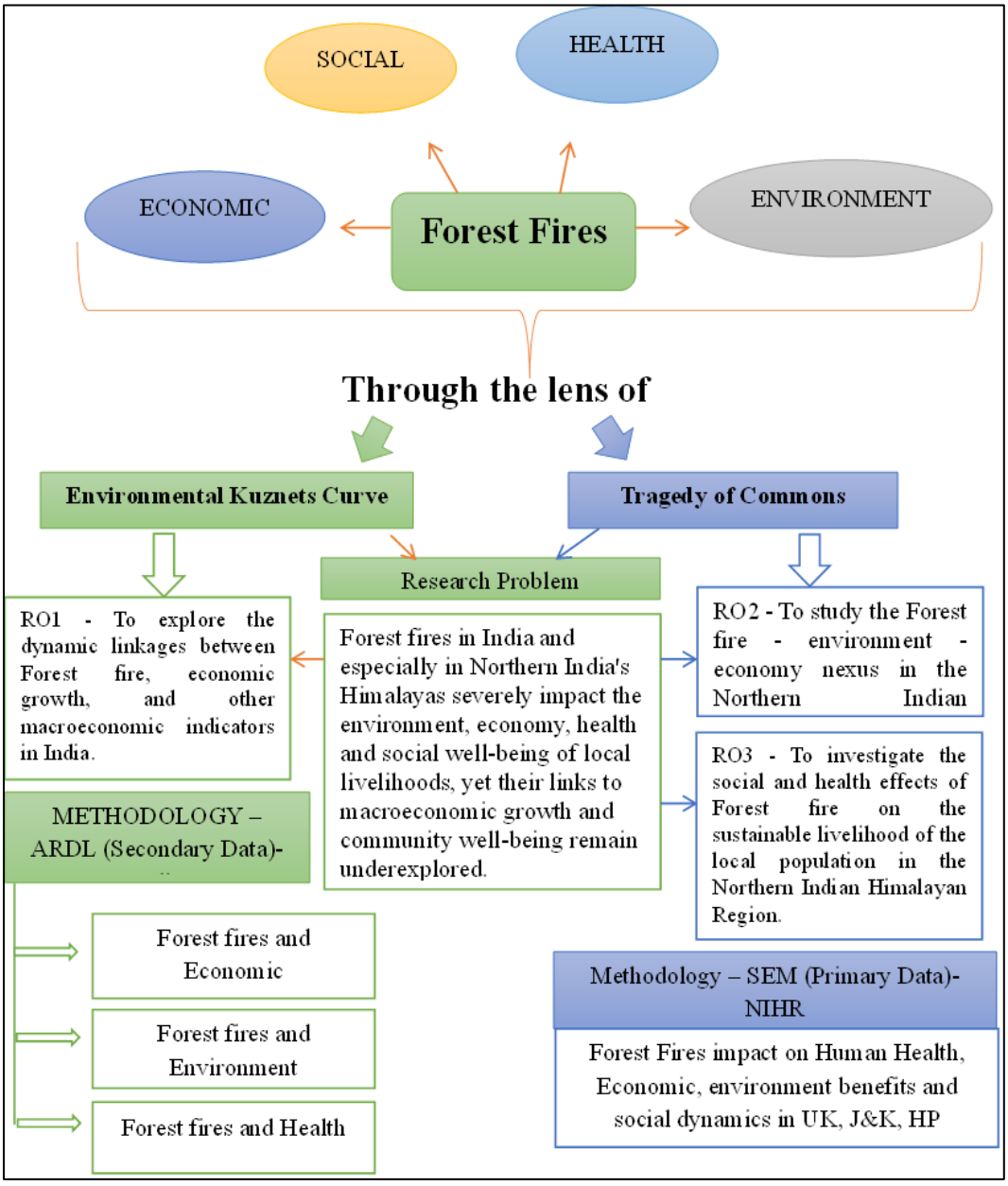
1.9. Organization of the Thesis

This thesis is organized into six chapters, each designed to systematically address the research objectives, explore the problem of forest fires, and provide actionable insights for mitigation strategies. The structure is as follows:

Chapter I introduces the study by emphasizing the ecological significance of forests and the growing challenge of forest degradation due to fires. It highlights the critical issue of forest fires in India and especially in the northern Himalayan region, focusing on Uttarakhand, Himachal Pradesh, and Jammu & Kashmir. Additionally, it underlines the ecological and socio-economic implications of forest degradation and the conceptual framework of the study. Chapter II is a comprehensive review of existing literature that summarizes global and regional studies on forest fires, their causes, impacts, and mitigation strategies. It identifies research gaps and establishes research problems, research objectives, questions, and the theoretical framework that guides this study. Chapter III studies geographical focus, including an in-depth examination of the forest ecosystems in India and then the northern Indian Himalayan Region - Uttarakhand, Himachal Pradesh, and Jammu & Kashmir. It also outlines the methodological approach, including data collection,

tools, and techniques used for analyzing forest fire impacts and patterns. Chapter IV presents the research methodology used in the study for different objectives, sampling technique and sample size and the preparation of the questionnaire and Data collection procedure, Chapter V presents the findings of the study, including statistical analysis, and the impact of forest fire on social, environmental, health, and economic conditions. A discussion of these results in the context of existing literature highlights the key insights derived from the study. The final chapter synthesizes the key findings of the study, highlighting its contributions to the understanding of forest fires in the northern Himalayan region. Based on the results, this chapter proposes mitigation strategies and management practices to address forest fires effectively. It emphasizes community involvement, policy recommendations, and technological interventions tailored to the study area.

Figure 1.2: Conceptual Framework of the study



1.10. Conclusion

This Chapter has established the significance of forests and the urgent challenge of forest degradation due to fires driven by human activities and climate change, focusing on Uttarakhand, Himachal Pradesh, and Jammu & Kashmir. It identifies the business problem of mitigating forest fires to protect ecosystems and livelihoods, offering operational definitions for clarity. The study area is defined as the northern Himalayan region, characterized by its ecological vulnerability. A conceptual framework links fire causes, impacts, and mitigation measures, guiding the research. The chapter highlights the study's significance in addressing knowledge gaps, informing policies, and fostering sustainable forest management. This foundation sets the stage for research ahead.

CHAPTER II
LITERATURE REVIEW

Chapter 2 primarily focuses on reviewing existing literature related to forest fires, including their definition and their wide-ranging effects on climate change, biodiversity, ecosystem services, the economy, suppression costs, human health, tourism, technology, and more. The key goal of this review is to offer an in-depth understanding of how forest fires impact economic growth, mental health, public health, and sustainable livelihoods, all within the context of forest economics. Addressing a critical gap in literature, where studies often focus on isolated aspects without a holistic perspective, the review synthesizes insights from various scholarly sources to explore the multifaceted impacts of forest fires. It aims to recalibrate cost estimation methods, particularly concerning suppression costs and firefighting expenses, by integrating economic and physical damage metrics and emphasizing the value of ecosystem services provided by forests. The review contributes to the existing body of knowledge by offering a broad analysis of economic impacts, ecosystem services, and social implications, while also examining the health, biodiversity, tourism, and climate change effects of forest fires.

2.1. Concept of Forest Fire

Over the past few decades, there has been a great impact on the environment and human welfare, economic growth, and tourism around the world due to forest fires, with prognostication pointing to a deteriorating scenario (Cammelli & Angelsen, 2019; Fitch & Kim, 2018; Meier et al., 2023). Noticeably, the

immensity and repercussions of recent forest fires point out that these events have become more frequent and more severe and have overshadowed historical events; this indicates the importance of studying changes in fire frequency over time especially in moderate ecosystem zones (Hantson et al., 2022). It is crucial to understand how these forest fires affect wildlife habitats, carbon sequestration, and plant life and eventually affect the behavior of humans (Feng et al., 2021; Seidl et al., 2014). Research has been done on the influx of affected areas, factors that cause previous forest fires, and pervading impacts of climate change (Gonzalez-Olabarria et al., 2019). Forests offer essential services such as food, raw materials, medicine, and water, while also playing a crucial role in regulating climate and reducing hazards (Hashida & Lewis, 2019; Baland et al., 2018; Unterberger & Olschewski, 2021). In addition, (Taye et al., 2021) highlights the cultural services of forests, contributing to human well-being, leisure, travel, scientific understanding, and spiritual and cultural identity. The various functions forests serve highlight their value beyond being conventional natural resources. It is crucial to understand and acknowledge these contributions; however, the current trend of forest degradation presents a danger to vulnerable communities and humanity. Implementing strategies to protect, restore and responsibly manage forests can positively impact human welfare and livelihood opportunities. Forest fires are getting more intense and prevalent in a variety of ecosystems throughout the world. The escalating forest fires are causing substantial ecological damage, consequences on human health, and infrastructure devastation (UNEP, 2021). These fires disrupt ecosystems and endanger lives, underscoring the importance of resilient forests for development, especially in developing nations (Fekete & Nehren, 2023; Belavenutti et al., 2022; Tian & Liu, 2011; Provencher et al., 2008). Conversely, forest degradation and loss hinder long-term economic growth, undermining development objectives (Woldemedhin et al., 2022). Recognizing the trade-offs and opportunities in forest-related policies can lead to more informed decision-making, aligning economic interests with the myriad benefits that forests offer (Saha et al., 2022; Saarikoski et

al., 2022). See Figure 2.1 for a visual representation of the rising forest fires from 2000-2019.

Drawing on a global evaluation spanning from 2003 to 2015, which observed a rise in burned hectares from 67 million in 2003 to an alarming 98 million globally in 2015, the warmest year of the decade (UNEP, 2020), the review underscores the growing severity of forest fires in the context of economic growth and sustainability. The novelty of this review lies in its holistic approach, combining economic, social, and environmental dimensions to offer practical recommendations for policymakers in forest fire suppression, rehabilitation, and risk mitigation while addressing the need for more accurate cost estimations and highlighting the importance of ecosystem service valuation. Highlighting the need to investigate health indicators and engage communities, the review underscores forest fires as a collective challenge requiring community involvement. Inspired by successes like the Chipko movement—a non-violent resistance in India where villagers, mainly women, hugged trees to prevent them from being cut down—community engagement is crucial. The argument for expanding analytical and empirical dimensions of forest fire literature aims to fill gaps in understanding the comprehensive relationship between forest fires and sustainable livelihoods. This approach guides practical strategies for mitigation, community involvement, and sustainable forest management.

2.2. Review Methodology

2.2.1. A systematic review protocol and literature search

The study has adopted systematic reviews that integrate the results of studies to answer a specified question by combining the results of many studies used in policy and practice (Gusenbauer & Haddaway, 2020). The standard procedures of the systematic review process frequently cover (i) literature search which comprises extensive and structured searching through electronic databases to detect related

sources; ii) Filtering the relevancy of studies retrieved; and iii) assessing eligibility for inclusion or exclusion based upon set criteria (Shaffril et al., 2020). So to ascertain the integrity of the finding, a meticulous review of pertinent studies of forest fire-induced degradation was carried out. The literature search concentrated on earlier research that looked at how forest fires affect growth in the economy, climate changes, tourism, health, technology development, and other macro factors that were considered for the degradation of forests and the sustainable livelihood of indigenous people. To find pertinent papers on research on forest fires carried out globally from 2000 to 2023, the two scholarly databases ScienceDirect and Scopus were searched. Research published in 2000 or after is taken into account when comparing research on the same topic conducted in the last two decades. Keywords listed in Table 1 were used to perform literature searching.

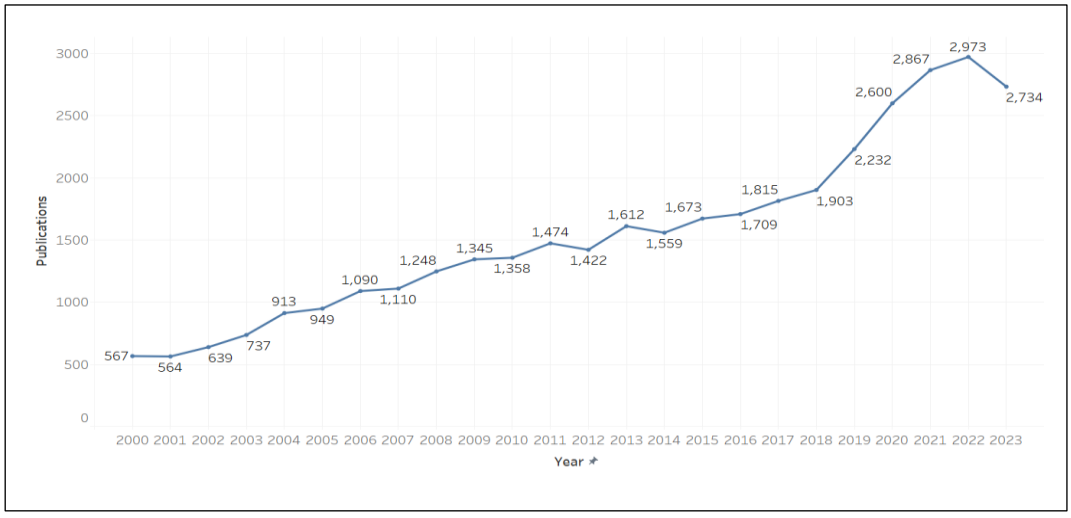
Table 2.1: Keywords and Publication Counts by Database

No.	Keywords used for both databases	Number of articles in each database	
		Science Direct	Scopus
1.	"Forest Fire" AND "Forest Degradation"	31,119	1648
2.	"Forest Fire" AND "Ecosystem Services"	20,823	1,139
3.	"Forest Fire" AND "Climate Change"	46,608	6,507
4.	"Forest Fire" AND "Economic Development"	31,308	617
5.	"Forest Fire" AND "Human Health"	25,779	758
6.	"Forest Fire" AND "Tourism"	6,226	178
7.	"Forest Fire" AND "Suppression Cost"	3,505	194
8.	"Forest Fire" AND "Technology"	39,789	1,023
9.	"Forest Fire" AND "Psychology"	3,041	59

2.2.2. Descriptive Analysis of Articles

This section presents a summary of the main features of the articles examined, encompassing year-wise publications, geographical distribution, journals, and document types. The analysis extends to the examination of publication patterns across different countries. The deliberate choice of the term 'forest fires' over 'wildfires' in this study's search strategy aimed to focus on the specific impacts of fires within forested areas. While 'wildfires' is a broader term, often encompassing fires in non-forest environments, concentrating on 'forest fires' allows for a detailed review of studies addressing the ecological, economic, and social dimensions within forest ecosystems, thus enhancing the depth and specificity of the analysis. The review revealed a scarcity of literature specifically on forest fires. Incorporating studies on forest fires mitigates this limitation, ensuring a comprehensive review and avoiding research gaps. While there is a considerable volume of publications on forest fires, there is a clear lack of research focused specifically on forest fires, highlighting the novelty and significance of this study in contributing to this underexplored research area. Figure 2.1 encapsulates the trends related to forest fires, presenting a comprehensive visualization of the research landscape.

Figure 2.1: Publications on Forest Fires by Year



2.2.3. Literature selection, inclusion, and exclusion criteria

The methodological framework and selection procedure for the systematic examination of literature is shown in the flow diagram in (Fig. 2.2 and 2.3). Following the criteria for inclusion and exclusion, pertinent studies were chosen and incorporated into this analysis. Publications that provide original data that were available in an English-language, peer-reviewed journal and made accessible online in the full-text form are required to be considered. However, to ensure the caliber of the research that was included, the thesis, dissertation and other unreleased publications were eliminated. Research that is included primarily examines how forest fires affect economic growth, public health, climatic changes, tourism, and the overall impact on indigenous cultures. The outcomes were only allowed to contain the top 1,000 articles in situations when the search yielded (n > 1,000 records). Therefore, only 6,000 publications overall from the Science Direct search and 4,144 studies from Scopus were obtained. The two databases yielded a total of 10,144 research, of which 20,134 papers were retained after duplication was eliminated. To choose the research examined, a two-phase procedure of screening was used. Based on an evaluation of the study's title, abstract, and keywords, studies were first evaluated for relevance. As a result, a work of literature will only be kept if the title, abstracts, and keywords all fulfill the criteria for inclusion or if it can't be ascertained only by looking at the abstract. As a result, 1097 studies were kept for the subsequent full-text evaluation. Following the first evaluation, a detailed text analysis of the research papers that succeeded was carried out. As a result, 140 papers altogether were kept for the conclusive synthesis. This study has also incorporated several reports and government-led projects aimed at improving forest fire mitigation efforts, highlighting their crucial role in addressing the growing threat of forest fires.

Figure 2.2: Schematic Figure outlining the methodology phases as well as the selection standards for the systematic literature review

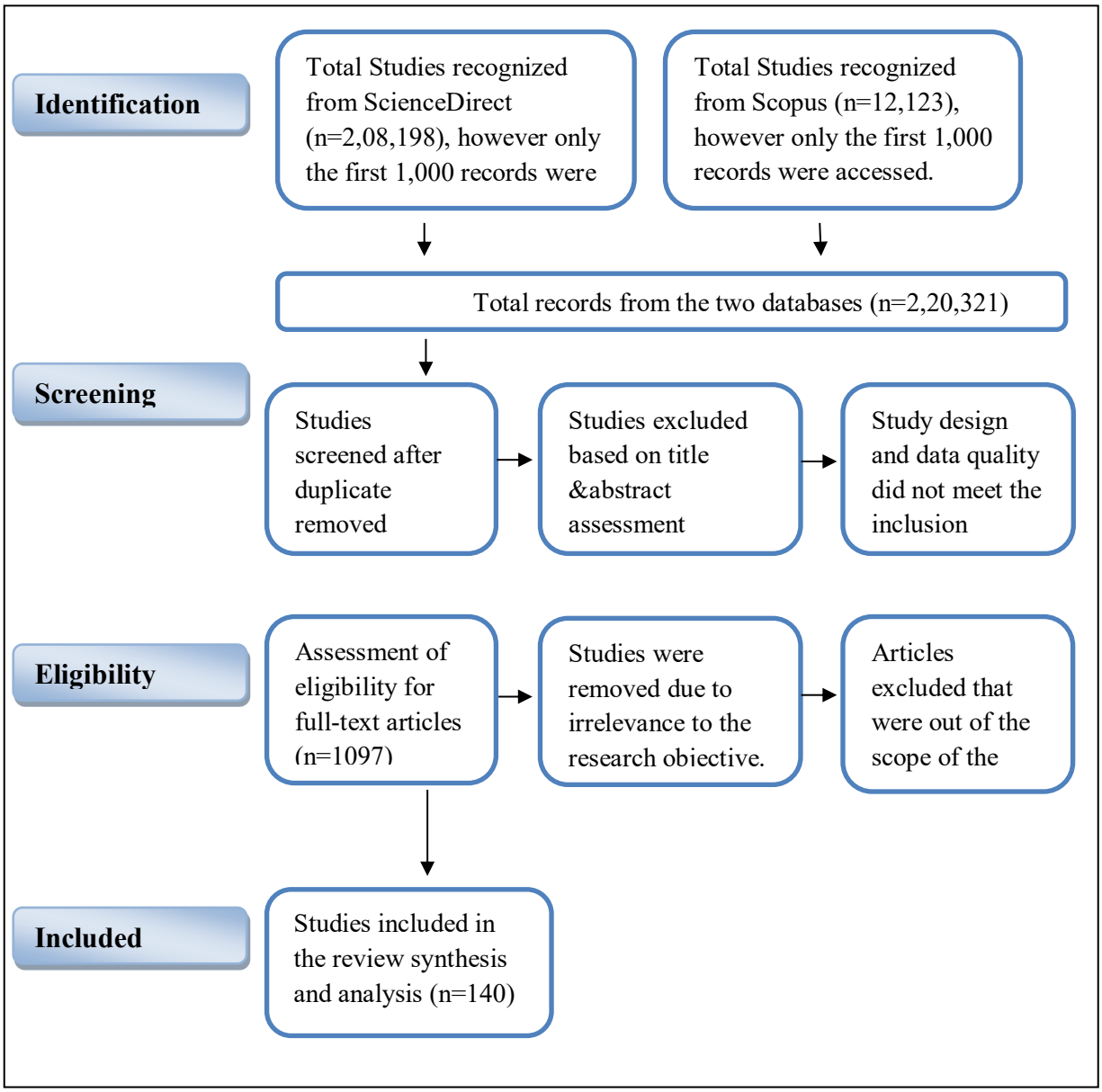
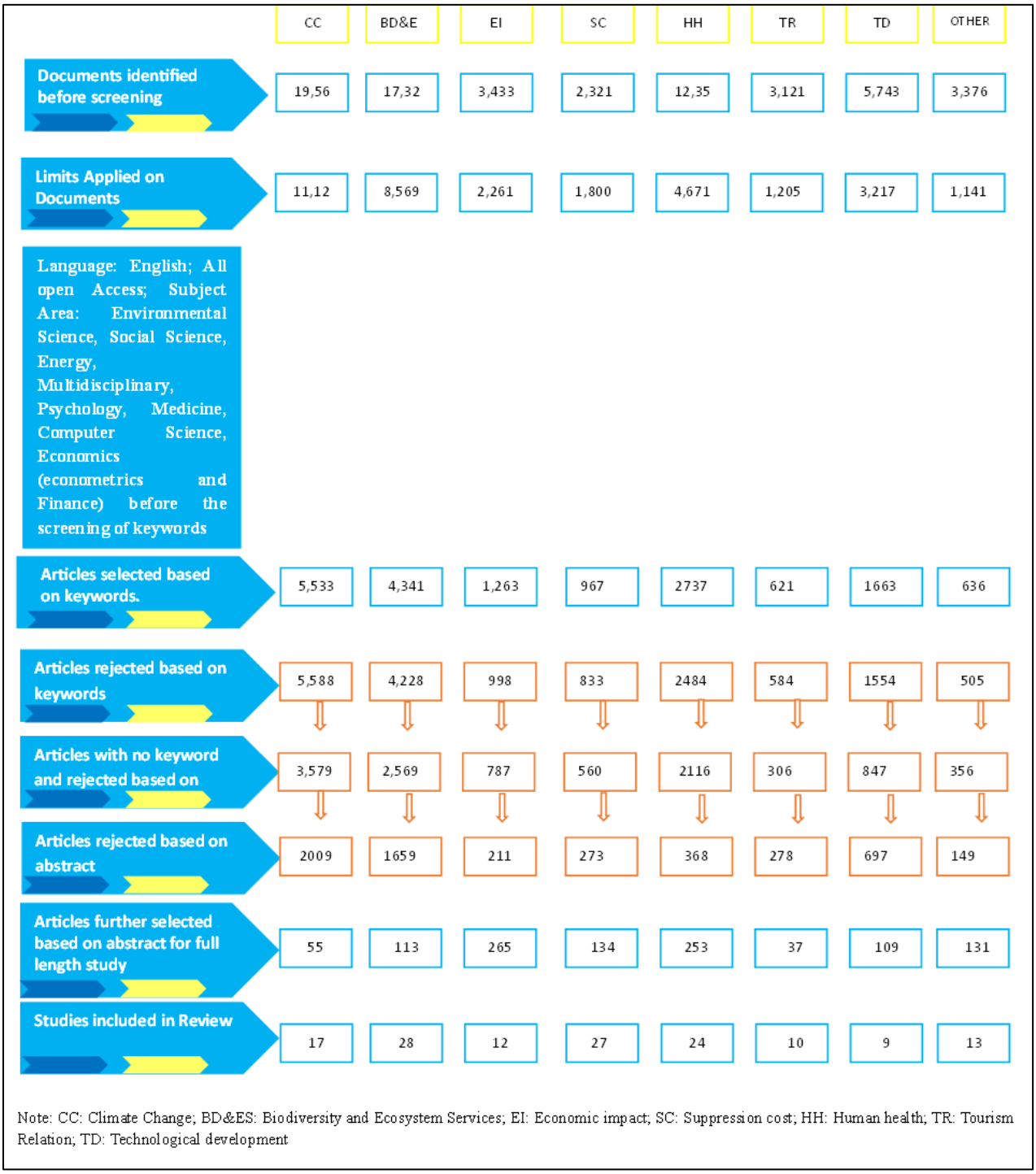


Figure 2.3: Document Selection & Screening Process



Note: CC: Climate Change; BD&ES: Biodiversity and Ecosystem Services; EI: Economic impact; SC: Suppression cost; HH: Human health; TR: Tourism Relation; TD: Technological development

2.2.4. Insights from Key Journals, Geographics

Figures 2.4 to 2.6 offer valuable insights into the literature review, derived from the papers utilized in this analysis. Figure 2.4 highlights the leading journals that are frequently cited, showcasing the primary sources influencing discourse. Figure 2.5 illustrates the geographical regions where research has been conducted, demonstrating the global distribution of studies. These figures enhance our understanding of the key journals and diverse locations that are prominent in the literature, emphasizing the extensive and collaborative nature of forest fire research. Figure 6 further classifies selected studies according to the context in which they were published. This figure illustrates the different document types and subject areas of the research that have been used in the review, highlighting the variety and scope of the studies analyzed.

Figure 2.4: Leading Lights: Key Journals in Review

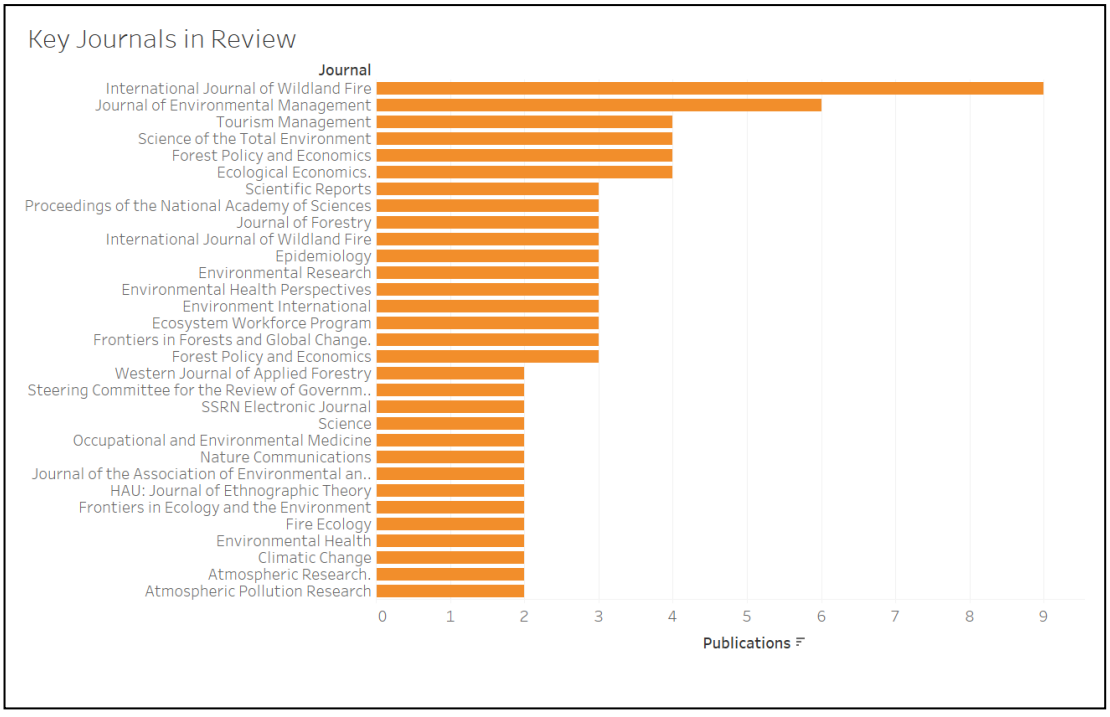


Figure 2.5: Leading Nations in Forest Fire Research Publications

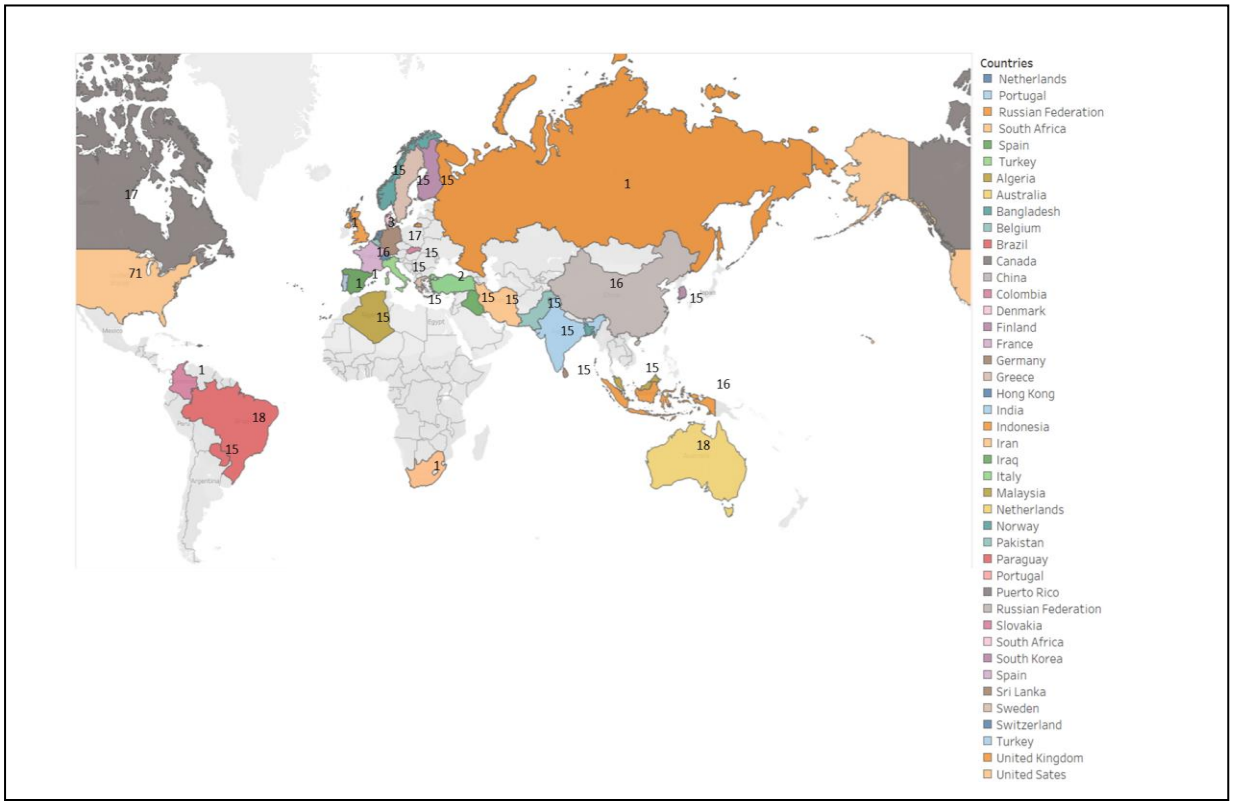
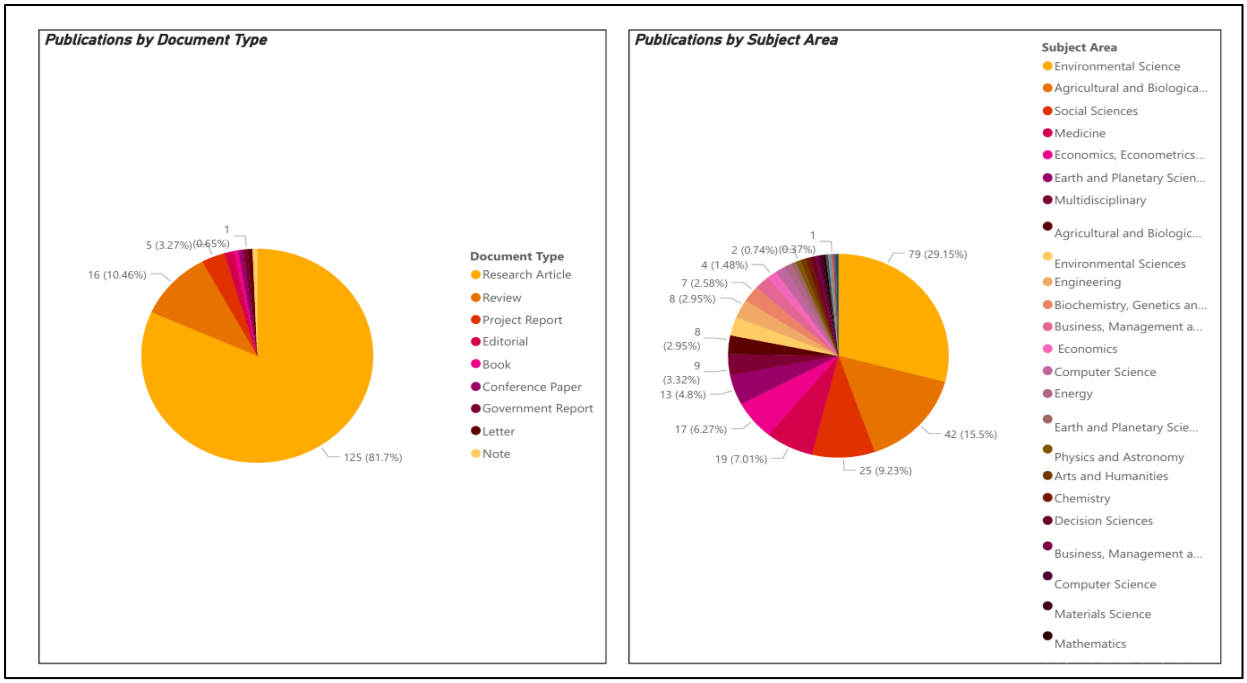


Figure 2.6: Classification of Publications: Document Types and Subject Areas



2.3. Forest Fires and Climate Change

Climate change and forest fires are linked in a self-reinforcing loop. Forest fires are caused by increasingly severe climate change, but in turn, these fires increase the intensity of this phenomenon. This feedback loop also demonstrates the compounding nature of climate change and underscores why emission reduction is so critical. Forest fires pose a high risk to human lives and have severe ecological implications also, contributing to climate change (Burke et al., 2021; Ertugrul et al., 2021). Various studies have shown the influence of climate change on fire season length, frequency, and burnt area (Westerling, 2016). Annually, these fires emit aerosols and greenhouse gases into the environment and destroy hundreds of thousands of acres of land (Williamson & Menounos, 2021). Lozano et al. (2016) used simulation modeling to reveal an increased likelihood of fires in the future, particularly from 2071 to 2100, as supported by higher Fire Weather Index (FWI) levels and more extreme fire days. Forest fires play a dual role, significantly contributing to greenhouse gas emissions, including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2o), thus positioning them as both consequences and contributors to the complex climate change equation (Volkova et al., 2019; Ribeiro et al., 2020). As forests burn, stored carbon is released, further elevating atmospheric GHG concentrations and exacerbating climate change. Climate change and land development's influence on lightning-sparked fires were assessed by Li et al. (2020), finding an increased occurrence in Canada due to human-induced climate change (Gillett et al., 2004). Mansoor et al. (2022) provided recommendations for forest fire control and forest management based on Halofsky et al., 2020 framework. Moris et al. (2020) examined methodological stances on lightning's impact on forest fires. Xu et al. (2020) studied the relationship between forest degradation, fire vulnerability, and climate variability, revealing that forest cover reductions exceeding 40% led to increased fire activity in over 80% of affected areas. Bowman et al. (2020) highlighted reduced water storage in

vegetation due to high evaporation and low precipitation, increasing fire risk. Flannigan et al. (2009) emphasized that climate change, weather conditions, combustible fuels, and ignition agents will impact future forest fires. Additionally, human activity, government regulations, and societal objectives will influence global fire trends. Williams et al. (2019) noted a potential strengthening of the link between human-made climate change and autumn forest fires as temperatures rise, potentially offsetting decreased offshore winter fires. A substantial research gap in the field of climate change and forest fires lies in the development and implementation of comprehensive, proactive, and region-specific mitigation and adaptation strategies. While there is a wealth of research on the impacts of climate change on forest fires, there is a limited focus on practical measures that can effectively reduce the risks and consequences of such fires in various ecological and geographical contexts. Closing this gap is vital, as it would empower communities and policymakers with evidence-based strategies to mitigate the increasing threat of forest fires in a changing climate.

2.4. Forest fires, Biodiversity, and Ecosystem Services

Forest fires are widely recognized as a major driver of disturbances in multiple types of ecosystem processes (Bixby et al., 2015; Roces-Díaz et al., 2019), and the impact on ecosystem services has been poorly assessed. Although for some forest ecosystem, forest fire works as a savior (Beerling & Osborne, 2006). Widespread, high-severity forest fires can disrupt critical ecological functions like changes in the soil properties, disrupting the carbon and water cycles and consuming vast quantities of biomass (Shakesby and Doerr 2006; Santín et al. 2015). Moreover, intense forest fires lead to reduced biodiversity and population declines in a number of species (Pastro et al., 2011; Lindenmayer et al., 2014; Lawes et al., 2015; Leahy et al., 2016; González et al., 2022). Furthermore, forest fires change the behavior of animals, communities, and vulnerability to pathogens (Albery et al., 2021). Pausas & Keeley (2019) argue that when viewed across a broader evolutionary and

socioecological spectrum, fires are beneficial to humanity in most environments. However, Sil et al. (2019) counter this point by suggesting that instead of "wildfire", refer to it as simply “fire” to enable a more balanced view of its impact on human well-being. The articles also underscore the intricate relationship of fire with other ecosystem features and processes and how it can interact to drive social benefits and drawbacks. An integrated ecosystem services–disservices approach to understand and manage practical implications of fire (Pausas & Keeley, 2019). Harper et al. (2018) reviewed a range of essential ecosystem services affected by prescribed fire, such as water quality, carbon dynamics, and habitat structure Schmerbeck et al. (2014) show the importance of fire-driven ecological services (FDES) in tropical dry forests in Andhra Pradesh, India and also demonstrate large economic losses due to forest fires in this region. Roces-Díaz et al. (2021) globally assessed the effects of persistent fires in the last 30 years on ecosystem services, obtaining mixed results, finding improvements in water supply but negative effects on water quality, climate regulation, and erosion control. Mediterranean climate has become a vulnerable site of forest fires that pose potential threats to both the landscape and human welfare (Coban & Erdin, 2020; Sivrikaya & Kucuk, 2021). These fires are hazardous for humans, environmental fauna and flora (Garbolino et al., 2017; Naderpour et al., 2019). Bo et al. (2020) underscored the role of forest fires in desertification, deforestation, land degradation and carbon dioxide absorption. However, despite the crucial part played by forest fires in maintaining ecosystem health, they have posed growing threats to biodiversity globally (Barlow et al. 2019; Feng et al. 2021). De Barros et al. (2022) assessed the substantial habitat loss caused by the mega-fires in 2020, especially by jaguars. Ward et al. (2020) highlighted the extent of Australia's 2019-2020 mega fires on wildlife, showing the aftermath for many native species. Species composition can shift with forest fires as the fire mortality rate changes (Brando et al., 2014; Massad et al., 2015). The post-fire succession is influenced by plant preferences and lifespan (He et al., 2019). In conclusion, forest fires have multifaceted effects on ecosystems,

impacting ecosystem services, biodiversity, and human well-being. An integrated perspective that considers both the positive and negative consequences of fire is crucial for understanding, managing, and communicating its real implications. Existing research predominantly emphasizes ecological aspects, yet a conspicuous gap exists in comprehending the broader, interconnected ramifications of forest fires on ecosystems and human well-being. Thorough socio-ecological assessments are required, encompassing the evaluation of social, economic, and cultural impacts alongside ecological consequences. A socio-ecological perspective can illuminate the extensive effects of forest fires, encompassing economic losses, cultural upheaval, and shifts in community dynamics.

2.5. Economic Impact of Forest Fires

In the global effort to combat forest fires, the "Geospatial-based Environment for Optimization Systems Addressing Fire Emergencies" project emerges as a notable initiative with a total cost of €1,386,000.00 (GEO-SAFE, 2023; Gallego et al., 2019). This project leverages geospatial technology to optimize systems addressing fire emergencies, utilizing advanced mapping and analysis for more precise and efficient emergency response strategies (European Commission, 2023). Alongside this project, various countries have implemented innovative financial strategies to address the threat of forest fires. Indonesia's 'Social Forestry Program', which is supported by the World Bank, empowers communities to sustainably manage forests themselves, ultimately cutting down fire risk (World Bank Group - International Development, Poverty, & Sustainability, 2023; Aryal, 2020). The "Amazon Fire Fund" is part of the Amazon Fund; its mission is to prevent deforestation in the Brazilian Amazon. It allocates resources for research, satellite monitoring, and community initiatives to strengthen the rainforest's defenses against fires and promote sustainability by raising non-reimbursable contributions (Amazon Fund, 2023). In California, the "Forest Resilience Bond" takes a proactive approach by funding critical restoration projects, including controlled burns and

brush removal, to address fire risks (Blue Forest Conservation, 2023). The billion-dollar NASA program "Global Fire Monitoring System", uses real-time fire data to assist with early warnings and rapid response actions (Global Fire Monitoring, 2023). Together, these financial firewalls are a powerful example of the critical importance that financial assistance can play a strong role in protecting forests from fires on an ever-growing scale. However, forest fires are still causing short-term economic losses and increasing firefighting costs. They lead to long-term, chronic economic damages through impacts on timber resources, ecosystems and habitats that often require expensive restoration or mitigation. Both short-term and long-term implications have been done, for instance, studies on economic costs of forest fires, in 2018 California forest fires generated $148.5 billion in short-run which is enough to shave 1.5% off of the state's annual GDP as well. Similarly, the Australian fires in 2020 led to economic losses estimated at roughly $20 billion (Filkov et al., 2020). Rodríguez y Silva et al. (2012) investigated ten large fires in Andalusia and found an 89.41% degradation of timber resources, with stand vulnerability estimated at €157,420,809. The short-term economic benefits of reducing energy poverty due to forest fires in Nepal were considerably lower, estimated at $0.12 million, compared to the expected economic benefit of $2.9 billion (Paudel, 2021). Nielsen-Pincus et al. (2011) observed an increase in federal salaries due to forest fire suppression, but private industry employment and earnings declined significantly. Nielsen-Pincus (2012) reported positive short-term impacts of large forest fires on local employment and wages in the western U.S. Conversely, long-term financial costs associated with U.S. Forest fires were substantial, ranging from $71.1 billion to $347.8 billion in 2016 (Thomas et al., 2017). Mosley et al. (2013) noted that Trinity County's Forest fires in 2008 led to suppression costs exceeding $1 million and over $2 million in private timber losses, resulting in road and forest closures. The tourism market also experienced a considerable decline in annual revenue for rural areas in the long run due to forest fires (Davis et al., 2011). In the long run, forest fires can have both positive and

negative economic impacts, influencing regular business operations and economic activity (Hystad & Keller, 2008). Additionally, a systematic review of forest fire suppression cost estimation by Mattioli et al. (2022) indicated that the cost of battling fires is steadily increasing due to the indirect impact of climate change and the rise in human activities. In India, Sewak et al. (2021) estimated revenue retention of INR.1101 crore due to forest fire damages.

One of the most critical research gaps is related to the absence of comprehensive works on region-specific empirical case studies that also address in-depth the compromising mechanism among the short-term and long-term economic consequences. Closing these gaps is critical to better understand and more effectively mitigate strategies.

2.6. Forest Fire and Suppression Cost

Recognizing the critical importance of understanding the environmental impact of forest fires for effective management (CIFFC, 2022), much research has traditionally centered on the economic aspects of fire control. While many studies have explored the causes of forest fires, such as air pollution Tariq et al. (2023) and fire incidence, including ignition potential Couto et al. (2020), and considered variables like forest fire size distribution Ning et al. (2022), policy tools Morello et al. (2017), and structural damage Alcasena et al. (2022), there has been relatively limited research Plantinga et al. (2022); Hesseln et al. (2010) addressing suppression costs and firefighting expenses in the context of economic versus physical damage metrics. Suppression costs represent a significant portion of the expenses associated with forest fire management (Report on Government Services, 2015). Studies have focused on identifying the main factors influencing these costs and the reasons behind their increase over the past two decades (Calkin et al. 2005; Thompson et al. 2013b; Gude et al. 2013). Notably, a critical research challenge involves identifying factors, interventions, and regulations that exhibit delayed

responsiveness to "significant" fires in terms of magnitude (Gebert et al. 2007; Liang et al. 2008). The increment in suppression cost will keep on increasing due to higher frequencies of these catastrophic climatic events (Barbero et al. 2017). Marshall et al. (2023) found that per-hectare suppression costs decline with an increase in fire area because of the reduction in perimeter-area ratio, whereas total suppression costs per fire rise. As the area increases with the growing population there is an increment in suppression cost and forest fires in these regions, leading to intensified suppression efforts (Sharples et al., 2016). It is unsurprising that fire suppression costs in Spain have surged over the last 20 years. According to data from major wildfires in the southern region between 1993 and 2012, cited by Molina et al. (2016), suppression expenses more than doubled even though the burned areas decreased. For example, the estimated cost of controlling a major fire in Beas in 1993 was €180,660 (equivalent to $205,750 in 2012), whereas extinguishing a fire in Con-Marbella in 2012 was projected to cost €510,000 (or $580,829) and resulted in an 8,230-hectare catastrophe. Global fire management faces the challenge of curbing fire suppression costs while addressing increasingly devastating fires with limited resources. This challenge has led to increased government funding for urgent suppression (Campos et al. 2019; Fisher, 2021; Mendes, 2010). Annual fire suppression costs in the United States are projected to increase by 67% over the next decade (Topik, 2015), having already surpassed $4 billion in 2021 (NIFC, 2021). Other nations also allocate substantial resources to combat fires, with Spain budgeting €600 million annually (MAPA, 2019), Portugal allocating €78.1 million (Comunicar, 2017), and Australia spending $553 million in 2019 (NSW, 2019). In Brazil, the average fire suppression budget in the Amazon and Cerrado biomes is $0.51 ha-1 year-1 and $5.32 ha-1 year-1, respectively. Brazil's fire suppression budget varies by biome (Oliveira et al. 2021). The escalation of using aircraft assets for rapid fire suppression, while seeking to extinguish fires promptly, can lead to ecological drawbacks, particularly in ecosystems adapted to regular fires. This situation underscores the need to balance

immediate suppression efforts and the long-term ecological impact of fire control, especially in fire-adapted ecosystems. Despite significant research, the practical application of proposed frameworks and decision support tools for suppression cost management remains limited. Addressing these challenges may necessitate reevaluating current concepts to encompass broader implementation options.

2.7. Forest Fires and Human Health

Forest fires have significant ecological impacts, one of the most significant being the pollution of the air, especially through particulate matter known as PM2.5. These contaminants may result in increased health issues like respiratory and cardiovascular illness (Stowell et al., 2019; Reid et al., 2016). Several detailed studies have investigated the relationship between forest fire smoke inhalation, specifically PM2.5, and a heightened risk for asthma, along with bronchitis, chronic obstructive pulmonary disease (COPD), and pneumonia (Gao et al., 2023; Liu et al., 2015). For instance, Cobelo et al. (2023) conducted a 16-year study that analyses the effects of forest fires on air quality and health, they concluded that PM2.5 can contribute to thousands of more deaths. Clarke et al. (2022) went into great detail on forest fires, stressing the importance of climate change mitigation. Matz et al. (2020) examined the consequences of forest fires at a local, national and global scale, and emphasized the need for efficient anthropogenic climate change mitigation to prevent such outcomes. Meanwhile, Fann et al. (2018) highlight the adverse economic effects of forest fires in the United States, estimating billions of dollars in healthcare costs. Delfino et al. (2009) investigated the relationship between particulate matter ($PM_{2.5}$) and cardiorespiratory hospital admissions during forest fires in Southern California. In particular, they concluded that there is a strong association between $PM_{2.5}$ and respiratory hospitalization events during fires, particularly among specific age groups. Examining the impact of forest fires on outdoor personnel, Evoy et al. (2022) reported increases in injuries during forest fire smoke episodes, particularly among those with more heat exposure and

agriculture and construction workers. Henderson et al. (2011) were able to show a straightforward association between the occurrence of health problems for patients with pre-existing respiratory diseases and high levels of PM10. Morgan et al. (2010) investigated the correlation between bushfire PM10 and hospital admissions, notably finding significant increases in respiratory diseases like asthma and chronic obstructive pulmonary disease. Künzli et al. (2006) assessed the health of children during forest fires, finding a strong relationship between exposure to forest fire smoke and an array of general symptoms that are most severe in children without pre-existing asthma. Furthermore, Hanigan et al. (2008) estimated daily emergent hospitalizations for cardio-respiratory diseases during fire Events PM10 which showed that associated hospitalization rates were higher, with a marked effect observed among the native population. Xue et al. (2021) evaluated the impact of landscape fire smoke on children's health in low to middle-income countries, revealing an increased risk of newborn deaths associated with $PM_{2.5}$ exposure. In 2010, during Moscow's heat wave and forest fires, Shaposhnikov et al. (2014) analyzed daily deaths, pollution, and temperatures from 2006-2009. They found nearly 11,000 extra non-accidental deaths, spanning different age groups. Roberts and Wooster (2021) estimated the annual mortality caused by landscape fire smoke, attributing millions of premature deaths to this phenomenon, with a significant portion affecting children under the age of five. Wettstein et al. (2018) analyzed emergency department visits for cardiovascular and cerebrovascular diseases linked to forest fire smoke exposure in California, reporting increased rates, especially among younger populations. Alman et al. (2016) highlighted an association between $PM_{2.5}$ from forest fires and hospital visits and stays for respiratory and cardiac outcomes. Studies by Faustini et al. (2015) and Requia et al. (2021) highlighted the relationship of forest fire with PM10 or $PM_{2.5}$ and increased mortality rates. Requia et al. (2021) reported increased respiratory and cardiac hospitalizations for $PM_{2.5}$ associated with forest fires by 23% and 21%, respectively in Brazil (2008-2018). Kollanus et al. (2017) particularly examined the

effect on public health in Europe from $PM_{2.5}$ emissions through vegetation burning, resulting in premature mortalities. Datar et al. (2013) concluded that natural disasters, including forest fires, are likely to have detrimental consequences on health problems and growth retardation in children. Liu et al. (2017) highlighted that Californian counties that experience more days of elevated $PM_{2.5}$ from forest fires are associated with births and asthma-related emergency room visits. A significant research gap in forest fire-related health outcomes is the lack of large-scale and long-term studies investigating the chronic health impacts of exposure to forest fires. Existing research often focuses on immediate or short-term health impacts, but a deeper investigation into the lasting consequences, especially in vulnerable populations, is essential for effective public health planning and intervention strategies.

2.8. Forest Fires and Tourism Relationship

The impact of forest fires on tourism should be distinguished from their broader economic effects. Tourism is uniquely sensitive to visitors' perceptions of safety and desirability, with immediate declines in bookings and cancellations. Reputation recovery is slow, affecting local businesses. Tourism's time-sensitive nature further sets it apart, requiring targeted mitigation strategies. Tourism is essential for the economic growth of various nations, particularly emerging economies (Bhat et al., 2022). However, the tourism industry is increasingly vulnerable to the rising threat of forest fires, leading to immediate repercussions like asset devaluation and decreased recreational appeal. Yet, quantifying the comprehensive economic costs associated with future declines in tourist numbers remains a significant challenge. Research by Otrachshenko and Nunes (2022) indicates that regions affected by forest fires have a substantial negative impact on both domestic and international tourist arrivals. For Portugal, they project economic losses of €17.03 to 24.18 million for domestic visitors and €18.26 to 38.08 million for foreign visitors by 2030, with these costs expected to multiply by at least four by 2050. Kim & Jakus

(2019), examined the impact of neighboring forest fires on visitor patterns in Utah's national parks, revealing economic losses ranging from $2.66 million to $4.50 million due to reduced visitor spending. Hystad & Keller (2008) found that forest fires can influence travelers' decisions, with 25% of respondents willing to postpone vacations due to forest fires. Thapa et al. (2013) explored the impact of forest fires on tourist behavior in Florida, whereas a catastrophic blaze in 1998 resulted in significant losses for the hospitality and other sectors (Butry et al., 2001). Forest fires have diverse effects on recreational demand and hiking, with post-fire hiking demand increasing but mountain biking demand decreasing in some cases (Loomis et al., 2001; Hesseln et al., 2004). Rosselló et al. (2020) found that forest fires are the second most economically damaging category of disasters, with each million dollars allocated to disaster assessment resulting in a 0.03% reduction in tourist numbers. Bauman et al. (2020) stressed the importance of travelers with a higher natural catastrophe empathy scale, especially against the background of natural disasters. To sum up, forest fires can generate significant economic consequences for tourism, which fully justify the need to implement appropriate measures of prevention. An important research gap is the need for the development of sustainable long-term strategies to offset the economic impacts on tourism by forest fires while focusing on adaptability, risk communication and infrastructural resilience. A more comprehensive evaluation of the economic importance of tourism, which also examines a broader base of employment types and revenue characteristics, is required.

2.9. Forest Fires and Technological Developments

The domain of forest fire management holds many scientific and technological breakthroughs that prove to be instrumental in limiting the losses due to these fires. Including technology advances in prevention, surveillance, suppression, land use planning and post-fire restoration indeed offers a set of powerful management tools for the development of more adaptive fire policies. For instance, Olmo et al. (2022)

delve into cutting-edge fire-fighting and forest fire control technologies, covering these innovations in their patented documents. They also expound on the essential programs and guidelines that Iberian organizations have implemented to combat and manage forest fires. Meanwhile, Gnusov et al. (2020) are dedicated to enhancing the efficiency of ground-throwing machines in forest fire prevention, employing techniques like the removal of combustible topsoil layers. Furthermore, Bouguettaya et al. (2022) prioritize early forest fire detection in forested and wilderness areas. They achieve this through the utilization of deep-learning computer vision systems, driven by artificial intelligence and UAV-based visual mapping, which markedly improve fire suppression by enabling the early detection of flames in these natural settings. Dampage et al. (2022) propose an efficient strategy for forest fire detection that relies on wireless sensor networks and machine learning. Their approach results in precise findings, aiding early detection and response to forest fires. Moreover, Cao et al. (2019) introduce the Attention Enhanced Bidirectional Long Short-Term Memory Network (ABi-LSTM) for recognizing forest fire smoke in video footage. This model incorporates spatiotemporal attributes and adjusts attention to different patches in the video, enhancing the accuracy of smoke detection. Joshi and Sukumar (2021) employ artificial neural networks to explore the complex relationships between forest fires and the socio-environmental drivers that influence them. Their models outperform many contemporary fire models in terms of accuracy, revealing the intricate geographical variances in these linkages worldwide. In a tropical peatland setting, Mezbahuddin et al. (2023) examine the benefits of simulating peatland hydrological dynamics for predicting forest fire activity. Their data demonstrates that incorporating eco-hydrologic dynamics significantly enhances the accuracy of fire predictions, particularly during acute drought episodes in regions like Indonesia's Riau. Al-Dhief et al. (2019) thoroughly analyze contemporary mobile ad-hoc network (MANET) routing protocols for forest fire detection. The study reveals that the LARRR protocol proves highly effective in enhancing the detection

of forest fires in these networks. Alkhatib et al. (2014) provides a comprehensive overview of various technologies employed for the detection of forest fires. Their analysis covers a range of methods, including human observation, satellite-based detection, optical sensors, and wireless sensor networks, offering insights into their methodologies and techniques. The existing literature highlights various technological innovations in forest fire management. However, a critical research gap is the need for more in-depth exploration of the practical implementation and effectiveness of these technologies in real-world forest fire scenarios. This entails examining the challenges, limitations, and successes of technology-based approaches, offering insights into more efficient forest fire prevention and control strategies.

2.10. Forest Fires and other effects

The published literature on forest fires highlights the deeply transformative effect of these events on human psychology and overall life satisfaction. Literature from scholars such as Kountouris & Remoundou, (2011) and Maida et al. (1989) studied the effects of fires on psychological health, with serious depressive disorders in the most widespread case, insomnia and fatalities. In addition, Kountouris and Remoundou (2011) explored in Spain, France, Italy and Portugal, the association between forest fires and individuals' happiness which revealed a signification reduction in life satisfaction. Maida et al. (1989) observed the effect of media coverage of fires on mental health status. Looking at this from a social perspective, Wunder et al. (2021) provides a systematic and scientifically accurate method for understanding how landscapes and communities might be resilient to fires by having an all-encompassing fire-prevention approach. (Li et al., 2022) assessed how anthropogenic drivers influence the probability of forest fire occurrence by accounting for factors such as population density, urban proximity, precipitation, altitude, and topographic wetness index and forest type. Analysis in their study found that the risk of forest fire occurrence was strongly correlated with

anthropogenic factors, especially population density and altitude during the 1990s. A recent study by Tariq et al., (2021) also looked at the effect of environmental (elevation, precipitation, forest types, terrain and moisture indices) as well as social-economic (population density, distance from roads and urban areas) on forest fire likelihood. This makes the risk of forest fires in the models almost exclusively an urban phenomenon and proves a sharp correlation between forest fires and factors like population density. Fox et al., 2018 concluded that forest fire occurrences are more in low-density areas. Moreover, Purnomo et al. (2017) talked about the political factors behind forest fires and H. Purnomo et al. (2019) highlighted the consequences of forest fires. They alter the water balance and increase levels of air pollutants in the atmosphere. For example., (Venkatesh et al., 2020), found that following fires causing vegetation loss, increased annual runoff by approximately 25% relative to a typical non-fire year. Comprehensive studies have been performed worldwide, in the United States (Cerdà 2009); and southern Europe (Van Eck et al. 2016; Cerdà et al. 2017) to show the significance of this impact. Yarragunta et al. (2020) noted a sharp uptick in CO, NOx, and O3 during the peak fire activity phase in the western Himalayas. Although extensive literature provided valuable insights on the holistic impacts of forest fires, from various perspectives relating to human and environmental well-being, there is a clear lack of research that addresses long-term social and psychological consequences arising from repeated or chronic exposure to forest fires resulting from these events in affected communities and individuals. Understanding how prolonged exposure to such traumatic events influences mental health, community cohesion, and overall life satisfaction would contribute to a more holistic understanding of the consequences of forest fires. This research could aid in developing more effective support systems and policies for fire-prone regions, ensuring the well-being of communities facing recurrent fire threats.

2.11. Beyond Forest Fires: Other Drivers of Deforestation

Deforestation is a multidimensional phenomenon, and forest fires represent only one of several critical drivers. A large body of research has shown that factors such as commercial logging, timber and paper industries, mining, agriculture, livestock expansion, horticulture, tourism, urbanization, and infrastructure development have historically contributed to forest loss in India (Rudel & Roper, 1997; Burgess et al., 2012; Samuelson, 2012; Surendra et al., 2020; Mishra et al., 2021). Population pressures, both human and bovine, further intensify pressure on forest ecosystems (Dubey et al., 2008). Against this backdrop, while deforestation in India is shaped by diverse and interacting factors, the present thesis focuses specifically on forest fires as a critical yet underexplored dimension.

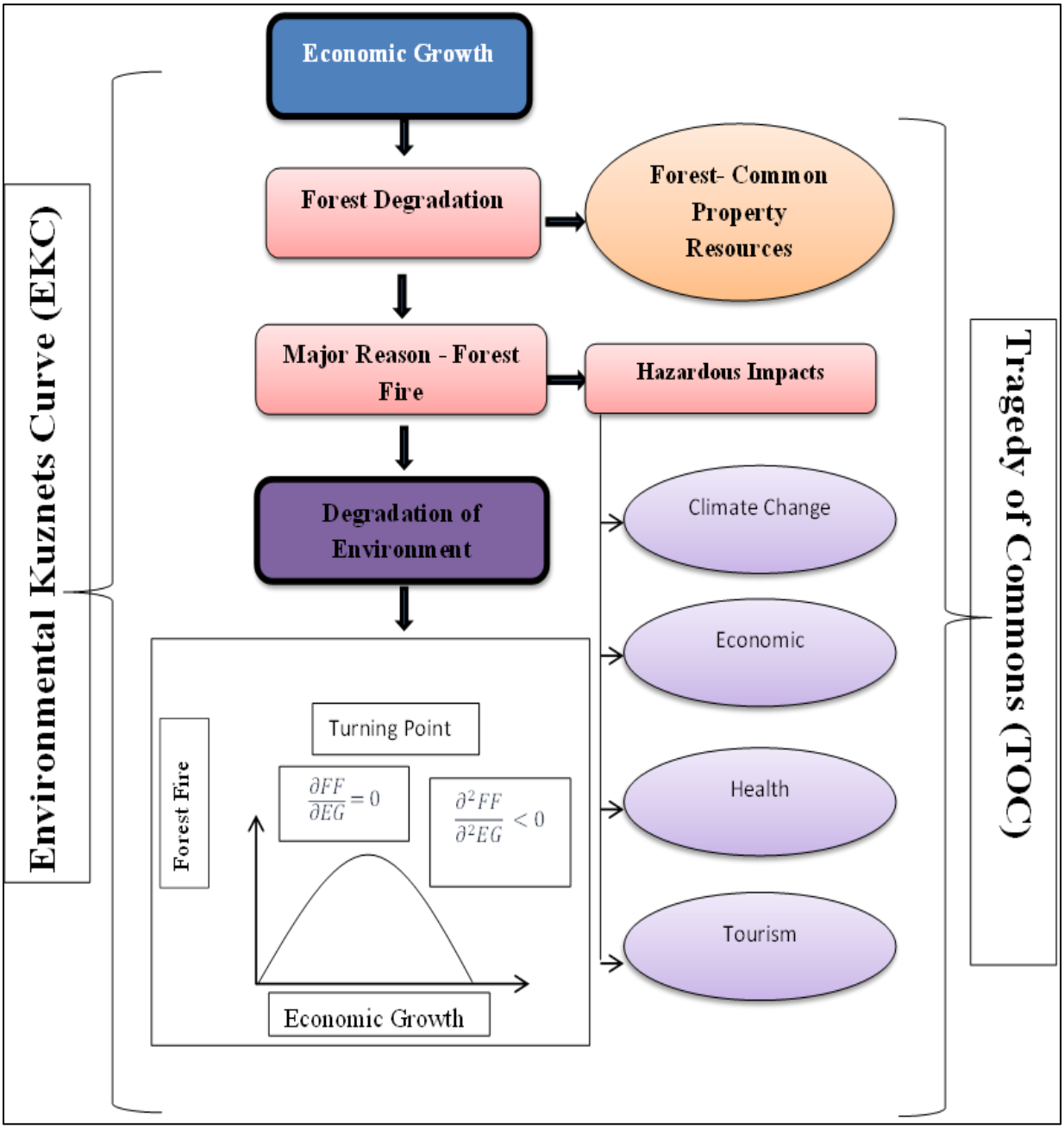
2.12. Theoretical Premise of the Study

In the realm of forest fire management, the integration of two influential theoretical frameworks, the Environmental Kuznets Curve (EKC) theory and the Tragedy of the Commons (TOC) concept, establishes a robust foundation for comprehending the intricate dynamics and implications associated with forest fire management. Originally formulated by Grossman and Krueger (1991), the EKC theory proposes a curvilinear relationship between environmental degradation and economic development. In the context of forest fires, this theory suggests that as economies grow and industrialize, there may be an initial upswing in forest fire incidents and deforestation (Akram et al., 2023; Do & van Noordwijk, 2023). Conversely, the TOC concept, introduced by Hardin (1968), delineates a scenario where self-interested individuals exploit communal resources, detrimentally affecting the collective interest. When applied to forests, the TOC concept implies that various stakeholders, each with independent control over aspects like land use, logging, or fire prevention, may inadvertently erode the forest's resilience to fires due to their limited accountability for ecological and economic costs (Walker et al., 2022; Lorenzen et al., 2022).

The integration of the Environmental Kuznets Curve (EKC) theory and the Tragedy of the Commons (TOC) concept provides a comprehensive framework for understanding forest fire dynamics. Initially, as economies grow, increased industrial activities and resource exploitation, including deforestation, lead to higher environmental degradation and forest fire incidents (Ozcan et al., 2020; Edwards et al., 2020). This phase exemplifies the TOC, where short-term economic gains are prioritized over long-term sustainability, increasing fire risks (O'Mahony, 2021; Vilar et al., 2016). The EKC theory suggests that as societies reach higher income levels, they begin to invest more in environmental preservation measures, such as regulatory frameworks, technological advancements, and proactive fire management strategies, which should help reduce forest fires (Balsalobre-Lorente et al., 2021). However, empirical evidence often contradicts this theory, showing that economic growth does not always lead to environmental improvement. Substantiating this theoretical foundation are empirical findings. Voumik et al. (2023) confirmed the EKC hypothesis, revealing an inverse U-shaped relationship between GDP and environmental degradation in BRICS nations. Meier et al. (2023) delved into the repercussions of forest fires on Southern Europe's economic growth and employment, showcasing the adverse impacts of uncontrolled forest fires on GDP and employment across various sectors. This underscores the pressing need for robust strategies in mitigating and preventing forest fires and addressing the associated challenges. Furthermore, Begum et al. (2021) underscored the pivotal role of effective governance in forest co-management. Positive outcomes, such as enhanced resource management and local empowerment, align with TOC mitigation strategies, while hurdles like top-down decision-making, financial constraints, gender disparities, corruption, and inadequate training mirror TOC dynamics. Integrating EKC and TOC helps to understand that while economic growth initially leads to resource depletion and increased fire risks, these can be mitigated through effective governance and preservation measures. This alignment ensures various stakeholders are accountable for their actions, reducing

overexploitation and enhancing forest resilience to fires. Thus, balancing economic development with ecological preservation is crucial for achieving long-term sustainability in forest fire management.

Figure 2.7: Theoretical Framework



2.13. Research Problem

Forest disruptions are changes in the environment and harmful occurrences that affect forest's structural or wellness, modify its resources, or alter its physical surroundings on any time- or space-scale (FAO, 2005). Although forests offer us numerous benefits for daily living, they are deteriorating quickly due to human activity, endangering the lives of those who are most susceptible. When we look at the USA, forest fires are one of the main symptoms of this decline. In the United States, the expenditure of putting out fires from 2017 to 2021 amounted $2,862,884,200 and an average of 58,985 fires per year and according to recent studies 7,125,643 acres of land were burned in 2021. Another region affected by Forest fires is Canada in 2022, 5,449 forest fires have already been reported nationwide, consuming a total of 1,610,216 hectares, according to the Canadian Interagency Forest Fire Centre National Fire Database. In Canada, there are large yearly variations in the number of forest fires. This is significantly lower than both the total number of fires as well as the territory burned last year (6,709 fires; 4,078,897 ha), as well as the 10-year average, according to the Canadian National Fire Statistics (5,900 fires; 2,785,532 ha). The bushfires that destroyed the temperate forests of southeastern Australia during the fire seasons of 2019–20 was unmatched in terms of extent, severity, and effects. The scale of these forest fires was unprecedented from both an Australian and global perspective because they consumed more than 23% of the temperate forests in southeast Australia. The Black Summer fires had severe social, ecological, and economic impacts. The direct societal repercussions included 33 fatalities and the destruction of more than 3000 dwellings. There have been an estimated 417 deaths from smoking-related causes and 3151 hospitalizations. According to the National Forestry Commission, 2021 will be one of Mexico's forest fire years (CONAFOR). 2,871 forest fires occurred during the first three months of the year, scorching 73,459 hectares of land.

According to CONAFOR, there are 87 active fires burning in 17 of Mexico's 32 states. In 2020, the entire country was shaken by forest fires in the Pantanal, a savanna affected by regular flooding (Marengo et al., 2021). Nearly 30% of the environment, or 40,606 km2, burnt, killing many creatures that couldn't escape the fire. More than 312,140 km2 of the country burned in 2020, with most of the fire foci concentrated in the Amazon basin (46.3%) and the Cerrado, the Brazilian savanna (28.6%), according to Brazil's National Institute for Space Research (INPE). In India, forest fires are a frequent event that occurs frequently in the summer. The MODIS (Moderate Resolution Imaging Spectro-radiometer) instrument found 52,785 forest fires between November 2020 and June 2021, and the SNPP VIIRS instrument found 3,45,989 fires (Suomi-National Polar-orbiting Partnership - Visible Infrared Imaging Radiometer Suite).

2.13.1. Statement of Research Problem

Forest fires pose significant environmental, economic, and social challenges in India, yet their complex interrelationships with economic growth and macroeconomic indicators remain underexplored. In the Northern Indian Himalayan Region, the impacts on environmental benefits, economic well-being, and local livelihoods are insufficiently studied. The social and health effects and sustainability challenges faced by local communities are poorly understood. This knowledge gap hinders effective mitigation strategies and sustainable development planning.

2.13.2. Research Gap

RG 1: There is scarcity of research in understanding the complex, dynamic interrelationships between forest fires, economic growth, and macroeconomic indicators in India.

RG 2: There is a lack of research on how forest fires affect environmental benefits and economic well-being in the Northern Indian Himalayan Region.

RG3: There is insufficient research on the effects of forest fires on social well-being, health, and sustainable livelihoods of local populations in the Northern Indian Himalayan Region.

2.1.3.3. Research Question

RQ 1- What are the dynamic linkages between forest fires, economic growth, and key macroeconomic indicators in India?

RQ 2- How does forest fires in the Northern Indian Himalayan Region impact environmental benefits and economic well-being?

RQ 3- How Forest fires in the Northern Indian Himalayan Region affect the social well-being, health, and sustainable livelihoods of the local population?

2.13.4. Research Objective

RO 1- To explore the dynamic linkages between Forest fire, economic growth, and other macroeconomic indicators in India.

RO 2 - To study the Forest fire - environment - economy nexus in the Northern Indian Himalayan Region.

RO 3 - To investigate the social and health effects of Forest fire on the sustainable livelihood of the local population in the Northern Indian Himalayan Region.

CHAPTER III
STUDY AREA: AN INTRODUCTION

Chapter 3 provides a detailed exploration of the geographical, biodiversity, forest fires point relevant to the study. By focusing on the regions of India, Uttarakhand (UK), Himachal Pradesh (HP), and Jammu & Kashmir (JK), the chapter aims to delineate the unique characteristics and interlinkages that underpin the study's objectives.

3.1. Indian forests

India's extraordinary and multifaceted biodiversity, which encompasses more than one-fifth of the nation's expansive geographical territory, serves as a habitat for approximately 173,000 forest villages, the majority of which are predominantly occupied by indigenous tribal communities that are profoundly dependent on forest resources for their daily sustenance and overall livelihoods, as highlighted by the research conducted by MOEFCC (2018). These tribal communities play a crucial role in contributing to governmental revenue through the extraction and trade of minor forest products, thereby underscoring the intricate and delicate equilibrium that exists between the sustenance of human livelihoods and the principles of sustainable forest utilization. The categorization of forest types into dense, moderately dense, and open forests, as delineated by authoritative bodies such as the Food and Agriculture Organization and the United Nations Framework Convention on Climate Change, is grounded upon specific criteria that include canopy cover measurements and tree height assessments. According to the comprehensive report published by the Forest Survey of India (FSI) in 2021, the total forest and tree cover within the country amounts to an impressive

80.9 million hectares, which represents approximately 24.62 percent of the total geographical area of India, reflecting a notable increase of 2,261 square kilometers compared to the previous assessment conducted in 2019. This expansion signifies a two percent contribution to the global forested area while accounting for one percent of the world's primary forests, thereby illustrating India's vital role in the global ecological landscape. The forests of India, characterized by their remarkable diversity, encompass 18 distinct types that can be systematically grouped into five major categories based on the prevailing dominant vegetation, which include tropical evergreen, tropical deciduous, tropical thorn, montane, and swamp forests, as comprehensively outlined in the FAO's findings from 2015.

3.1.1. Forest fires in India

The occurrence of forest fires in India constitutes a pressing and critical concern, particularly in regions such as Madhya Pradesh, Odisha, and Chhattisgarh, where the prevalence of dry deciduous forests creates an environment conducive to fire outbreaks. Traditional agricultural practices, such as Jhumming, which is a form of shifting cultivation, significantly contribute to the incidence of forest fires, especially in the northeastern states of India. Given the limitations of available statistical information concerning fire incidents, the utilization of satellite data becomes indispensable for accurately monitoring and assessing the situation. It is noteworthy that human activities are responsible for approximately 90 percent of all forest fires in India, thus necessitating the implementation of robust and effective prevention strategies to mitigate these occurrences. Forest fires can be classified into two primary categories, namely natural and human-induced factors, with a comprehensive understanding of these contributing factors being essential for effective mitigation efforts. Dry deciduous broadleaved forests are particularly susceptible to calculated outbreaks of fire, particularly during the dry pre-monsoon periods when incendiary conditions are best. MODIS however indicate fire clusters

in parts of central and east-central India. Recent literature stresses that climate change will affect forest fire systems in many ways. Shivanna et al., 2022 links the rise in frequency of forest fires with climate change resonating with its effects on biodiversity and carbon emissions. Moreover, Mohanty and Mithal (2022) present a nearly ten-fold increase in fires during the previous two decades emphasizing improved forest management practices and approaches. Barik and Baidya Roy (2023) predict substantial changes in fire weather regimes mediated through a climate feedback mechanism, whereas Sewak et al. (2021) provide a comprehensive overview of the growing prevalence and severity of forest fires identifying climatic drivers; regional socio-economic impacts are also discussed for this societal challenge. Collectively, the wisdom gleaned from this body of research gives us a foundation to understand the dynamic relationship between forest fires and climate change. Over the last few years, incidences of forest fires have surged alarmingly and unprecedentedly across regions in India. The forest fire numbers recorded are staggering as the Real Time Forest Alert System, maintained by the Forest Survey of India (FSI), highlighted that 4,225 incidences over November 2018 to February 2019 rose dramatically to a high of 14,107 in one month itself. The Forest Alert System constitutes a component of the Large Forest Fire Monitoring Programme inaugurated by the Forest Survey of India (FSI) on January 16, 2019, which utilizes near real-time data derived from the SNPP-VIIRS satellite. Recent data from the FSI indicates a significant escalation in fire incidents during the summer months, rising by 49.3% over the past three years: from 24,817 incidents in 2016 to 35,888 in 2017 and 37,059 in 2018. While it is well-documented that forest fires frequently occur naturally in the arid summer period preceding the monsoon, the recent devastation observed in Bandipur underscores their increasing unpredictability year after year. As of the initial three months of 2019, there have been approximately 2,500 forest fire alerts recorded nationwide. The rapid onset of destruction and damage caused by forest fires can swiftly escalate beyond control. In Bandipur, estimates suggest that between 10,000 and

20,000 acres of forested land were incinerated within a mere five-day span. Most state forestry departments have established protocols to manage forest fire incidents; however, the rising frequency and intensity of these wildfires present considerable challenges in containment. With 2019 projected to be the hottest year in India since the year 1901, the combination of drier forest floors and extreme temperatures will exacerbate the ongoing struggle against forest fires. Furthermore, it is imperative to train and equip ground-level forestry personnel effectively. The initiation of forest fires is prohibited under the Indian Forest Act of 1927 and the Wildlife (Protection) Act of 1972. The FSI,2017 elucidated various reasons prompting individuals to ignite fires in forested areas, including the clearing of land for shifting cultivation, the preparation of forest floors for the collection of non-timber forest products, and for purposes of hunting or poaching. The phenomenon of uncontrolled forest fires presents a multifaceted challenge that necessitates a comprehensive and long-term policy response, involving enhanced coordination with local communities. Such incidents should be classified as disasters, thereby enabling disaster management authorities to assume a pivotal role in their prevention. The National Forest Commission of 2006 also recommended that any fires consuming an area exceeding 20 square kilometers should be formally recognized as a state disaster. The newly implemented Real Time Forest Alert System of India, which identifies potential fire-prone areas across the nation, must be accorded significant attention by state forestry departments. The World Bank has emphasized that forest fires pose a substantial threat to India's ambition to augment its forest and tree cover by the year 2030. This enhancement could facilitate the creation of an additional carbon sink ranging from 2.5 to 3 billion tonnes of CO_2 equivalent, aligning with India's Nationally Determined Contributions, which are integral to the Paris Climate Agreement and the realization of its long-term objectives.

3.1.1.1. Forest Fire Points

"Forest fire points" designate sites where forest fires have been identified or are currently burning, serving a vital function in environmental conservation, disaster management, and public safety within the Indian context (Figure 3.1). India has a diverse forest cover, with varying biodiversity and plant contents, but the terrain is prone to continuous burning of the forest caused by various reasons that include transition in climatic changes and anthropogenic effects. Understanding these dynamics is essential to enable early interventions, the allocation of resources and policymaking. Kumar et al. (2019) used Geographic Information System (GIS) analysis to rank forested locations by fire risk from very high to less fire prone. According to the Forest Survey of India (FSI) 2021, around 10.66 percent of India's forest region is in extremely to very highly fire-prone zones, with Mizoram, Tripura, Meghalaya and Manipur showing the greatest risk of forest fires. Roughly 65 percent of India's deciduous forests are vulnerable to fires, leading to an annual economic detriment estimated at approximately $104 million (Ashutosh et al., 2019). By 2030, India aims to increase its tree cover to 33 percent of total geographical area (as covered under the framework of Intended Nationally Determined Contributions (INDC). However, the growing number of forest fires will expose a major threat against these goals and demonstrate an urgent need for holistic and sustainable fire management strategies (Dogra et al., 2021).

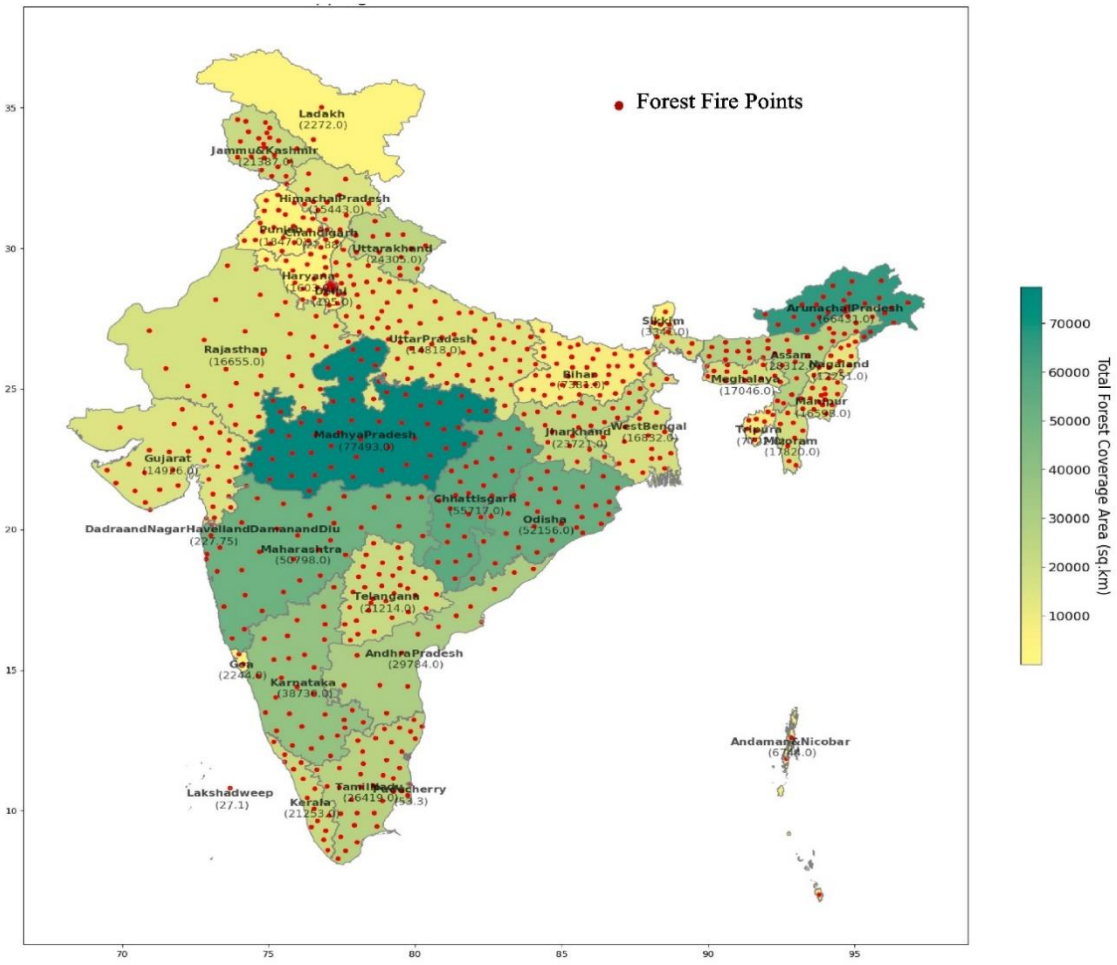


Figure 3.1. Map illustrating forest coverage and historical hotspots of forest fires across India. Source - (Sagar et al., 2024)

Figure 3.2 illustrates annual tree cover loss due to forest fires, measured in hectares, from 2015 to 2023. Significant peaks are observed in 2017 (930.2 ha) and 2019 (883.84 ha), indicating years of intense fire activity. The fluctuating pattern across the years reflects varying fire severity and potential environmental or climatic drivers influencing forest vulnerability.

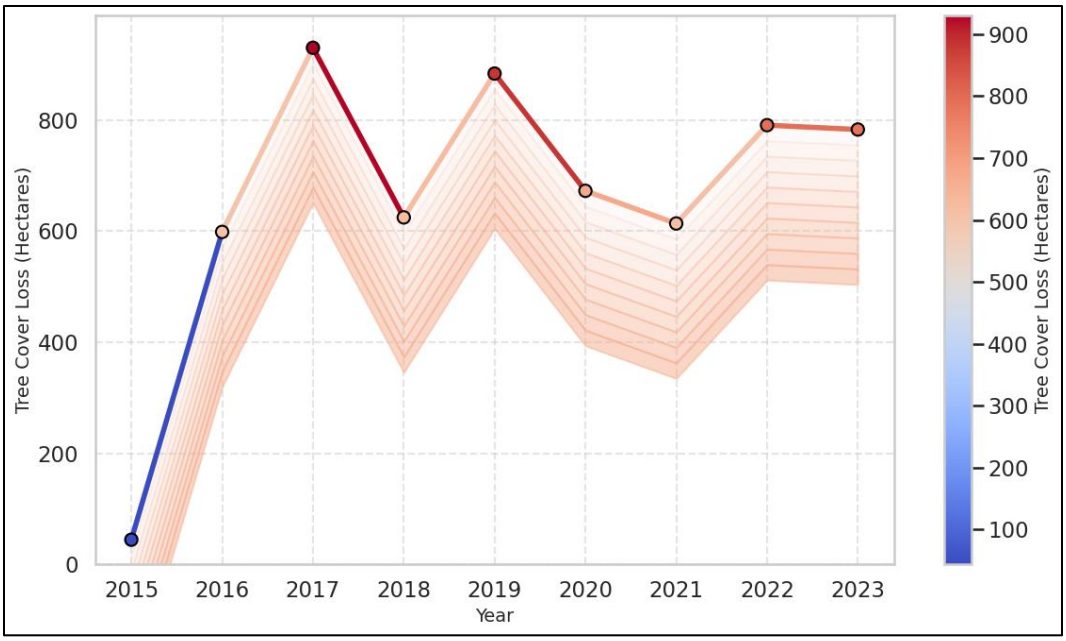


Figure 3.2. Tree cover loss in India caused by forest fires from 2015 to 2023 (in hectares)
Source – Statista (2025)

3.1.1.2. Tree cover loss due to Forest Fires

According to GFW (2024), India's tree cover loss from 2001 to 2023 reflects a highly dynamic and concerning trend, with significant fluctuations indicating periods of both moderate and severe deforestation. The data set begins in 2001 with a tree cover loss of 62,361 hectares, establishing a baseline for the analysis. Over the next two years, this loss gradually decreased, reaching its lowest point of 47,750 hectares in 2003. This period might suggest some level of improvement or stabilization, possibly due to effective conservation efforts or reduced deforestation activities. However, in 2004 tree cover loss suddenly rose to 74,129 hectares and showed a large increment. This may be due to increased land use changes, urban development or industrial expansion. The 8-year period from 2005–2013 saw losses bouncing up and down, with no sign of forest improvements or declines, just a 2nd decade of forest mismanagement. Notable years include 2008 with a peak of

85,953 hectares of tree cover loss over this period and 2011 which had another high value of 88,460 hectares. Once again, 2014 was a milestone because tree cover loss skyrocketed to 139,138 hectares, over two times the extent of earlier years.

Such an extraordinary spike could have been triggered by the phenomenon of big infrastructure projects, agricultural exploitation or even accountable to natural disasters like cyclones and floods. This disturbing trend did not only continue but escalated in terms of deforestation level by reaching an all-time high loss value in the dataset 175,362 hectares as recorded in the year 2016. The economic boom and population growth during this time likely contributed to higher land and resource demand. After this peak, loss of tree cover started to level off somewhat i.e. years 2017 (189,421 hectares) and 2018 (132,233 hectares) still show a high loss but lower than before. Nonetheless, the numbers were still disproportionately high compared to years prior, showing that the battle against deforestation had not yet won. The annual loss estimates ranged from roughly 120,000–137,000 hectares during 2019–20, likely indicating both the effectiveness of conservation efforts in some areas and the continuing pressure to deforest elsewhere. What is interesting is that tree cover loss fell slightly in 2021 to 132,748 hectares and even further in 2022 to a total of 122,629 hectares; this could indicate the implementation of improved forest management practices or environmental policies. But still, 2023 has witnessed another reversal of this trend and the total tree cover loss in India is increased to 143,591 hectares pointing towards consistent vulnerabilities and pressure on the forests across the country. These data emphasize the vital yet continuous issue in forest conservation in India.

3.2. Uttarakhand

3.2.1. Geography and Demographics of Uttarakhand

Uttarakhand is a predominantly mountainous state located in the northern part of India, with an area of 53,483 square kilometers (i.e., 1.63% of total geographical size of India). Geographically, the state is located between latitude 28°43′N to 31°28′N and longitude 77°34′E to 81°03′E. It borders Himachal Pradesh in north, and U.P state in south; but having international borders with Nepal and China thus making its geographical significance enormous. Being partly in the range of Himalayas, Uttarakhand has a variety of terrains including hills and high mountains which contribute to a large elevation difference. The various altitudes create a variety of ecological zones that include glacial areas high in the mountains and subtropical forests lower down. These varying ecological zones result in an extremely diverse climate throughout the state, including temperature variations ranging from 0°C in the colder highlands to 43°C in the warmer valleys and average annual rainfall of approximately 1,500 mm. Ice and bare rock dominate the highlands, while forest cover is denser at lower elevations across the state. Several lifelines of the state such as Ganga, Yamuna, Ramganga and Sharda by and large drain the state that influence not only some local ecosystems but also water resources in nearby plains. These rivers and their many tributaries serve agriculture, hydropower, and water needs for local and regional populations. Administratively, Uttarakhand is divided into 13 districts, all of which are hilly. Unlike other Indian states, Uttarakhand does not have any designated tribal districts, though there is a tribal population component that constitutes 2.89% of the total population. According to the 2011 Census, the state had a population of approximately 10.09 million people, accounting for 0.83% of India's total population. The population density is 189 people per square kilometer, which is lower than the national average. This lower density can be attributed to the challenging topography that

restricts widespread settlement. Rural residents make up a significant portion of Uttarakhand's population, with 69.77% living in rural areas and 30.23% residing in urban centers. Livestock is an integral part of Uttarakhand's rural economy. According to the 19th Livestock Census of 2012, the state had around 4.79 million livestock animals, which play an important role in local agriculture and serve as an economic resource, particularly in the more remote areas where agriculture and pastoralism are prominent. This agrarian and pastoral dependence also increases the local communities' reliance on forest resources for fodder, fuel, and small timber.

3.2.2. Land Use and Forestry Overview in Uttarakhand

Uttarakhand's geography and natural resources make it a state deeply dependent on forest resources. The report indicates that out of the total reported land area of 5,993,000 hectares (ha), about 63.41% (approximately 3,800,000 ha) is classified as forested. This is a significant portion, demonstrating the critical role forests play in both the environment and the economy of the region. Other land classifications include areas not available for cultivation, covering 452,000 ha or 7.54% of the total reported area, as well as permanent pastures and grazing lands, which occupy around 192,000 ha (3.21%). In addition to naturally occurring forests, Uttarakhand has a range of land types dedicated to other vegetation or potential vegetation uses. For instance, 388,000 ha (6.47%) are covered by miscellaneous tree crops and groves, and approximately 317,000 ha (5.29%) are classified as culturable wasteland, indicating land that could potentially be rehabilitated for agricultural or forestry purposes in the future. There are also sections of land marked as fallow (57,000 ha for current fallows and 87,000 ha for other fallows), with cultivated land accounting for 700,000 ha or 11.68% of the total reported area. Uttarakhand's forestry scenario is not just a natural resource aspect; it's central to the livelihood of many residents. The report details the presence of "Van Panchayats," unique

community institutions established in 1921 specifically for forest management. Van Panchayats empower local communities to sustainably manage and utilize forest resources, and as of the report's publication, 12,167 such panchayats are managing a substantial area of 732,688 hectares of forest. These community-managed forests are vital to the state's largely agrarian economy, supporting both agriculture and pastoralism. The Van Panchyats not only allow most locals to freely benefit from the forests for fuel, fodder, and materials for traditional industries, but they also prevent over-exploitation and other threats such as illegal logging or uncontrolled fires. Forest fires are common in dry seasons and require constant monitoring and response action to reduce damage. The state has 38,000 sq km of the Recorded Forest Area (RFA), which is 71.05 percent of the total geographical area of Uttarakhand. Of this, 26,547 sq km are Reserved Forest, 9,885 sq km Protected Forest and 1,568 sq km Unclassed Forests. However, despite this conservation status, a portion of these forests are being diverted to non-forestry use. However, from January 2015 to February 2019, about 2,850.87 ha of forest land was diverted for development activities under the Forest Conservation Act (FCA), 1980 continuing the balancing act between conservation and developmental needs. The state has a network of six National Parks, seven Wildlife Sanctuaries and four Community Reserves protecting its rich biodiversity which in totality covers an area of 3.24% of total geographical area of the State. Corbett National Park is the most famous of all these protected areas and serves as a crucial refuge for several endangered species while also serving the biodiversity tourism sector in Uttarakhand. From alpine meadows to temperate and subtropical to tropical forests, these protected areas play a significant role in the preservation of ecosystems contributing towards making Uttarakhand one of the biodiversity hotspots of Indian Himalayan Region.

3.2.3 Forest Cover Analysis

Periodic assessment of forest cover in Uttarakhand is done using satellite data, and the latest studies use the IRS Resourcesat-2 LISS III satellite for the time span between October 2017 and October 2018. Through this detailed analysis, forest cover in Uttarakhand has been reported to be 24,303.04 sq km accounting for about 45.44% of the geographical area of the State. This is 8.04 sq km more from its previous assessment in 2017 and a positive sign of reforestation, afforestation and conservation efforts taken place in the state. And the forest cover is classified into even finer details through canopy density which indicates how much of the ground is shaded by forest canopy and this also provides information about health and maturity of forest regions. Uttarakhand's forests are classified into three density types:

Very Dense Forest (VDF): These areas have maximum canopy cover, i.e canopy density more than 70%. VDFs are often carbon-storing, diverse forests that is also important for habitat and water retention. Of these, 5,046.76 square kilometers (or 9.44% of the area of the state) is in Uttarakhand. These dense forests are found mainly in remote and protected areas, and they play an important part of the state's life balance and biodiversity.

Moderately Dense Forest (MDF) – any forest whereby the canopy density varies between 40% and 70% Like VDF, but with slightly less canopy coverage so that they still look like semi-mature forests of a dense and biodiverse type. MDF constitutes 12,805.24 sq kilometer which is 23.94 % of the total area of Uttarakhand. These areas support a mix of biodiversity and are critical for the livelihoods of communities that may depend on forest resources.

Open Forest (OF): Open forests have the lowest canopy density, ranging from 10% to 40%. These are typically younger or regenerating forests, often located near

human settlements, or in areas subject to logging and agricultural expansion. Uttarakhand's open forests cover 6,451.04 square kilometers, or 12.06% of the state. These forests still provide essential ecosystem services but are more vulnerable to environmental pressures.

Additionally, scrub areas (land with sparse or degraded forest cover) account for 383.17 square kilometers, or 0.72% of the state's area. These scrub lands are often transitional zones that could be restored to more productive forest types or are areas naturally unsuited for dense forest growth due to soil or climatic conditions. Forest cover gained since the last assessment largely results from focused efforts on afforestation, national forest protection policies, and community initiatives. This is aided by various programs such as Van Panchayats, community forest management practices and plantation drives led by the government. Such efforts not only help to bring more of the state under forests, but also enhance biodiversity, soil quality and water retention capacity in the region that will make it resilient against climate variability and environmental stressors. The forests of Uttarakhand sustain regional biodiversity and a few threatened species as well as river systems that are important for the whole northern Indian subcontinent. In addition, the forests fill an important part in carbon cycles containing large amounts of carbon because of carbon sinks. They sequester carbon that not only benefits Uttarakhand, but the whole world and helps to dampen climate change impacts. These forests provide timber, fodder, fuelwood and medicinal plants that ensure the economic well-being of rural and forest-dependent communities.

Total forest RFA of 38,000 sq.km. is in Uttarakhand covering about 71.05% of geographical area of the state. These areas cover Reserved Forests (RFA, 69.86%), Protected Forests (26.01%) and Unclassed Forests (4.13%), which offer both a basis for conservation efforts and resource extraction on limited grounds. Canopy density-based classification for the forest cover within and outside the RFA. Within the RFA, there are 4,261 sq. km of Very Dense Forest (VDF), 9,269 sq. km of

Moderately Dense Forest (MDF), and 3,260 sq. km of Open Forest (OF), totaling 16,790 sq. km. Outside the RFA, forested land includes 786 sq. km of VDF, 3,536 sq. km of MDF, and 3,191 sq. km of, adding up to 7,513 sq. km. These areas often consist of smaller forest patches and trees beyond formal forest boundaries, managed less strictly but crucial for biodiversity conservation by providing habitat continuity and ecological corridors. The combination of RFA and non-RFA forest cover highlights the importance of balancing formal conservation efforts with sustainable practices on agricultural and communal lands to ensure the health of broader ecosystems.

3.2.3.1. Forest Types and Biodiversity

Uttarakhand's forests are highly diverse, with nine main forest type groups and a total of 43 distinct forest types as per the Champion & Seth Classification (1968). These types span several ecological zones:

a) Moist Siwalik and Terai Sal Forests, representing 15.61% of the forested area, dominate the lowland regions with dense Sal trees (Shorea robusta), adapted to subtropical climates.

b) Subtropical Pine Forests, primarily Chir Pine (Pinus roxburghii), cover nearly 28% of the forested land, dominating the mid-altitude zones and providing both timber and resin.

c) Himalayan Oak Forests, including species like Ban Oak (Quercus incana), make up a substantial portion, with Ban Oak alone covering about 13.86% of the forest area. Oak forests are critical for soil stabilization and water retention, playing a significant role in watershed protection.

d) Alpine and Sub-Alpine Forests are present in high-altitude zones and include unique species adapted to cold, dry climates, such as Juniper and Rhododendron

scrub and alpine meadows. These forests cover about 5.54% of the area and offer habitats for high-altitude wildlife.

A Rapid Biodiversity Assessment conducted between September 2018 and May 2019 highlights the richness of the species within these forest types, cataloging 112 tree species, 73 shrub species, and 94 herb species across various ecological zones. The Shannon-Wiener Diversity Index, a measure of biodiversity, varies widely across forest types. The Himalayan Moist Temperate Forests exhibit the highest tree species diversity (index value of 2.41), indicating a rich and complex ecosystem, while the Dry Alpine Scrub shows the lowest values, reflecting the harsher conditions and limited species diversity typical of high-altitude ecosystems.

3.2.3.2. Tree Cover and Trees Outside Forests (TOF) in Uttarakhand

Tree cover includes smaller forest patches (less than one hectare) and scattered trees within Uttarakhand's agricultural lands, urban areas, and other non-forest areas. This category is assessed separately from the main forest cover, as it comprises trees in both rural and urban landscapes that fall outside the recorded forest areas (RFAs). The report estimates that the tree cover of Uttarakhand increased by 74 square kilometers compared to the previous assessment in 2017, indicating growth in green cover across non-forested areas.

Trees Outside Forests (TOF) provide essential ecological services, including carbon sequestration, habitat for biodiversity, soil protection, and watershed management. This section of the report emphasizes that TOF encompasses both:

- Tree Cover within the RFA: This includes patches of smaller trees interspersed in recorded forest areas, often contributing to the understory in open forests.

- Tree Cover Outside the RFA: Comprising 7,513 square kilometers, this represents tree cover in lands that are not classified as official forests, such as farmlands, residential areas, and along roadways.

The TOF areas in Uttarakhand are diverse, featuring several native and economically valuable species. The most common species in rural areas are Pinus roxburghii (chir pine), Grewia oppositifolia (bhimal), and Quercus leucotrichophora (banj oak). These species play critical roles in local ecosystems and support rural livelihoods. In urban areas, species like Mangifera indica (mango), Cedrus deodara (deodar), and Cupressus spp. are prominent, contributing to urban greenery and enhancing biodiversity.

3.2.4. Forest Fire Prone Areas in Uttarakhand

Forest fires are a critical environmental issue in Uttarakhand, driven by its dry climatic conditions, the presence of highly flammable pine forests, and varied terrain that creates unique fire hazards across regions. The report categorizes Uttarakhand's forests by fire-prone classes, demonstrating that forest fire susceptibility varies across the state. The classifications are as follows:

- Extremely Fire Prone: Comprising 45.56 square kilometers (0.17% of the forested area), these areas are the most susceptible to forest fires. This classification often applies to regions with dense vegetation and dry conditions that facilitate quick fire spread.
- Very Highly Fire Prone: Covering 443.12 square kilometers (1.6%), these areas also present a high risk of fire. The dense presence of pine trees, particularly chir pine (Pinus roxburghii), increases fire susceptibility due to their resinous nature, which easily ignites.
- Highly Fire Prone: This classification represents 2,689.15 square kilometers, or approximately 9.32% of the forested area. These areas have moderately dense

to dense vegetation, often on slopes or ridges that can accelerate fire spread due to wind patterns.

- Moderately Fire Prone: Spanning 7,316.58 square kilometers, or 21.66% of the total area, these forests are somewhat prone to fires but are typically at lower altitudes or with less flammable vegetation.
- Less Fire Prone: The majority of the forested area, 32,275.70 square kilometers (67.25%), falls under this category. These regions often consist of moist temperate forests or areas with higher humidity, making them less likely to experience frequent fires.

3.2.4.1. Tree cover loss due to Forest Fires

According to (GFW, 2024), the tree cover loss in Uttarakhand from 2001 to 2023 reveals a troubling pattern of environmental degradation, driven by forest fires, climate change, and anthropogenic pressures. Starting with a baseline loss of 330.25 hectares in 2001, the figures show significant fluctuations over the years. Losses increased to 534.73 hectares in 2002, followed by a reduction to 269.26 hectares in 2003, indicating effective fire control or fewer incidents that year. However, 2004 saw a sharp rise to 800.36 hectares, and this elevated trend persisted in 2005 with 631.44 hectares lost. A major spike occurred in 2006, with 1147.8 hectares of tree cover loss, reflecting a severe fire season likely exacerbated by prolonged drought. The following years, 2007 and 2008, saw consistently high losses of 1013.89 hectares and 1708.56 hectares, respectively, the latter being among the highest losses recorded, driven by intensified forest fires and dry conditions. In 2009, despite being one of the warmest years, the loss decreased to 951.23 hectares, followed by a further decline to 700.66 hectares in 2010. However, 2011 saw a moderate increase to 811.47 hectares, and 2012 marked another significant spike, with 1363.77 hectares lost due to widespread fire incidents. A

notable reduction occurred in 2013, with only 468.19 hectares lost, reflecting a quieter year for forest fires. The trend reversed in 2014, with losses rising to 606.9 hectares, and continued to climb in 2015 to 778.67 hectares. Another peak was observed in 2016, with 885.09 hectares of tree cover lost during a severe fire season. Losses slightly reduced in subsequent years, with 689.92 hectares in 2017 and 622.17 hectares in 2018, indicating relative stability. However, the figures climbed again in 2019 to 788.27 hectares and sharply increased in 2020 to 991.96 hectares, highlighting persistent vulnerabilities. The year 2021 was one of the worst, with 1778.39 hectares of tree cover lost, reflecting a devastating fire season and environmental stress. While losses decreased in 2022 to 812.68 hectares, 2023 witnessed the highest recorded loss of the period at 1977.24 hectares, marking an alarming peak. Trends in the data show a strong correlation between tree cover loss and forest fire events, with: (i) accumulation of Chir Pine needles due to land-use practices - which favours intense wildfires; (ii) increase length of dry periods, accompanied by elevated temperatures because of climate change. Human activities like grazing, deforestation, and human encroachment have also exacerbated forest degradation. Such patterns point at an immediate necessity for integrated planning based on scientific studies and principles, fire management regimes, as well as tree cover restitution to address the loss of forest in Uttarakhand.

3.3. Jammu and Kashmir

3.3.1. Geography and Demographics of Jammu and Kashmir

Union Territories of Jammu & Kashmir and Ladakh, carved out from erstwhile state of Jammu & Kashmir on October 31, 2019, with an area of 222,236 square kilometers that is about 6.76% of total geographical area of India. With temperate valleys and forested areas to the north, as well as high-altitude deserts on the southern edge of the Himalayas region in Ladakh, this region has multiple unique

ecological zones. The climate varies widely, with sub-zero temperatures in Ladakh's alpine areas and up to 40°C in lower altitudes during summers, while rainfall patterns range from 600 to 800 mm annually, with Ladakh receiving minimal precipitation compared to the lush vegetation supported in parts of Jammu & Kashmir. The region's hydrology is defined by vital rivers like the Jhelum, Chenab, Indus, Ravi, and Tawi, which sustain agriculture, drinking water, and biodiversity. Strategically bordered by Pakistan, Afghanistan, and China, these UTs face challenges in resource management influenced by international policies and ecological disturbances. According to the 2011 Census, the population of the two UTs is approximately 12.54 million, accounting for 1.04% of India's total population, with 72.62% living in rural areas and 27.38% in urban pockets, heavily reliant on agriculture, forestry, and animal husbandry. Scheduled tribes comprise 11.91% of the population, yet neither UT has designated tribal districts. The region also supports 9.2 million livestock, which are integral to rural and tribal economies. Land use patterns reveal 56.65% of the reporting area under forests, 18.69% as cultivable land, and smaller portions for pastures and grazing, reflecting the limited arable land and the influence of challenging terrain and mountainous landscapes.

3.3.2. Forest Area and Classification

The forest area in the Union Territories of Jammu & Kashmir and Ladakh is classified under the Recorded Forest Area (RFA) system. This system designates and legally records forested regions, setting aside lands for conservation and controlled usage based on forest laws.

The total RFA in Jammu & Kashmir and Ladakh covers approximately 20,230 sq. km, representing around 9.10% of the total geographical area of these UTs. The RFA is further subdivided into three categories of protection:

- Reserved Forests: Comprising 87.21% of the RFA, reserved forests have the strictest level of protection where logging, hunting, and other activities are highly regulated or prohibited.
- Protected Forests: Covering 12.61% of RFA, these areas permit limited human activity under regulated conditions.
- Unclassed Forests: Only 0.18% of the RFA falls under this category, typically unprotected and allowing various land-use activities based on local rules.

The forest types in Jammu & Kashmir and Ladakh are the most heterogeneous of all forests in India. These forested areas are classified into eight major groups of forest types (Champion & Seth 1968) and 42 distinct forest types. This diversity is because of differences in altitude, climate and topography creating differing habitats throughout the region. Well known examples include subtropical pine, coniferous, temperate deciduous, and alpine forests. The Jammu & Kashmir Forest Act, 1987 is enacted for conservation/protection of forest and forest land over Jammu & Kashmir. The administration has created a specialized Forest Protection Force that helps enforce forestry laws and guard against illegal logging, poaching, and other aggressive threats. Other forest management schemes support these endeavors, such as the Rehabilitation of Degraded Forests, which emphasizes restoring health and biodiversity of forests, and Eco Task Force that promotes community involvement in reforestation/conservation activities. On similar lines, urban forestry and afforestation programs seek to increase green cover in and around these urban/semi-urban areas through participatory approach incorporating ecological sustainability.

3.3.3. Forest Cover Analysis

According to information obtained from satellite data of IRS Resourcesat-2 LISS III (Sept-Nov 2017), the total forest cover in present JK-Ladakh has been assessed

as 23,611.89 sq. sq km, which is about 10.63 percent of the total area of these UTs. The forest cover has three major types based on the density of canopy.

- Very Dense Forest (VDF): Forests with more than 70% canopy density -- Covering around 4,280.48 sq km, or 1.93% of the area. Such regions are essential for biodiversity preservation as well as carbon capture.
- Moderately Dense Forest (MDF): MDF is 8,612.36 sq. with canopy density of 40-70% km (3.88% of the area), a major part of the forest landscape
- Open Forest (OF): Canopy density varies from 10-40%, area covered: 10,719.05 sq. km (4.82% of the area). These areas are often located in lower altitudes and are important for community forestry and resource provision.

The forests of Jammu & Kashmir and Ladakh have experienced a net increase of 370.89 sq. km in forest cover since the 2017 ISFR assessment, a gain attributed to large-scale plantation and conservation activities, as well as advancements in satellite imagery analysis that have improved the accuracy of forest area assessments. These forests are distributed across various altitude zones, with the 2,000-3,000-meter range hosting the largest forest area of 8,942 sq. km (37.87% of the total forest cover), predominantly comprising coniferous species like pine, fir, and spruce. The 1,000-2,000 meter and 3,000-4,000-meter ranges also support substantial forest cover, accounting for 6,357 sq. km (26.92%) and 3,631 sq. km (15.38%), respectively. However, forest cover significantly declines above 4,000 meters due to the harsh climatic conditions that restrict vegetation growth.

3.3.3.1. Conservation and Protected Areas

Jammu & Kashmir and Ladakh specifically emphasise on the preservation of biodiversity, conservation of important wildlife habitats national parks; wildlife areas, separate programmes for PAN (Protected Areas Network) expanded inclusion 15,912 sq. km, which is 15.59% of the total geographical area and among

the highest PAN [Protected Area Network] in India. They consist of five national parks, which are mainly for biodiversity conservation and involve serious restrictions on human activities; fourteen wildlife sanctuaries where various species can live while allowing tourism and research in regulated forms; and thirty-five conservation reserves that combine biodiversity protection with development practices often involving local communities. In terms of conservation, the region has endangered species like the Kashmir stag (Hangul), snow leopard and Himalayan brown bear along with several bird and plant species that need to be protected. Major initiatives comprise of anti-poaching to counter illegal animal trade, Barry ESZ management controlling developmental activities around PAs and community participation through eco-development practices such as afforestation, training sessions on community awareness along with eco-tourism for ensuring sustainable livelihoods. Emphasizing the planetary significance of these regions, with the PAN network protecting nearly 10% of total protected area footage in India, it highlights both the biodiversity value and continued conservation/restoration need for such landscapes across India.

3.3.3.2. Tree Cover and Trees Outside Forests (TOF)

Tree cover in Jammu & Kashmir and Ladakh, defined as patches of trees with canopy density above 10% but not large enough to qualify as forest cover, spans an estimated 7,944 sq. km and significantly contributes to the region's ecological health by supporting biodiversity, providing resources to communities, and enhancing carbon sequestration capacity. Trees Outside Forests (TOF), which include trees outside recorded forest areas, are categorized into rural and urban TOF. Rural TOF, found on farmlands, grazing lands, and community lands, provide essential resources like shade, fodder, fuelwood, and timber for rural communities, while urban TOF, including roadside trees, park vegetation, and private gardens, improve air quality, offer aesthetic and cooling benefits, and mitigate urban heat

zones. Dominant TOF species in rural areas include Grewia oppositifolia (15.12%), Populus species (6.62%), Quercus leucotrichophora (5.28%), Pyrus species (5.26%), and Salix species (4.29%). In urban areas, the leading species are Grewia oppositifolia (12.76%), Leucaena leucocephala (7.19%), Populus species (6.13%), Acacia modesta (5.56%), and Salix species (5.45%). TOF plays a critical role in carbon sequestration, supporting agriculture and animal husbandry, and serving as a vital resource for local communities to be reliant on these trees for fuel, timber, and fodder, thus enhancing the region's total carbon storage capacity even outside designated forest areas.

3.3.4. Forest Fire Prone Areas

Forest fires are a significant environmental issue that can affect biodiversity, soil quality, and carbon stocks. The report classifies the forest areas in Jammu & Kashmir and Ladakh by fire proneness, aiming to identify regions at high risk and inform management practices. The ISFR 2019 divides forest areas into five classes of fire-proneness:

- Extremely fire prone: 0 sq. km, indicating no areas fall into this highest risk category.
- Very highly fire prone: 24.99 sq. km (0.08% of total forest cover).
- Highly fire prone: 124.96 sq. km (0.38%).
- Moderately fire prone: 924.51 sq. km (2.65%).
- Less fire prone: Most of the forest area, 70,420.60 sq. km (96.89%), is classified as less fire prone.

With nearly 97% of the forest cover categorized as "less fire prone," the forests of Jammu & Kashmir and Ladakh are at a lower risk of widespread fires than many other regions in India. However, the regions marked as moderately, highly, or very

highly prone to fire require targeted fire prevention and rapid-response strategies. Fire management strategies might include building awareness among local communities, establishing fire breaks, implementing controlled burning in certain areas, and maintaining equipment and trained personnel to respond to fire outbreaks effectively. Altitude, temperature variations, and vegetation type influence fire risk in this region. Coniferous forests, which contain resinous trees like pines, are more susceptible to fires, especially in the dry season. Climate change, with rising temperatures and fluctuating rainfall patterns, could also increase the likelihood of forest fires in these areas over time.

3.3.4.1. Tree cover loss due to Forest fires

According to Global Forest Watch, tree cover loss in Jammu and Kashmir from 2001 to 2023 showcases significant variations over the years, reflecting the region's vulnerability to environmental and anthropogenic factors. In 2001, the loss was relatively low at 98.92 hectares, but it surged to 400.41 hectares in 2002, marking a sharp increase likely influenced by deforestation and land-use changes. The loss dropped to 162.08 hectares in 2003, only to peak dramatically at 889.57 hectares in 2004, the highest in the recorded period, indicating a potential spike in forest fires, illegal logging, or large-scale land clearing activities. The subsequent year, 2005, saw a significant reduction to 168.31 hectares, followed by another rise to 519.48 hectares in 2006. Losses then varied moderately, with 219.69 hectares in 2007 and 267.03 hectares in 2008, before slightly declining to 249.1 hectares in 2009 and 288.22 hectares in 2010. A sharp reduction occurred in 2011, with losses dropping to 80.47 hectares, followed by another spike to 399.4 hectares in 2012. Notably, 2013 recorded the lowest loss of 27.93 hectares, reflecting a period of relative stability or effective forest management. Losses remained minimal in 2014 (41.12 hectares) and reached a record low of 1.29 hectares in 2015, with marginal increases in 2016 (4.75 hectares) and 2017 (65.39 hectares). From 2018 to 2023, tree cover

loss remained relatively low compared to earlier years but fluctuated slightly, with 71.95 hectares in 2018, 25.90 hectares in 2019, and 41.27 hectares in 2020. The years 2021 and 2022 saw minor losses of 38.38 hectares and 25.31 hectares, respectively, but 2023 marked a return to higher figures with 99.59 hectares lost. This trend suggests that while there were efforts to stabilize and reduce tree cover loss, periodic spikes occurred due to natural calamities like forest fires, land-use changes, and possibly climate-driven impacts. The data underscores the importance of sustained forest management strategies, particularly in this ecologically sensitive and strategically important region, to curb future losses and promote environmental conservation.

3.4. Himachal Pradesh

3.4.1. Geography and Demographics of Himachal Pradesh

Himachal Pradesh, spanning a geographical area of 55,673 square kilometers (1.69% of India's total area), lies between latitudes 30º22'N to 33º12'N and longitudes 75º45'E to 79º04'E. It shares borders with Jammu & Kashmir to the north, Punjab to the west, Haryana to the south, Uttarakhand to the southwest, and an international boundary with China to the east, underscoring its geopolitical significance. Himalayas state is topographically diverse and is categorized into three regions, namely Shiwalkis (up to the altitude of 1500 m): dry scrub forest and agriculture land, Middle Himalayan Region (1,500 — 3,000 m) temperate forests such as pine, oak and deodar trees; Himadris (above the altitude of 3000m), snow-covered peaks with alpine vegetation. Annual rainfall is 1,800 mm and the climate varies from a near monsoonal sub-tropical in the lowlands (temperatures of up to 35°C) to a harsh sub-alpine zone where sub-zero temperatures can occur. Numerous hydroelectric projects identified on rivers Satluj, Beas, Ravi, Chenab & Yamuna have resulted in bigger and more populous Hydro province yet. With a population

of 6.86 million (0.57% of India's population) as per the 2011 census, the state is predominantly rural (89.97%) with a tribal population comprising 5.71%, residing in districts like Chamba, Kinnaur, and Lahaul-Spiti. The population density is low at 123 people per square kilometer, reflecting the challenging terrain. The state's land use pattern is influenced by its mountainous geography, with 4,576,000 hectares under reporting land use areas. Forests occupy 1,126,000 hectares (24.61%), non-cultivable land 1,127,000 hectares (24.64%), and permanent pastures and grazing lands the largest share at 1,511,000 hectares (33.01%). Miscellaneous tree crops cover 64,000 hectares (1.39%), culturable wasteland 122,000 hectares (2.66%), fallow lands 76,000 hectares (1.67%), and agricultural land (net area sown) 550,000 hectares (12.02%). This land distribution underscores the limited arable land, reliance on forests, and the importance of pastoral resources for the rural economy.

3.4.2. Forest Classification and Types

Himachal Pradesh's forests, exhibiting substantial diversity, are classified into eight main type groups and 39 unique forest types according to the Champion & Seth Classification of Forest Types (1968), reflecting the varied climatic zones, altitudes, and ecological conditions across the state. Broadly categorized into coniferous and broad-leaved forests, the coniferous forests, found at higher altitudes, include species like deodar, pine, and spruce, while the broad-leaved forests, found at lower to middle altitudes, include oak and deciduous species. The vegetation follows distinct altitudinal zonation: lower altitudes (up to 1,500 m) are dominated by dry scrub forests with thorny and dry deciduous vegetation; middle altitudes (1,500-3,000 m) feature mixed deciduous forests, bamboo groves, chir pine forests, oak, and deodar; and higher altitudes (above 3,000 m) are characterized by alpine pastures, fir, spruce, and temperate to sub-alpine forests. Himachal Pradesh hosts over 95 endemic species native to the Western Himalayas,

alongside approximately 150 exotic species (about 5% of its flora) introduced over the past 150 years to enhance forest productivity and conservation. These exotic species have influenced the region's biodiversity while posing challenges for native flora conservation. To support ecosystem services, biodiversity, and climate change mitigation, the state government aims to bring 50% of its geographical area under forest cover through forest restoration, afforestation, and management strategies to combat threats like forest fires and invasive species.

3.4.3. Forest Cover Analysis

The forest cover in Himachal Pradesh, determined using satellite data from the IRS Resourcesat-2 LISS III (October-December 2017), spans 15,433.52 sq km, accounting for 27.72% of the state's geographical area. Forest cover is categorized based on canopy density into Very Dense Forest (VDF), Moderately Dense Forest (MDF), and Open Forest (OF). VDF, with canopy cover greater than 70%, covers 3,112.71 sq km (5.59% of the state area), MDF, with 40-70% canopy cover, covers 7,125.93 sq km (12.80%), and OF, with 10-40% canopy cover, spans 5,194.88 sq km (9.33%). The distribution of forest cover includes areas within and outside the Recorded Forest Areas (RFAs), which legally occupy 37,033 sq km or 66.52% of the state's geographical area. Within RFAs, VDF and MDF dominate, accounting for 10,638 sq km, while forest cover outside RFAs totals 4,796 sq km, managed largely by communities or private stakeholders. The forest cover has increased by 333.52 sq km compared to the 2017 assessment due to plantation drives, natural regeneration, and effective conservation measures. Significant district-wise variation exists, with Shimla (47.14%) and Sirmaur (49.23%) boasting high forest cover due to dense, protected forests, while Lahaul & Spiti has only 1.16% forest cover due to its high-altitude, arid conditions. Forest density also varies by altitude, with the 1,000-2,000 m range supporting the largest forest area with diverse

vegetation types, whereas areas above 4,000 m have minimal forest cover, limited to sparse shrubs and alpine pastures due to harsh climatic conditions.

3.4.4. Biodiversity

Himachal Pradesh's forests, spanning tropical to alpine ecosystems, support a rich array of flora and fauna, thanks to the state's varied altitude and climatic conditions. A rapid biodiversity assessment conducted between September 2018 and May 2019 identified 116 tree species, 99 shrub species, and 109 herb species across different forest types. The Shannon-Wiener Index, used to measure species diversity, revealed that Himalayan Moist Temperate Forests exhibit the highest diversity with indices of 2.95 for trees, 3.25 for shrubs, and 3.48 for herbs, while Subtropical Pine Forests and Tropical Dry Deciduous Forests also display high diversity, supporting species adapted to moderately dry climates. The report highlights biodiversity within specific forest types: Moist Temperate Forests at middle altitudes host a mix of coniferous trees like deodar and oak, while Alpine Scrub and Pastures above 3,000 meters are home to hardy shrubs, grasses, and specialized alpine flora. Himachal's forests also include numerous endemic species critical for regional biodiversity, many of which are conserved in protected areas such as national parks and wildlife sanctuaries. Biodiversity indices confirm rich diversity in Himalayan temperate forests (values above 2.5), while lower values in alpine and subtropical dry forests reflect the limiting effects of harsh climates. However, biodiversity faces significant threats from forest fires, invasive species like Lantana camara and Ageratina adenophora, and climate change impacts, which displace native plants and disrupt forest ecosystems.

3.4.5. Forest Dependence

Himachal Pradesh's rural and forest-fringe communities heavily depend on forest resources for essential needs such as fuelwood, fodder, small timber, and bamboo,

particularly in mountainous regions where forests provide vital energy and materials for daily living. The estimated annual demand for fuelwood is approximately 592,761 tonnes, primarily used for cooking and heating in areas where alternative fuels are costly or inaccessible. Livestock rearing, a cornerstone of the rural economy, requires an estimated 3,255,579 tonnes of fodder annually, which is largely supported by the state's forest cover, grazing lands, and accessible forest types. Additionally, small timber, essential for household construction and maintenance, sees an annual demand of 11,264 cubic meters, while bamboo, though less widely used, is in demand for construction and crafts, amounting to 593 tonnes per year. Such significant reliance poses challenges to forest sustainability, with risks of degradation if resources are not harvested sustainably. The report emphasizes the need for sustainable management practices to balance ecological integrity with the needs of local communities.

3.4.6. Forest Fire Prone Zones

Forest areas in Himachal Pradesh are classified according to fire risk levels. This classification is essential because forest fires can cause significant environmental and economic damage. The classification includes:

- Moderately Fire Prone: Around 1,204.52 sq km of forest area falls under the moderately fire-prone category, accounting for 4.59% of the forest area. This moderate risk is often associated with dry deciduous and coniferous forest types, which have flammable undergrowth and a dry climate for part of the year.
- Less Fire Prone: Most of the state's forests, 35,829.66 sq km or 94.20%, are classified as less fire prone. These areas are typically higher-altitude or moist forest types, which are less susceptible to fire due to cooler temperatures and higher humidity.

- Highly and Very Highly Fire Prone: A small fraction of the forests is classified as highly fire-prone (220.4 sq km) and very highly fire-prone (4.76 sq km). These zones are particularly vulnerable and require close monitoring and management to prevent destructive fires.

The state's Forest Department has implemented fire management strategies, such as the "HP Forest Fire Manual," which outlines procedures for fire prevention, monitoring, and control. It includes community involvement in fire mitigation, as local communities are both affected by and responsible for managing forest resources. This collaborative approach helps reduce fire incidences in the identified zones.

3.4.6.1. Tree cover loss due to Forest Fires

According to GFW (2024), tree cover loss due to forest fires in Himachal Pradesh from 2001 to 2023 highlights notable fluctuations, reflecting the region's vulnerability to environmental and climatic factors. In 2001, the recorded loss was 344.37 hectares, followed by a slight decrease to 338.40 hectares in 2002. A significant reduction occurred in 2003 with 87.86 hectares lost, but 2004 saw a dramatic surge to 716.02 hectares, marking one of the highest losses in the period, likely driven by widespread and severe forest fires. Losses then decreased to 332.28 hectares in 2005 and 203.94 hectares in 2006, indicating potential improvements in fire control or less intense fire seasons. However, 2007 experienced an increase to 358.43 hectares, followed by a moderate decrease to 257.81 hectares in 2008. The trend reversed in 2009 with 428.75 hectares lost, showing the persistence of forest fire threats. A gradual decline was observed in 2010 (219.00 hectares) and 2011 (52.96 hectares), which marked one of the lowest losses in the dataset. In 2012, however, the loss spiked again to 716.59 hectares, mirroring the peak of 2004. This was followed by a substantial decline in 2013 (64.85 hectares) and 2014 (55.32 hectares). Remarkably, 2015 and 2016 recorded minimal losses of 13.28 hectares

and 13.89 hectares, respectively, indicating relatively stable years with fewer fire incidents. Losses rose again in 2017 to 85.07 hectares and continued to climb in 2018 (176.65 hectares) and 2019 (161.75 hectares). A smaller decrease occurred in 2020 with 71.68 hectares, but the following years showed an upward trend: 122.48 hectares in 2021 and 201.96 hectares in 2022. In 2023, the loss rose to 308.17 hectares, reflecting another challenging year for forest conservation. The data underscores the recurring nature of forest fires in Himachal Pradesh and their impact on tree cover. Peaks in losses, such as in 2004 and 2012, coincide with severe fire seasons, while years like 2015 and 2016 highlight periods of effective fire management or favorable climatic conditions. This trend emphasizes the need for sustained efforts in forest fire prevention, climate adaptation strategies, and conservation measures to protect Himachal Pradesh's valuable forest resources.

3.5. Conclusion

Chapter 3 provides an in-depth examination of India’s forest resources, focusing on Uttarakhand, Himachal Pradesh, and Jammu & Kashmir, and their vulnerability to forest fires. These states, known for their dense and diverse forest ecosystems, face significant challenges from the increasing frequency and intensity of fires, driven by climatic changes and human activities. The analysis highlights considerable forest and tree cover loss, with Uttarakhand’s pine forests, Himachal Pradesh’s Shivalik hills, and Jammu & Kashmir’s alpine and temperate regions being particularly affected. Forest fires not only reduce forest cover but also disrupt biodiversity, degrade ecosystems, and impact livelihoods. This chapter underscores the critical need for robust forest monitoring systems and effective fire management strategies to address these challenges and protect the ecological integrity of the Northern Indian Himalayan region.

CHAPTER IV
MODELS, DATA SOURCES AND ESTIMATION METHODS

This chapter outlines the research methodology employed to achieve the stated research objectives, providing a comprehensive framework for the quantitative techniques and approaches utilized. It begins with a discussion of the underlying research philosophy, which guides the study's approach to knowledge creation and aligns the methodology with the objectives of this study. This is followed by a detailed explanation of the research design, including the rationale behind choosing a quantitative approach, and situating the design within the broader context of environmental and socio-economic impact analysis. The chapter then addresses the methodological strategy, elaborating on how it is structured to systematically investigate the multi-dimensional effects of forest fires across health, social, economic, and environmental domains. The selected strategy discusses the specific challenges and demands of studying forest fire impacts in the Northern Indian Himalayan context, justifying the techniques chosen to capture and analyze complex interdependencies. Subsequently, the chapter describes the data collection procedures, providing a thorough account of the materials and instruments used, such as survey tools, datasets, and any relevant secondary sources. The sampling method is outlined, including sample size determination, population characteristics, and sampling technique, along with the rationale for these choices to ensure robust and representative findings.

4.1. Research Philosophy

In research, philosophical foundations shape our understanding of reality (ontology) and our approach to producing and validating knowledge (epistemology). Philosophical "isms" abound that researchers draw on as particular ways of seeing, understanding and exploring reality. They include positivism, empiricism, realism, critical realism, constructivism, interpretivism and pragmatism (Lawani,2021). Each of these philosophies offers different assumptions about what constitutes reality and knowledge, and they are sometimes used interchangeably due to overlapping ideas.

In the realm of social research, the term paradigm is frequently used to describe these philosophical foundations or the fundamental beliefs that guide researchers' actions and worldviews. The term was popularized by Kuhn (1970) to signify a shared framework of concepts, values, and methods within a community of specialists. Paradigms provide a framework for researchers to formulate research questions, and devise methods and analysis, while simultaneously attempting to cope with the complexity of the real world. Related, worldview is a term that has been used interchangeably with paradigm (Creswell & Clark, 2011) and can be defined as "a mental model of reality" or "a way of thinking about the real world as how to interpret the complexities of the real world" (Patton, 2002, p. 69). This study is grounded in pragmatism as a research philosophy because it allows for flexibility and is particularly appropriate to multi-dimensional, complex research questions. Pragmatism as a philosophical tradition emphasizes practical consequences and real-world use, arguing that we must deploy both quantitative and qualitative methods in pursuit of concrete problems. The mixed-methods design gives a base for this research on forest fires, enabling the combination of quantitative congeniality with portrayals that qualitative aspects provide. Although this research is mainly quantitative, pragmatism can be affirmative to use the techniques that fit best for investigating the parts of the research problem (for all types). To achieve

this, two main methods that are used in this study: an Autoregressive Distributed Lag (ARDL) model and Partial Least Squares Structural Equation Modeling (PLS-SEM). The pragmatism paradigm outlined the aim of approaching the research problem from multiple perspectives with the goal of solid, usable findings (Creswell et al., 2007). Consistent with the pragmatic approach, choice of methods is driven by how to best meet the aims of the research. Although the research design is primarily quantitative, its pragmatic roots recognize that qualitative elements, in the form of community assessments or strategies to adapt, are likely important and may both stand-alone or complement quantitative results for a more comprehensive evaluation of fire effects on livelihoods. This study aims to offer pragmatic, evidence-based solutions that can help develop sustainable forest and environmental management policies in the Northern Indian Himalayan region by integrating these approaches into a consistent framework.

4.2. Research Design

A research design is a plan that is designed to direct a researcher when conducting his/her research problem. It contains general guidelines to accomplish the aims of the research, providing it with a structural framework for carrying out the research. Research design points towards making the research more credible by avoiding errors and biases (Kothari, 2004). The solution to the problem that will be studied in this research design is considered specific and based on proper tools and techniques are applied. Research design helps to ensure that research is both valid and reliable. The focus of this research is exploratory with some descriptive elements to it. Exploratory research seeks to investigate unfamiliar situations. The research is exploratory and represents the first time that the phenomenon has not been delved into detail. This is basic open-ended research with an investigation of the unknown (Malhotra et al., 2017). Descriptive research has the goal of acquiring insights into a certain phenomenon or scenario and systematically elucidating it

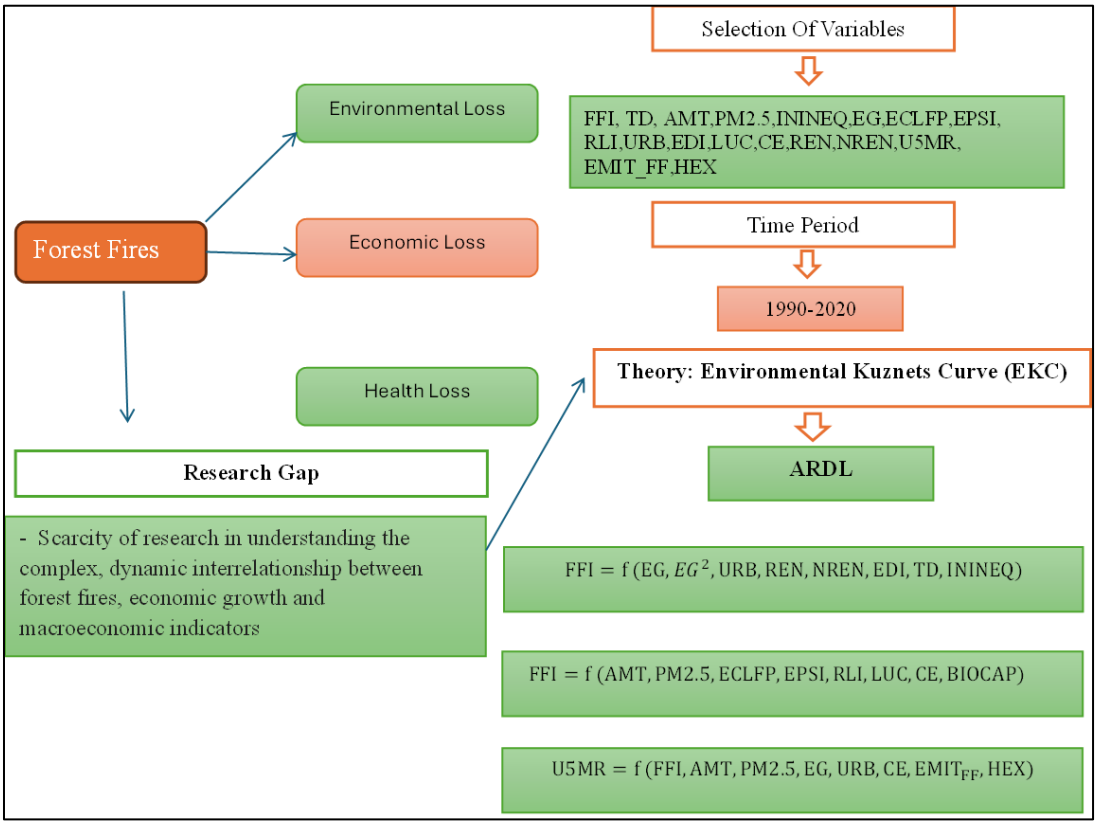
based on inferences. It answers the how, when, what, and where questions of a specific research problem (Kothari, 2004). The study is analytical after the identification of variables and formulation of the hypothesis, and the relationship between validated factors is tested using appropriate statistical techniques. Furthermore, in terms of when the data were obtained, the research can be categorized as cross-sectional and time series. In a cross-sectional survey, all the information is collected from the respondents at one point in time. In contrast, time series research comprises observations collected consecutively across time and at evenly spaced periods. There is a time component in each observation meaning that researchers can study time series data for patterns, trends, and cycles.

4.3. Research Methodology for Objective 1

4.3.1. Conceptual Framework

The conceptual framework (Figure 4.1) for studying forest fires in India, focusing on the economic, health, and environmental nexus, integrates the Autoregressive Distributed Lag (ARDL) model and the Environmental Kuznets Curve (EKC) theory. The ARDL model allows for analyzing both short- and long-term relationships between these variables. The EKC theory is applied to examine whether increasing economic development initially exacerbates environmental damage from forest fires, followed by a mitigation phase as income levels and technological advancements enable better management and prevention strategies. This nexus approach underscores the interconnectedness of forest fires with socio-economic and ecological systems, aiming to inform sustainable policy interventions in India.

Figure 4.1- Conceptual Framework for Objective 1



4.3.2. Hypothesis Development

The hypotheses focus on the complex relationships between forest fires, the economy, health, and the environment in India, built upon the vast global theoretical body relating to environmental, economic, and health interactions. Every hypothesis explores a different sphere of forest fire impact.

4.3.2.1. Forest Fires and Economic Loss

Forest fire incidences in India are significantly influenced by economic and demographic factors, including urbanization and income inequality. Increased

forest fire risks reduce timberland value, as evidenced by an 8.78% decline in timberland values in the U.S. (Wang & Lewis, 2024). The short-term economic benefits of reducing energy poverty due to forest fires in Nepal were considerably lower, estimated at $0.12 million, compared to the expected economic benefit of $2.9 billion (Paudel, 2021). In the context of Nepal, Sapkota (2017) reports that an average forest fire leads to an estimated economic loss of approximately 1.093 million US dollars, while not accounting for the cost of environmental damage and the destruction of flora and fauna. In India, Sewak et al. (2021) estimated revenue retention of INR.1101 crore due to forest fire damages.

H_1: Forest fire incidences are significantly influenced by economic and demographic variables in India.

4.3.2.2. Forest Fires and Environmental Loss

Environmental factors such as soil degradation, rising temperatures, and drought significantly impact forest fire occurrences. Fires deplete soil nutrients, increase erosion, and worsen forest vulnerability (Gómez-Rey et al., 2013). In the Amazon, millions of hectares have burned in the last decade, causing large-scale carbon emissions and biomass loss (Fonseca et al., 2017; Vasconcelos et al., 2013). During the 2015 drought, fire incidents rose by 36%, emitting 454 Tg CO_2 (31% of deforestation-related emissions) (Aragão et al., 2018). The study done by (Jodhani et al., 2024) in Gujarat, India, using Google Earth Engine (GEE) and machine learning models, found a strong correlation between forest fires and rising land surface temperatures (LST), indicating large-scale thermal effects and increased vegetation flammability.

H_2: Forest fire incidences are significantly influenced by environmental variables in India.

4.3.2.2. Forest Fires and Human Health

Forest fires have significant ecological impacts, one of the most significant being the pollution of the air, especially through particulate matter known as PM2.5. These contaminants may result in increased health issues like respiratory and cardiovascular illness (Stowell et al., 2019; Reid et al., 2016). Several detailed studies have investigated the relationship between forest fire smoke inhalation, specifically PM2.5, and a heightened risk for asthma, along with bronchitis, chronic obstructive pulmonary disease (COPD), and pneumonia (Gao et al., 2023; Liu et al., 2015).

H_3: Forest fire incidences significantly affect human health in India.

4.3.3. Model Specification

To comprehensively analyze the impact of forest fires on economic growth and related factors, we propose incorporating these mechanisms into a neo-classical framework of economic growth, akin to the Solow model (Solow, 1956). By doing so, we aim to unravel the intricate ways in which forest fires can influence economic growth dynamics, alter ecological balances, and affect the path toward sustainability.

In the context of a model of economic growth and development, such as the Solow model, forest fires can be characterized as a scalar because they perturb the growth curve. The neoclassical production function approach that links economic growth (Y) with the production factors such as labor (L), capital (K), and Forest (F) is represented as follows:

$$Y = BK^{\alpha}F^{\beta}L^{1-\alpha-\beta} \tag{4.1}$$

where $\alpha > 0$, $\beta > 0$, and $1 - \alpha - \beta > 0$

α, β are the elasticities of Y for K, F, and L, respectively; B is Solow's residual. The above equation can be represented by transforming it into logarithm form, such that:

$$lnY = lnB + \alpha lnK + \beta lnF + (1 - \alpha - \beta) lnL \quad (4.2)$$

Forests are essential ecosystems providing diverse cultural, regulatory, supporting, and provisional services. Culturally, they offer spaces for recreation and spiritual contemplation. Regulating water cycles, preventing erosion, and mitigating floods are vital functions. Supporting biodiversity and ecosystem health, forests sustain complex food webs and carbon sequestration. Provisionally, they supply timber, fuel wood, and medicinal plants, supporting livelihoods and economies. However, forest fires pose severe threats, causing biodiversity loss, habitat destruction, and economic damage. They endanger human life, property, and infrastructure. Mitigating the impact of forest fires is critical for preserving forests' invaluable services and ensuring sustainability.

$$F_t = F_{t-1} + I_t - O_t \quad (4.3)$$

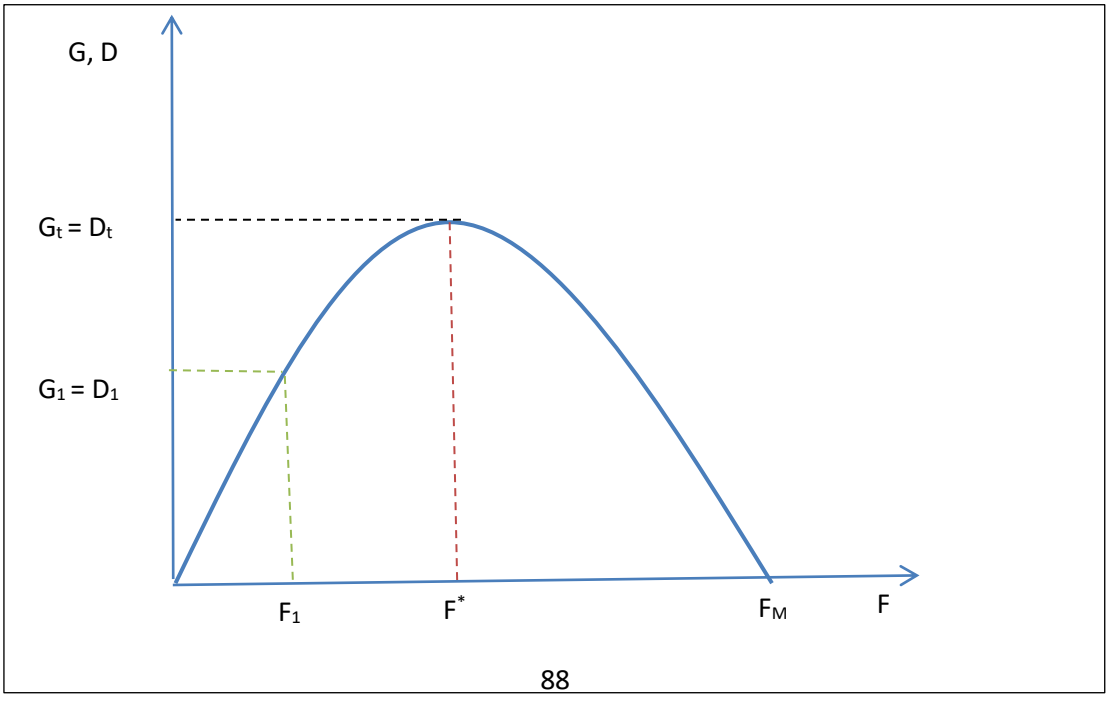
The above equation (4.3) represents a simple model for calculating the current forest area F_t based on the previous year's forest area F_{t-1} the increment in forest area I_t and the decrease in forest area O_t.

$$F_t = F_{t-1} + G_t - D_t \quad (4.4)$$

In equation (4.4) the G_t represents Growth Rate of Forest and D_t as depletion rate. When the growth rate G_t equals the depletion rate D_t , the forest area remains constant ($F_t = F_{t-1}$). This equilibrium signifies sustainable resource management, where forest utilization matches replenishment. Conversely, if depletion exceeds growth, unsustainable resource use occurs, often exacerbated by factors like forest fires. Thus, sustainable forest management is crucial for balancing resource

utilization and conservation, with effective fire management playing a key role in maintaining forest health and resilience. This approach offers a structured lens through which to investigate the complex and multifaceted relationship between forest fires and sustainable economic growth. Figure 4.2 portrays the relationship between forest size (F) and growth (G). Growth initially increases with forest size until reaching a peak at G_m (optimal forest size, F*). Beyond this point, growth declines as forest degradation intensifies. This underscores the importance of maintaining optimal forest sizes for sustainable growth and highlights the need for informed conservation strategies. This study has extended the identical framework used to analyze how forest fires are influenced by the nation's economic performance, environmental degradation, and energy consumption. However, in this context, this study introduces environmental policy stringency, biodiversity loss, tourism development, and natural resource depletion as additional factors that contribute to the exacerbation of forest fires. In this research endeavor, our objective is to evaluate the influence of socioeconomic and environmental variables on forest fires, recognizing their interplay within the neo-classical framework.

Figure 4.2 - Optimal Forest Size and Growth Dynamics



The fundamental model expressed is as follows:

$$\mathrm{FFI} = \mathrm{f}\,(\mathrm{EG}, EG^2, \mathrm{URB}, \mathrm{REN}, \mathrm{NREN}, \mathrm{EDI}, \mathrm{TD}, \mathrm{ININEQ}) \quad (4.5)$$

After logarithmic transformation, equation (4.5) results in the following equation:

$$LnFFI_t = \alpha_0 + \alpha_1 LnEG_t + \alpha_2 LnEG_t^2 + \alpha_3 LnURB_t + \alpha_4 LnREN_t + \alpha_5 LnNREN_t + \alpha_6 LnEDI_t + \alpha_7 LnTD_t + \alpha_8 LnININEQ_t + \varepsilon_t \quad (4.6)$$

$$\mathrm{FFI} = \mathrm{f}\,(\mathrm{AMT}, \mathrm{PM2.5}, \mathrm{ECLFP}, \mathrm{EPSI}, \mathrm{RLI}, \mathrm{LUC}, \mathrm{CE}, \mathrm{BIOCAP}) \quad (4.7)$$

After logarithmic transformation, equation (4.7) results in the following equation:

$$LnFFI_t = \alpha_0 + \alpha_1 LnAMT_t + \alpha_2 LnPM2.5_t + \alpha_3 LnECLFP_t + \alpha_4 LnEPSI_t + \alpha_5 LnRLI_t + \alpha_6 LnLUC_t + \alpha_7 LnCE_t + \alpha_8 LnBIOCAP_t + \varepsilon_t \quad (4.8)$$

$$\mathrm{U5MR} = \mathrm{f}\,(\mathrm{FFI}, \mathrm{AMT}, \mathrm{PM2.5}, \mathrm{EG}, \mathrm{URB}, \mathrm{CE}, \mathrm{EMIT_{FF}}, \mathrm{HEX}) \quad (4.9)$$

After logarithmic transformation, equation (4.9) results in the following equation:

$$LnU5MR_t = \alpha_0 + \alpha_1 LnFFI_t + \alpha_2 LnPM2.5_t + \alpha_3 LnAMT_t + \alpha_4 LnEG_t + \alpha_5 LnURB_t + \alpha_6 LnCE_t + \alpha_7 LnEMIT_{ff_t} + \alpha_8 LnHEX_t + \varepsilon_t \quad (4.10)$$

Where the intercept is denoted as α_0 and the coefficients are $\alpha_1, \alpha_2, \alpha_3, \ldots . \alpha_8$.The error term is indicated by ε_t.

4.3.4. Variables and Data Sources

Table (4.1) demonstrates how each variable contributes to understanding the dynamic interplay between forest fires, economic growth, and broader macroeconomic indicators in India.

Table 4.1. – Environment, economic and health variables and Data sources

Variable	Source	Relevance
FFI (Forest Fire Incidence)	Land Processes Distributed Active Archive Center (LPDAAC)	Represents environmental stress, essential for studying the impact of forest fires on the economy.
TD (Tourist Demand)	UNWTO	Tourism is sensitive to environmental disasters like forest fires, influencing local and national economies.
AMT (Average Mean Temperature)	Berkeley Earth	Affects forest fire frequency and severity, impacting various economic sectors.
PM2.5 (Air Pollution)	Atmospheric Composition Analysis Group, Washington University in St. Louis	Air quality impacts health and economic productivity, especially during forest fires.
ININEQ (Income Inequality)	WDI	Reflects socio-economic disparities that influence vulnerability and resilience to environmental crises.
GDP (Cons.)	World Bank	A key indicator of economic growth and resilience to environmental shocks like forest fires.
Urbanization	World Bank	Urban expansion affects forest cover and increases fire risk, influencing economic outcomes.
ECLFP (Ecological Footprint)	Global Footprint Network	Measures environmental pressure, providing insights into the sustainability of economic growth.

EPSI (Environmental Policy Stringency Index)	OECD	Indicates the effectiveness of environmental policies in mitigating forest fire risks and their economic implications.
RLI (Regulatory and Legislative Index)	OECD	Assesses governance and legislative frameworks in managing natural resources, influencing economic stability.
EDI (Electoral Democracy Index)	OWD	Reflects governance quality and public participation, key to forest fire management.
Land Use	OECD	Land management impacts forest fire incidence and economic productivity.
CE (Carbon Emissions)	Climate Watch Historical GHG Emissions	Forest fires contribute significantly to carbon emissions, affecting climate policy and economic development.
REN/NREN (Renewable & Non-Renewable Energy)	Our World in Data	Energy choices influence mitigation strategies for fire risks and economic sustainability.
IMR (Infant Mortality Rate)	UNICEF	Reflects the indirect health impacts of environmental disasters on economic conditions.
U5MR (Under-5 Mortality Rate)	UNICEF	Highlights public health challenges related to air pollution from forest fires, influencing economic burdens.

EMIT_FF (Emissions from Forest Fires)	FAO	Direct measure of environmental and economic damage caused by forest fires.
HEX (Health Expenditure)	World Health Organization	Captures the economic cost of healthcare related to forest fire-induced pollution and respiratory diseases.

4.3.5. Econometric Approach: Auto Regressive Distributed Lag (ARDL)

When only one cointegrating relationship exists among variables, the Johansen and Juselius (1990) cointegration method may not be appropriate. In such cases, it is more suitable to apply the Autoregressive Distributed Lag (ARDL) bounds testing approach developed by Pesaran and Shin (1995) and further expanded by Pesaran et al. (1996b). The ARDL method is particularly useful because it accommodates variables regardless of whether they are integrated of order zero [I(0)], order one [I(1)], or a combination of both. This flexibility allows for more accurate and reliable estimation of long-run relationships. Unlike the Johansen procedure, which is a system-based approach, the ARDL model works within a single-equation framework. Each variable in the model can be analyzed for its long-term relationship with the dependent variable, making it possible to identify a unique cointegrating vector. Once a cointegrating relationship is found, the ARDL model can be restructured into an Error Correction Model (ECM). This transformation enables the separation of short-run dynamics from the long-run equilibrium relationship, providing deeper insights into both aspects of the data. The ARDL framework includes lags of both the dependent and independent variables without imposing any prior restrictions, hence the term "distributed lag." The main advantage of this procedure lies in its ability to determine whether a long-run equilibrium exists among the variables, given a specific dependent variable. However, when there are multiple cointegrating vectors, the ARDL approach

becomes insufficient, and the Johansen and Juselius (1990) method is preferable due to its system-based nature and ability to handle multiple long-run relationships.

The ARDL$(a, b_1, b_2 \ldots\ldots b_k)$ model specification is given as follows;

$$\varpi(l,t)\mathrm{y}_t = \sum_{i=1}^{k} \beta_i \ (l,k_i)X_{it} + \delta v_t + \varepsilon_t \qquad (4.11)$$

Where,

$$\varpi(l,t)y_t = 1 - \varpi_1 l - \varpi_2 l^2 \ldots\ldots\ldots - \varpi_n l^n$$

$$\beta(l,k) = 1 - \beta_1 l - \beta_2 l^2 \ldots\ldots\ldots\ldots - \beta_f l^{mf}$$

$$for\ i = 1,2,3 \ldots\ldots k, \varepsilon_t \sim iid(0;\delta^2).$$

l is a lag operator such that $l^0 y_t = Z_t, l^1 y_t = y_{t-1}$, and v_t is a s x1 vector of deterministic variables such as the intercept term, time trends, seasonal dummies, or exogenous variables with the fixed lags. t=0,1,2…, m, k=0,1,2….

n=0,1,2……,m, f=0,1,2….,m, i=1,2….,m: namely a total of $(m+1)k+1$ different ARDL models. The maximum lag order, m, is chosen by the user. Sample period, $t = m+1, m+2 \ldots., n$.

4.3.5.1. Requirements for the Application of Autoregressive Distributed Lag Model (ARDL)

1. The ARDL methodology can be employed regardless of whether the variables in the model are purely stationary at level [I(0)], at first difference [I(1)], or a combination of both. This advantage eliminates the need for preliminary unit root testing, which is a common prerequisite in traditional cointegration methods. As a result, the ARDL bounds testing approach

effectively bypasses the pre-testing issues and remains valid when only one long-term relationship exists among the variables.

2. When the F-statistic (based on the Wald test) confirms the existence of a unique long-run relationship and the sample size is relatively small, the ARDL error correction model tends to produce more consistent and efficient estimates compared to other cointegration techniques.
3. In cases where the F-statistic reveals the presence of more than one cointegrating relationship, the ARDL approach becomes unsuitable. Under such circumstances, a multivariate framework, such as the Johansen and Juselius (1990) technique, is more appropriate. This is particularly necessary when different model specifications (each treating a different variable as the dependent one) suggest feedback relationships or multiple long-run equilibria among the variables.
4. When indicators such as the trace test, maximum eigenvalue statistic, or the F-statistic suggest a single cointegrating relationship, it is preferable to use the ARDL approach rather than the Johansen and Juselius method, especially due to the ARDL model's efficiency and simplicity in estimating long-run and short-run dynamics.

4.3.5.2. The Steps of the ARDL Approach

The ARDL (Autoregressive Distributed Lag) cointegration approach is a widely employed method to analyze the long-run relationships among variables, particularly in cases where the variables under consideration are integrated at different levels, i.e., a mix of $I(0)$& $I(1)$.This section outlines the procedural steps for implementing the ARDL approach.

Step 1: Testing for Long-Run Relationship

The first step involves determining whether a long-run relationship exists among the variables. This is done using the Bounds F-test, where the F-statistic is calculated to test the joint null hypothesis that the coefficients of the lagged level variables are equal to zero. The null hypothesis (H_0) assumes no cointegration $(\delta_1 = \delta_2 = 0)$, while the alternative hypothesis (H_1) suggests a cointegrated relationship $\delta_1 \neq \delta_2 \neq 0$. Each variable to be tested serves as a dependent variable, while the others are treated as exogenous. The critical values for the F-statistic are obtained from Pesaran et al. (2001) and Narayan (2005), adjusted for small samples. A computed F-statistic that exceeds the upper critical value indicates rejection of the null hypothesis in favor of cointegration. Cointegration is rejected if it is less than the lower critical value. If the value is between the bounds, no conclusion can be drawn and further tests must be performed (for example, unit root testing) to determine the integration order of each variable.

Step 2: Selecting the Optimal Lag Length

After confirming cointegration, the next step is to determine the appropriate ARDL lag orders. The selection of the correct lag is significant in order to obtain a model with Gaussian error terms (normality, autocorrelation, heteroskedasticity). To select the appropriate lag structure, several criteria such as Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan-Quinn Criterion (HQC), are used. The model with the smallest AIC, SBC, or HQC value is considered optimal. This process ensures robust estimates for the long-run coefficients.

Step 3: Estimation of the Long-Run and Short-Run Dynamics

The ARDL model is reparametrized into an Error Correction Model (ECM) to capture both short-run and long-run dynamics. While differencing variables may resolve issues of stationarity, it eliminates long-run information, which the ECM

seeks to restore. The ECM incorporates the lagged levels of the variables (to capture long-run relationships) and their first differences (to capture short-run dynamics). The error correction term (ECT) reflects the speed at which deviations from the long-run equilibrium are corrected. A statistically significant and negative ECT coefficient confirms the adjustment process, indicating the presence of a stable long-run relationship. By not requiring any unit-root testing, as long as the variables are not I(2), the ARDL approach is flexible compared to others, and it does well even with small sample sizes. However, this may not be the case, if there is more than one long-run relationship between the variables, these methods are no longer appropriate and others such as Johansen cointegration test can be used. In summary, the ARDL framework is a powerful and versatile tool for the analysis of long-run economic relationships, leveraging the advantages of flexibility, optimality in lag selection, and error correction properties.

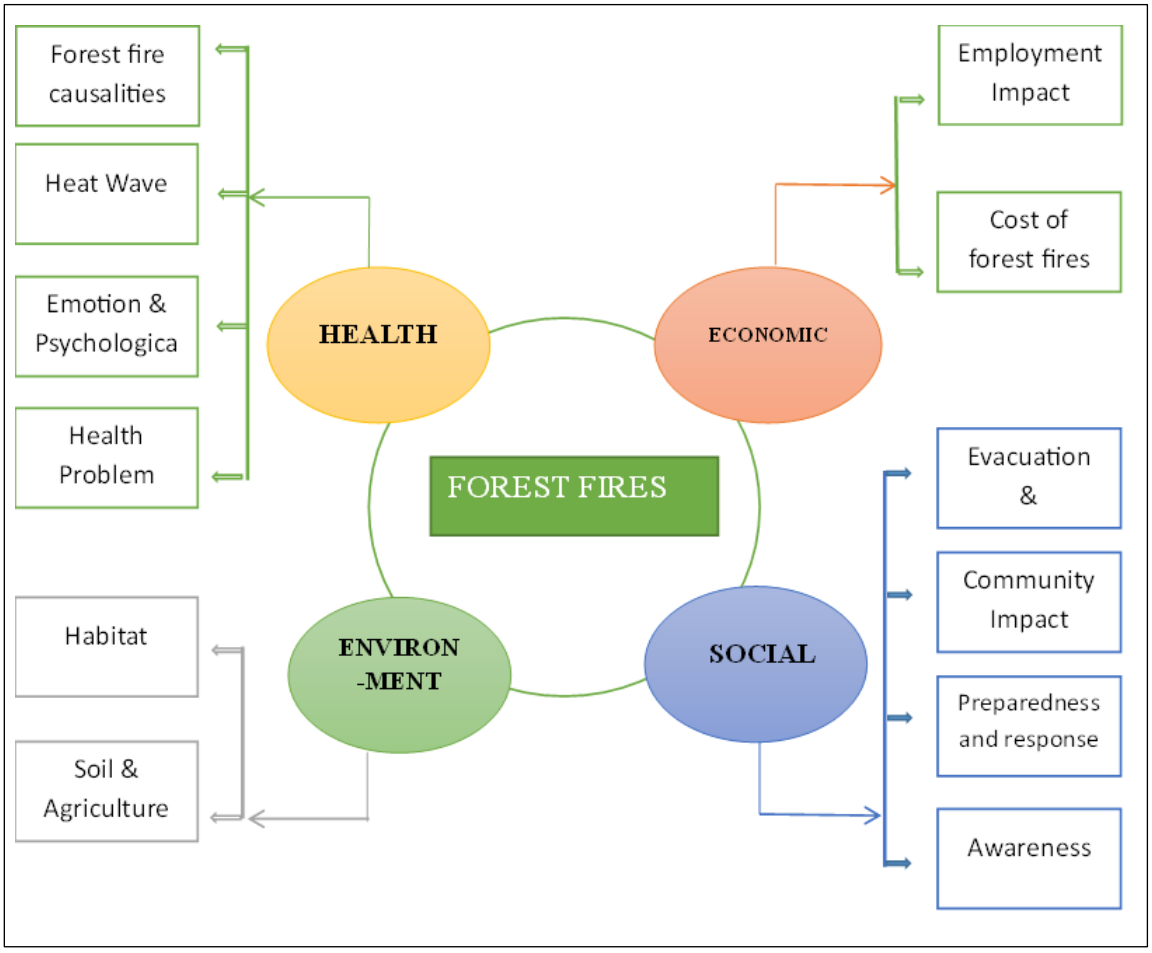
4.4. Research Methodology for Objectives 2 and 3

4.4.1. Conceptual Framework

This study provides a conceptual framework that is constructed to simplify the complex interplay between forest fires, the environment, and the economy in the Northern Indian Himalayan Region by focusing on the socio-economic and health costs of these disasters and their impact on sustainable livelihoods. The underpinnings of this model are based on the theory called "Tragedy of the Commons", that Hardin (1968) originally formulated concerning sustainability and how individual exploitation can lead to a collectively destructive outcome. Forest, as a common-pool resource squeeze to over-harvesting and mismanagement are being incurred leading to increased vulnerabilities to forest fires and their cascading impacts. The relationship between forest fires, the environment, and the economy is presented in this model as an evolving interaction. These forest fires are

damaging the environment as they take away biodiversity, change ecosystems, and release plenty of greenhouse gases into the atmosphere. Consequently, these environmental changes change ecosystem services important for people such as clean air, water regulation, and soil fertility. At the same time, forest fires also have enormous socioeconomic and health costs. The smoke and particulate matter released into the atmosphere due to fires worsen respiratory and cardiovascular diseases, further harming vulnerable populations. The economic impact of Forest Fires includes loss of forest-dependent livelihoods and sustainability of agriculture production, as well as tourism revenue that worsens other development challenges.

Figure 4.3 - Conceptual Framework of RO2 & RO3



4.4.2. Hypotheses Development

These hypotheses focus on the complex relationships between forest fires in the Northern Indian Himalayan Region built upon the vast global theoretical body relating to environmental and socio-economic interactions. Every hypothesis explores a different sphere of forest fire impact, with data and theoretical arguments.

4.4.2.1. Forest Fires Impact the Economy

Several studies have documented the significant direct and indirect economic losses caused by forest fires (Wang et al., 2020; Bayham et al., 2022). Direct losses include the destruction of timber resources, agricultural crops, and infrastructure (Silva et al., 2012). Additionally, forest fires disrupt tourism, a major source of income in forested regions, and adversely affect forest-dependent livelihoods (Suhardono et al., 2024). These economic impacts can exacerbate poverty and reduce regional resilience to climate change (Paudel, 2023)

H1: Forest Fires significantly impact economy.

4.4.2.2. Forest Fires Impact Environmental Benefits

The adverse environmental effects of forest fires are well-documented (Reis et al., 2021). Studies show that fires result in the loss of biodiversity, degradation of soil quality, and reduced carbon sink capacity, which undermines long-term ecosystem stability (Agbeshie et al., 2022). Soil erosion following forest fires severely impacts natural regeneration processes, making it difficult for vegetation to recover (Girona-García et al., 2021). These environmental losses significantly reduce

critical ecosystem services such as carbon sequestration, water regulation, and habitat provision.

H2: Forest fires significantly degrade environmental benefits.

4.4.2.3. Forest Fires Impact Health

Forest fires release vast amounts of smoke and particulate matter (PM), including harmful pollutants like carbon monoxide (CO), nitrogen oxides (NOx), and volatile organic compounds (VOCs) (Costa et al, 2023). Numerous epidemiological studies have linked exposure to forest fire smoke with respiratory illnesses, cardiovascular diseases, and increased mortality rates (Cascio (2018); Chen et al., 2021). Vulnerable populations, such as children, the elderly, and individuals with pre-existing conditions, are particularly at risk (Lindsay et al., 2023). Prolonged exposure to such pollutants can lead to chronic health issues, rising healthcare costs, and decreased life expectancy.

H3: Forest fires significantly impact Human Health.

4.4.2.4. Forest Fires Impact Social Dimensions

Forest fires can have profound social consequences, especially in communities that are heavily dependent on forests for their livelihoods and cultural identity (Wen et al., 2024). Studies have shown that forest fires often lead to displacement, loss of homes, and destruction of culturally significant sites (Knapp et al., 2021). The exhaustion of common-pool resources due to repeated fires can escalate community conflicts and rivalry over scarce resources (Cain, 2023; Ostrom, 1990). Additionally, the psychological toll of losing homes, livelihoods, and community networks can result in long-term mental health issues, social fragmentation, and weakened community cohesion (Shavit et al., 2013).

H4: Forest fires adversely affect social well-being, leading to displacement, psychological stress, and weakened community cohesion.

All these causal hypotheses point out the importance of further research and policy action as they lead to health, social stability, and economic and environmental consequences of forest fires.

4.4.3. Sampling Procedure

A multistage random sampling strategy is applied to capture the representativeness of respondents influenced by forest fires throughout the Northern Indian Himalayan Region (NIHR) with a primary focus on Jammu & Kashmir (J&K), Uttarakhand (UK) and Himachal Pradesh (HP). This is a multi-stage process, which goes as follows:

Stage 1; Selection of States; Jammu and Kashmir, Uttarakhand, and Himachal Pradesh have been selected as the three states/union territories because of their representative geographical, ecological, and socio-economic conditions in the NIHR. **Stage 2; Selection of Districts;** Districts are chosen from each state/UT based on their vulnerability to forest fires, identified through historical data and secondary reports on forest fire incidences and intensity. **(***Criteria: Forest fire-prone districts identified through Forest Survey of India (FSI) reports and state forest department records.)* **Stage 3; Selection of Villages;** Villages within the selected districts are randomly chosen, focusing on areas directly affected by forest fires. The selection is based on proximity to forest fire zones to capture variations in impacts. **Stage 4; Selection of Households**; Households are selected using simple random sampling from village-level records.

4.4.4. Data Collection Procedure

Primary data collection focuses on gathering information from households directly affected by forest fires in Jammu & Kashmir (J&K), Uttarakhand (UK), and Himachal Pradesh (HP). The primary respondents are households located in villages vulnerable to or directly affected by forest fires. These households are chosen to capture the impacts of forest fires on their environment, economy, health, and overall livelihood. A structured questionnaire was designed to study the impact of forest fires and the extent of household dependency on forests, including the use of firewood, fodder, non-timber forest products (NTFPs), and grazing resources, as well as to capture perceptions regarding the frequency and trends of forest fire occurrences over time. Environmental Impact was categorized through the positive Effects of Forest Fires on the Environment; the respondents were aware that there can be ecological advantages such as soil fertility. Economic Impact was captured through loss in local business, employment, and cost of forest fires. Health Impacts were a major issue, and respiratory problems, psychological effects, and heat wave impacts were asked. Community preparedness and awareness were also indirectly asked for by the local households. Further, A questionnaire is pretested in one of each state's villages to finalize the questions and their relevance to local culture and language. In the final version, feedback from pretesting is integrated to provide clarity and assure reliability. After that household survey administration has been done - The questionnaire administration is done through face-to-face interviews with the heads of households or other household-informed members and in a local language (Hindi) so that respondents understand the questions and provide appropriate answers. Additionally, the villages located in the forest fire-prone areas were included in the sampling frame, villages were identified based on information obtained from government reports, data from the Forest Survey of India (FSI), and inputs from local authorities.

Respondents were informed about the intent of the survey and were assured that their responses would remain confidential. Such a systematic and comprehensive data collection process helps establish credibility and validity of primary data, which in turn allows extensive analysis to understand the forest fire–environment-economy nexus as well as socio-economic implications on local people.

4.4.5. Sampling Technique

Multistage random sampling was adopted in the study design (Figure 4.4), to ensure geographical and socio-economic representativeness. Multistage random sampling is highly appropriate for achieving the study's objectives, which focus on understanding the health, social, economic, and environmental impacts of forest fires in the Northern Indian Himalayan Region (NIHR). This technique balances efficiency and representativeness by narrowing down sampling units in stages, making it feasible for large, dispersed populations. It ensures geographical representation across diverse ecological and socio-economic contexts, capturing regional variations in impacts. By incorporating vulnerability-based criteria, the sampling design focuses on high-risk areas, ensuring the inclusion of the most affected populations. Additionally, the method ensures socio-economic diversity, capturing variations in income, occupation, and forest dependency, which are crucial for a comprehensive analysis. Overall, multistage random sampling aligns well with the study's objectives, offering a representative and balanced sample for robust conclusions and policy recommendations.

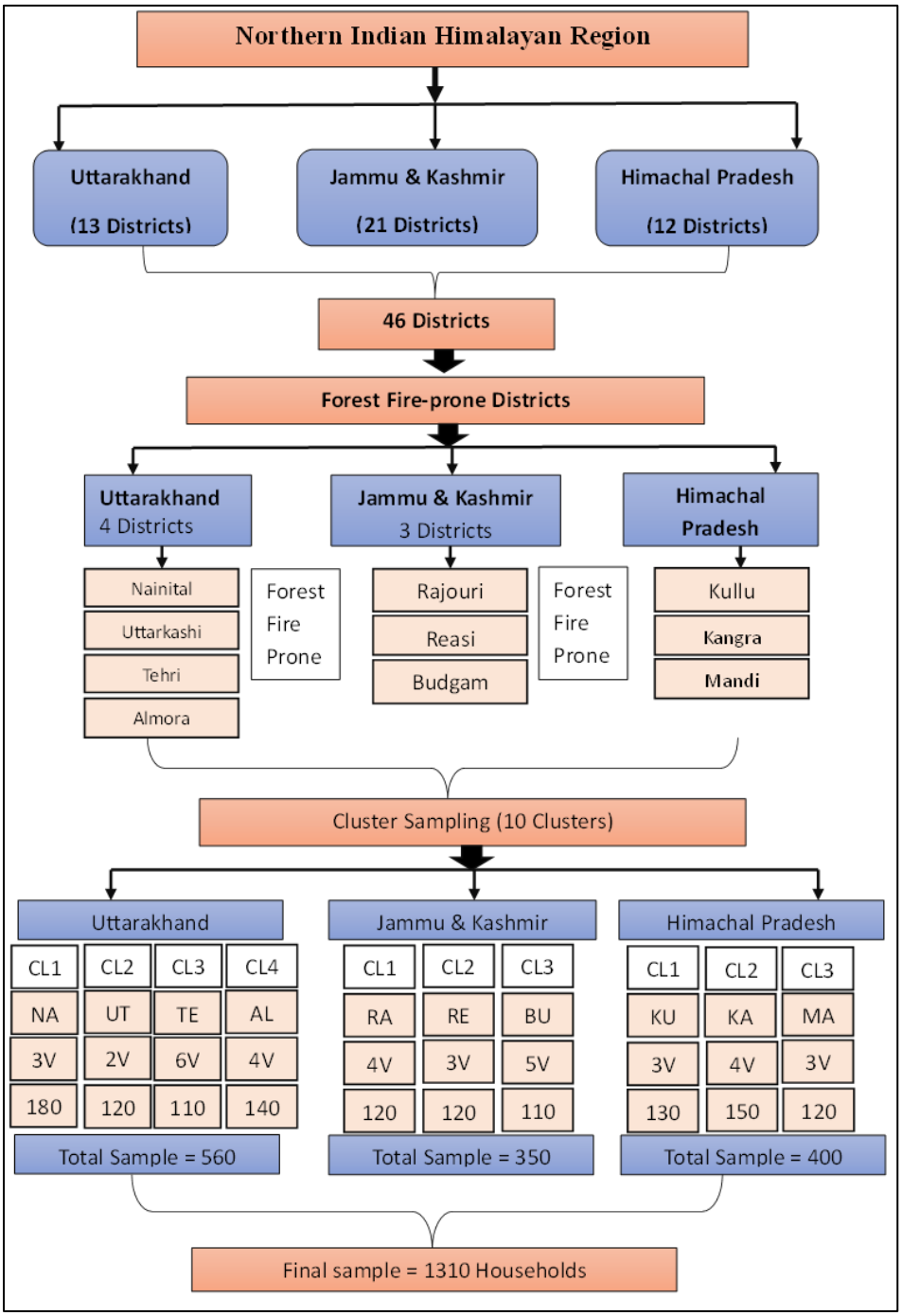
4.4.5.1. Sample Size

In this study the estimation of sample size will be done by using Krejcie and Morgan (1970) formula – $S = X^2NP(1 - P) / d^2(N - 1) + X^2 P(1 - P)$

S = required sample size; X^2 = the table value of chi-square for one degree of freedom at the desired confidence level; N = the population size; P = the population proportion and d = the degree of accuracy expressed as a proportion

Sample sizes adjusted by population proportions are Jammu & Kashmir – 350, Uttarakhand – 560, and Himachal Pradesh – 400.

Figure 4.4 - Multistage Random Sampling



4.4.6. Research Instrument

4.4.6.1. Structure of the Questionnaire

The questionnaire was structured into five sections to comprehensively explore the impacts of forest fires across various dimensions. The sections were designed to capture data relevant to health, social, economic, and environmental impacts, guided by theoretical constructs and empirical studies. Each section contained items addressing specific constructs and sub-constructs to ensure a detailed understanding of the phenomena under investigation.

4.4.6.2. Deciding the Items and Their Scales

The items for the constructs were adapted from validated scales in the literature to ensure the reliability and validity of the measurements. The constructs were divided into higher-order constructs and their respective lower-order sub-constructs (Table 4.2). In Structural Equation Modeling (SEM), constructs represent latent variables that cannot be directly observed but are inferred from measured indicators (Hair et al., 2019). These constructs are categorized into lower-order constructs (LOCs) and higher-order constructs (HOCs) based on their level of abstraction and measurement structure (Sarstedt et al., 2019). Lower-order constructs are the first-level latent variables that are directly measured by observed indicators, representing specific dimensions of a broader concept and serving as the foundational components of SEM models (Koufteros et al., 2009). Higher-order constructs (HOCs) in Structural Equation Modeling (SEM) represent abstract latent variables measured through multiple lower-order constructs, enabling a hierarchical understanding of complex phenomena (Crocetta et al., 2021). Each item was carefully selected and modified to align with the context of forest fires in the Northern Indian Himalayan Region.

Table 4.2- Constructs and Their Adapted Scales:

Higher Order Constructs	Lower order Constructs	Scales adapted from
Health	Health Problem	Agyapong et al. (2020)
	Emotional and Psychological Impact	Brown et al. (2019)
	Heat Wave Impact	Nunes et al. (2020)
	Forest Fire Casualties	Duan and Bombara (2023)
Social	Evacuation and Displacement	Ager et al. (2015)
	Community Impact	Martin et al. (2009)
	Preparedness and Response	Anton and Lawrence (2015)
	Awareness	Tedim and Leone (2020)
Economic	Employment Impact	Fann et al. (2017)

	Cost of forest fires	Troumbis et al. (2021)
Environment	Habitat	Kooistra et al. (2017)
	Soil & Agriculture	Bayne et al. (2019)

These adapted scales ensure that the questionnaire is grounded in established literature while being contextually relevant to the study's objectives.

4.4.6.3. Questionnaire Drafting

All presumptions and unnecessary complexity were stripped out and there was no ambiguity in the questions themselves. The researcher had thought of conducting two types of questions i.e. open-ended and closed-ended but decided to choose only the closed-ended because of their better response rate as compared to open-ended ones along with ease of analysis (Kothari, 2004). The questionnaire was designed using a 5-point Likert scale to capture responses, which included a range from Strongly Agree (5), Agree (4), Neither Agree nor Disagree (3), Disagree (2), and Strongly Disagree (1). This structure helped in giving a systemized and quantifiable way to pipe the feedback of respondents.

4.4.6.3.1. Seeking Expert Opinions

The first draft of the questionnaire was submitted to four experts for testing in terms of language, clarity, and order of questions. The panel included three experts from reputed academic institutes —Xi'an Jiaotong-Liverpool University, BITS Pilani

(Goa Campus), and Jamia Millia Islamia University, and the fourth was a renowned social activist practicing in Dehradun with significant field experience in forest fire management and sustainable livelihoods. These specialists were selected from the professional network of the research supervisor. With the help of experts, we were able to refine our questionnaire. The constructive feedback was mainly aligned with improving the language—being precise, honest, and inclusive; and making the questions more logical. Drawing from hands-on experience in social issues due to forest fires, the expert from Dehradun laid down guidelines for framing questions regarding health, social, economic, and environmental impacts. The distinct viewpoint was significant in recognizing the root-cause gaps and guaranteeing context-specific adaptation of the questionnaire to the Northern Indian Himalayan Region. The questionnaire was further refined based on their recommendations and then underwent pilot testing. The initial version included 59 items across several constructs.

4.4.6.3.2. Pilot Testing

Pilot testing is an essential step used to evaluate the clarity, relevance, and reliability of the questionnaire before administering it on a larger scale. As Cope (2015) states, "A pilot test is the mini version of the research aimed at identification of issues and seeking a solution" (p.197). Following the guidelines of Malhotra and Dash (2011), pilot testing was conducted before administering the final questionnaire. Viechtbauer et al. (2015) suggested that a minimum of 56 respondents are necessary to pilot test at the 95 percent confidence interval (p-value 0.05), while Hair et al. (2011) advise that this could be between 25 and 100. For this study, the pilot testing sample size was set at 91 after removing incomplete responses and outliers.

The data for the pilot test were collected through primary surveys targeting local community members, and representatives affected by forest fires in the Northern

Indian Himalayan Region. Responses were analyzed using SPSS 29.0 software. The constructs' structural validity was determined using Principal Component Analysis (PCA). The questions were then slightly revised to improve the framing and sequencing of questions based on these findings. In addition, Cronbach's Alpha during pre-testing was also used to ensure that all the constructs met the accepted value of 0.7 as suggested by Hair et al., 2011, thus confirming scale reliability for the administration of the final survey.

4.4.6.3.3. Composition of the Final Questionnaire

After completing pilot tests, 14 items were removed empirically as a matter of redundancy/irrelevancy. Those were then taken away for greater recognizability and specificity following the process of creating the instrument. Thus, the final questionnaire included 45 items that were condensed to efficiently measure information relevant to the study objectives. The final constructs are Forest fire exposure (FFE); FD (Forest Dependency); HP (Health Problem); EP (Emotional and psychological impact); HWI (Heat Wave Impact); FFC (Forest Fire Causality); ED (Evacuation and Displacement); CI (Community Impact); PR (Preparedness); AW (Awareness); FS (Forest Soil); FH (Forest Health); CFF (Forest fire Cost); EI (Economic Impact). However, the refined questionnaire retained a proportional representation of all constructs to ensure that the health, social, economic, and environmental impacts of forest fires are adequately covered. This structure not only helped to increase the clarity and coherence of the questions but also the engagement of respondents and the accuracy of their responses. It was determined that this optimized questionnaire was fit for final deployment in the field to yield robust actionable data for the research.

Table 4.3 - Final Questionnaire items

Constructs	**No. of Items**

FFE	4
FD	3
HP	3
EP	3
HWI	4
FFC	3
ED	2
CI	4
PR	3
AW	3
FS	2
FH	2
CFF	5
EI	4

4.4.6.3.4. Data Coding

The dataset was classified into discrete items; numerical codes were assigned to responses in the questionnaire. This coding process is necessary because data must be in a numeric format for statistical analysis software to read. Table 4.4 provides the specific codes for the different data points.

Table 4.4 - Codes

Measures	**Items**	**Codes**

Gender	Male	0
	Female	1
Age	<18	0
	18-30	1
	30-42	2
	42-64	3
	64-76	4
Education	Not educated	0
	High school or below	1
	Intermediate	2
	Under-Graduate	3
	Post-Graduate or above	4
Number of Family Members	1-5	0
	5-10	1
	10-15	2
	15-20	3
	20-25	4
Male in each Family	0-5	0
	5-10	1
	10-15	2
	15-20	3

Female in each Family	0-5	0
	5-10	1
	10-15	2
	15-20	3
Economic Status	BPL	0
	APL	1
Caste	(i) General	0
	(ii) OBC	1
	(iii) SC	2
	(iv) ST	3
	(v) Others	4
Likert Scale		
Strongly Agree	1	
Agree	2	
Neutral	3	
Disagree	4	
Strongly Disagree	5	

4.5. Data Analysis Tools and Techniques

This segment sketches tools and techniques employed by the researcher to analyze data and draw big statistical insights.

4.5.1. Diagnostic and Tools used for Objective 1

4.5.1.1 Software Used

For the data analysis in the 1st objective of the study, the Autoregressive Distributed Lag (ARDL) model was employed. Statistical software packages, EViews and Stata were used to perform the analysis.

4.5.1.2 Diagnostic Test

To ensure the validity and robustness of the ARDL model, a series of diagnostic tests were conducted. The unit root test was performed using techniques like the Augmented Dickey-Fuller (ADF) test to check the stationarity of variables, a prerequisite for time-series models. Descriptive statistics were calculated to summarize the central tendency, dispersion, and overall distribution of the **Jarque-Bera test** was applied to assess the normality of residuals, verifying that the error terms follow a normal distribution. To detect multicollinearity among the independent variables, the **Variance Inflation Factor (VIF)** test was employed, ensuring minimal correlation between predictors. Autocorrelation in the residuals was checked using the **Breusch-Godfrey test**, ensuring no serial correlation, while heteroscedasticity was evaluated using the **White test**, confirming constant variance of error terms. These tests were performed using **Stata** to guarantee the reliability and accuracy of the results. Lastly to check the robustness of the results causality test (**Granger**) was done.

4.5.2. Diagnostic and Tools Used for Objectives 2 and 3

4.5.2.1 Software Used

IBM SPSS version 29.0 and SMARTPLS version 4 were used to analyze the data in the 2nd and 3rd objectives of the study. SPSS 29.0 was used to conduct exploratory

factor analysis (EFA) and normality tests, while Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were done using SMARTPLS 4.0.

4.5.2.2. Normality

Normality is a condition relating to the type of statistical distribution called normal distribution or bell curve or Gaussian distribution. The data in a normal distribution varies over a continuous curve and is symmetrical about the mean and standard deviation. The normality test determines whether the sample data follows a normal distribution. The Shapiro-Wilk and Kolmogorov-Smirnov tests were employed to assess normality. For both tests, the null hypothesis assumes the data are normally distributed. A significance level (p-value) greater than 0.05 indicates normality, while a p-value below 0.05 suggests the data deviates from a normal distribution.

Since the Likert scale, based on rankings, is ordinal rather than continuous, it does not adhere to a normal distribution (Jamieson, 2004). The 5-point Likert scale ranges from "strongly disagree" to "strongly agree," with values from 1 to 5, making it ordinal rather than an interval scale. Sullivan et al. (2013) further assert that real-world data rarely follows a normal distribution.

4.5.2.3. Multicollinearity

Multicollinearity arises when two or more independent variables in a regression model exhibit strong intercorrelations. This issue can diminish the statistical significance of the independent variables, complicating the analysis of their individual effects on the dependent variable. Regression analysis aims to identify relationships between independent and dependent variables, but the presence of multicollinearity makes it challenging to attribute effects to specific variables. Consequently, the p-values of regression coefficients may lose interpretability.

4.5.2.4. Factor Loading, Reliability and Validity

Factor loadings are numerical values that represent the strength and direction of the relationship between observed indicators and their corresponding latent constructs in Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) (Brown et al., 2012). A factor loading essentially measures how well a particular item contributes to defining a latent construct, making it a key indicator of construct validity (Hair et al., 2012).

Reliability assesses the consistency of measurements for the same variables. According to Kothari (2004), reliability ensures consistent results under similar conditions. Syed and Nelson (2015) describe reliability as the extent to which a scale or test produces consistent scores across repeated applications. Cronbach's Alpha is the most used measure for evaluating internal consistency, which refers to the degree to which items within a scale correlate with one another. A composite scale comprises multiple items designed to measure a single latent construct. Composite reliability evaluates the consistency of the scale by analyzing the items as separate scales, calculated using the sum and squared correlations of the AVE (Average Variance Extracted). Validity ensures the accuracy and quality of data, with two main types:

1. Convergent Validity: Measures how well a scale correlates with other items of the same construct, assessed through factor loadings and AVE.

2. Discriminant Validity: Ensures constructs that should be unrelated are indeed uncorrelated, evaluated using correlations and the square root of AVE.

4.5.2.5. Structural Equation Modeling

Structural Equation Modeling (SEM) is a statistical technique used to analyze relationships among multiple variables (Chin, 1998; Hair et al., 2019). By

integrating aspects of factor analysis and multiple regression, SEM examines the structural relationships between exogenous (independent) and endogenous (dependent) variables. This method is preferred as it allows for the estimation of numerous interrelated dependencies within a single analytical framework (Kemp, 2003; Li & Li, 2021). SEM involves creating a model to represent various components of an observable or theoretical phenomenon that are believed to be causally or structurally connected. The model's structural elements define the theoretical relationships between variables, offering insights into the dynamics of the phenomenon under investigation (Barrett, 2006; Kelloway, 1995; Thakkar, 2020).

4.6.Conclusion

Chapter 4 detailed the methodology used to address the research objectives, ensuring alignment between the methods and the study's aims. The structured questionnaire, a key data collection tool, was designed for clarity and relevance, following best practices to enhance reliability. These methodological steps provide a strong foundation for analyzing the results in the next chapter

CHAPTER V

DATA ANALYSIS & RESULTS

This chapter presents the results and analysis derived from the methods explained in Chapter 4. The findings comprehensively address the research objectives by applying econometric and structural equation modeling techniques. Specifically, Objective 1 is analyzed using the Autoregressive Distributed Lag (ARDL) approach, which examines the existence of a short-run and long-run relationship. For Objectives 2 and 3, Structural Equation Modeling (SEM) is employed to explore the hypothesized relationships and the underlying causal mechanisms. The chapter systematically interprets the results, linking them to the research questions and broader theoretical implications, while ensuring alignment with the study's overarching objectives.

5.1. Objective1: Results

5.1.1. Unit Root Test

It is essential to comprehend a variable's intrinsic properties regardless of whether it is integrated at I (0) or I (1) before doing any time series data analysis. There may be seasonal fluctuations to consider, and not all regressors need to be included in a first-order analysis (Sarkodie et al., 2019). When doing a time series data analysis, it is crucial to guarantee the stationarity of the data series. Castle et al., 2020 claim that non-stationary data might lead to erroneous outcomes. Additionally, the data must be stationary for ARDL analysis at either I (0), I (1), or a mix of both. When the dataset size is limited, it is unethical to include data at I (2).

Table 5.1 – Unit Root (ADF) Test for all the Variables

Variable	Level/Difference	ADF Test	P value
FFI	Level	-3.663**	0.004
TD	First Difference	-4.798***	0.000
$ININEQ$	Level	-5.528***	0.000
EG	First Difference	-4.765***	0.000
EG^2	Level	-5.098***	0.000
URB	Level	-4.089***	0.001
EDI	First Difference	-4.663***	0.000
$NREN$	First Difference	-5.671***	0.000
REN	First Difference	-5.879***	0.000
AMT	Level	-6.670***	0.000
$PM2.5$	Level	-3.246*	0.017
$ECLFP$	Level	-4.013***	0.001
$EPSI$	First Difference	-3.332*	0.013
RLI	First Difference	-7.825***	0.000
LUC	First Difference	-4.663***	0.000
CE	Level	-4.273***	0.000
$BIOCAP$	Level	-4.700**	0.000
$EMIT\_FF$	First Difference	-9.606***	0.000
HEX	First Difference	-4.828***	0.000
$U5MR$	First Difference	-2.630*	0.086

Note: The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, while NS indicates "Not Significant."

5.1.2. Forest Fires and Economic Variables

This study explores how these economic variables influence forest fire incidences. This analysis demonstrates the diverse ways that human-driven activities and forms of governance contribute to environmental degradation, such as forest fire occurrence. For instance, land use changes might increase fire risk through tourism and urbanization, while energy dependence and inequality could reshape resource management, economic growth, and its square, explore whether non-linear effects exist, where certain levels of economic growth increase the reception of forest fires or vice versa. This analysis is critical in recognizing and facing ecological implications in sustainable development.

5.1.2.1. Descriptive Statistics

The descriptive statistics in Table 5.2 summarize key economic variables. Forest Fire Incidences ($LnFFI$) have a mean of 9.22 with moderate variability ($Std.Dev.$ 1.36), ranging from 4.95 to 10.87. Tourism Development ($LnTD$) shows a high average of 15.17 with low variability (0.63), indicating consistent growth across regions. Income Inequality ($ININEQ$) has a narrow range, with a mean of 0.57 and minimal deviation (0.06). Economic Growth ($LnEg$) averages 27.94, while its squared term ($LnEG^2$) shows greater variability, averaging 55.90. Urbanization ($LnUrb$) is stable with a mean of 19.66 and little variation (0.25). The Electoral Democracy Index (EDI) has a mean of 0.65 and moderate variability (0.12). Renewable Energy ($LnREN$) consumption shows moderate variation around a mean of 4.89, while Non-Renewable Energy ($LnNREN$) has a mean of 8.44 and low variability (0.47), reflecting stable energy use patterns across regions.

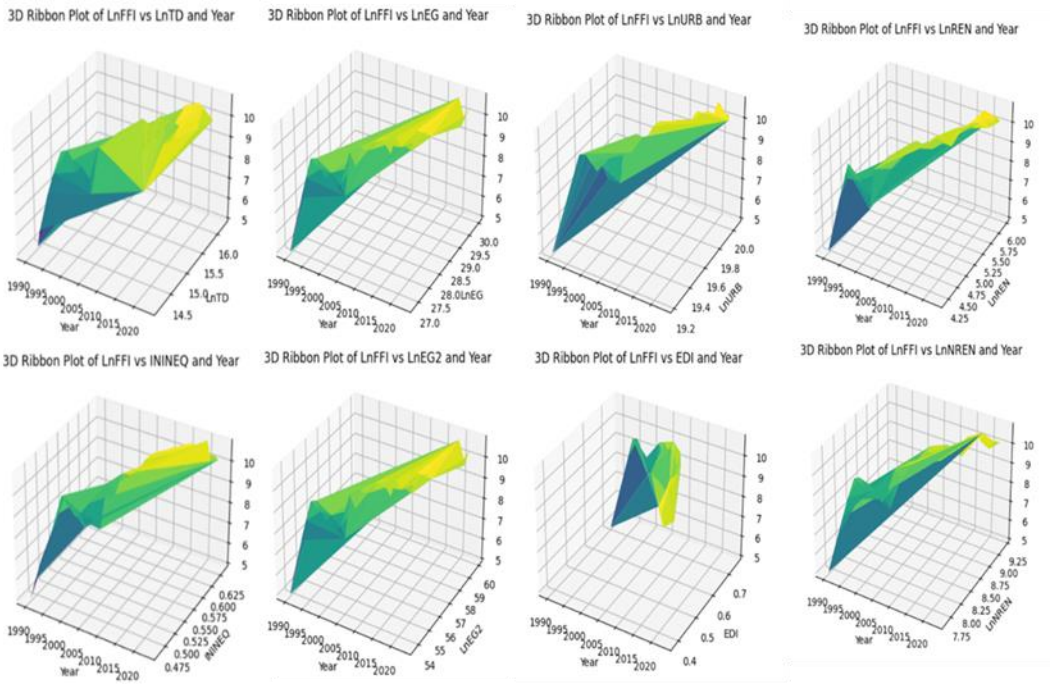
The 3D ribbon plots (Figure 5.1) illustrate the relationship between log-transformed forest fire incidences ($LnFFI$) and key economic, social, and environmental variables over the period 1990–2020. The plots indicate a positive correlation between forest fire incidences and economic factors, including tourism development ($LnTD$), economic growth ($LnEG, LnEG^2$), and urbanization ($LnURB$), suggesting that increased human activity contributes to fire risks. Additionally, income inequality ($ININEQ$) and non-renewable energy consumption ($LnNREN$) exhibit a rising trend alongside fire occurrences, highlighting socio-economic disparities and fossil fuel dependency as influencing factors. Renewable energy consumption ($LnREN$) and electoral democracy index (EDI) show more complex variations over time. The findings suggest that economic expansion, energy consumption patterns, and governance structures significantly impact forest fire incidences, underscoring the need for integrated policy responses.

Table 5.2 - Descriptive Statistics

Variable	***Mean***	***Std. Dev.***	***Min***	***Max***
$LnFFI$	9.224	1.363	4.953	10.874
$LnTD$	15.170	0.630	14.160	16.203
$ININEQ$	0.565	0.063	0.460	0.633
$LnEG$	27.943	0.847	26.865	29.941
$LnEG^2$	55.897	1.712	53.731	59.882
$LnURB$	19.662	0.255	19.219	20.046
EDI	0.645	0.123	0.385	0.750

LnREN	4.886	0.570	4.196	5.945
LnNREN	8.442	0.4731	7.643	9.176

Figure 5.1 – Graphical Plot of Forest fires and Economic Variables



5.1.2.2. Normality, Autocorrelation and Heteroscedasticity Test

In Table 5.3, the normality test indicates that the residuals are normally distributed, as the chi^2 value of 0.467 exceeds the 0.05 significance level, meaning the null hypothesis of normality cannot be rejected. Similarly, the Breusch-Godfrey LM test for autocorrelation shows a chi^2 value of 0.073 with a p-value of 0.787, which is greater than 0.05. Therefore, the null hypothesis is no serial correlation and alternative Hypothesis: There is a serial correlation; so null hypothesis cannot be

rejected, confirming that the residuals in the model are free from autocorrelation. These results validate key model assumptions, ensuring reliable regression estimates. For Heteroscedasticity, the chi-square test indicates that the p-value is greater than 0.05, leading to the failure to reject the null hypothesis of constant variance at the 5% significance level. This result suggests that heteroscedasticity is absent, confirming homoscedasticity in the residuals.

Table 5.3 – Normality, Autocorrelation and Heteroscedasticity

$\boldsymbol{Normality\ Test}$:			
$Jarque-Bera\ normality\ test$:		$Chi\ Square$	
1.523		0.467	
$\boldsymbol{Autocorrelation}$: $\boldsymbol{Breusch-Godfrey\ LM\ test}$			
$lags(p)$	$Chi\ Square$	df	$Prob > chi2$
1	0.073	1	0.7876
$\boldsymbol{White\ Test\ for\ Heteroscedasticity}$:			
$Chi\ Square$		df	$Prob > chi2$
33.00		32	0.418

5.1.2.3. Multicollinearity

The multicollinearity test using Variance Inflation Factor (VIF) evaluates the extent of correlation between independent variables in a regression model. A VIF value under 5 typically indicates acceptable multicollinearity, meaning the variables are not excessively correlated. So, there is no multicollinearity issue.

Table 5.4 – VIF values

Variable	***VIF***
REN	1.09
$NREN$	2.22
EG	2.22
EDI	1.88
$ININEQ$	1.50
URB	1.47
TD	1.17

5.1.2.4. Cointegration Test

The Johansen Cointegration Test was conducted to determine whether a long-term equilibrium relationship exists among the variables in the dataset. The results indicate the presence of cointegration.

Table 5.5 **– Cointegration Test Results**

Test	Hypothesized No. of CE(s)	Statistic	Critical Value (0.05)	P-Value
Trace Test	None	269.952	125.615	0.000
	At most 1	149.387	95.754	0.000
	At most 2	81.998	69.819	0.003
	At most 3	48.614	47.856	0.042
Max-Eigen Test	None	120.565	46.231	0.000

	At most 1	67.388	40.078	0.000

5.1.2.5. ARDL Results

Table 5.6– ARDL Results

Variable	$Coefficient$	$Std.Error$	$t-Statistic$	$Prob.*$
		SHORT RUN		
TD	0.671^{**}	0.303	2.212	0.038
ININEQ	12.124	11.337	1.069	0.297
EG	2.231^{***}	0.578	3.855	0.000
EG^2	6.542^{**}	2.741	2.386	0.027
URB	0.117^{**}	0.055	2.117	0.046
EDI	3.693	3.897	0.947	0.354
REN	-2.447^{**}	0.940	-2.603	0.017
NREN	2.800^{**}	1.250	2.235	0.032
C	-0.039	1.297	-0.030	0.975
		LONG RUN		
TD	1.741^{***}	0.483	3.598	0.001
ININEQ	31.438^{*}	15.581	2.017	0.052
EG	5.785^{***}	1.5708	3.682	0.000
EG^2	16.963^{***}	3.858	4.396	0.000
URB	0.303^{**}	0.112	2.695	0.013

EDI	9.576^{**}	3.507	2.730	0.010
REN	-6.347^{***}	1.598	−3.971	0.000
NREN	7.260^{**}	3.168	2.291	0.021
C	−0.103	3.362	−0.030	0.975

Note: $***,**,$ and $*$ represent the significance levels at 1%, 5%, and 10%, respectively. (Source: Authors' estimations and results are obtained by using EViews).

5.1.2.5.1 Short-Run Dynamics

A 1% increase in tourism development leads to an approximate 0.671 increase in forest fire incidences, which is statistically significant. Similarly, a 1% rise in economic growth results in an increase of 2.231 in forest fire incidences, while the squared term of economic growth indicates that higher levels of growth disproportionately amplify fire risks. Urbanization also has a significant short-term effect, where a 1% increase in urbanization contributes to a 0.117 rise in forest fire incidences. Renewable energy consumption reduces forest fire incidences significantly, with a 1% increase lowering forest fire incidences by 2.447. Conversely, non-renewable energy consumption significantly increases forest fire incidences, where a 1% rise contributes to a 2.800 increase.

5.1.2.5.2 Long-Run Dynamics

A 1% increase in tourism development leads to an approximate 1.742 rise in forest fire incidences, which is highly significant. Economic growth continues to exhibit a nonlinear relationship, with a 1% increase in growth contributing to a 5.785 increase in forest fires, and higher levels of growth, represented by the squared term, further amplifying this effect. Urbanization also remains significant, with a 1% rise leading to a 0.304 increase in forest fire incidences. Renewable energy

consumption significantly mitigates fire risks, with a 1% increase reducing incidences by 6.347. On the other hand, a 1% rise in non-renewable energy consumption increases forest fire incidences by 7.260. Income inequality and Electoral Democracy Index, while not impactful in the short run, show long-term effects, where higher inequality and stronger governance both significantly influence forest fire patterns. These findings emphasize the need for immediate and sustained policy interventions targeting tourism, urbanization, income inequality, energy consumption to mitigate forest fire risks effectively.

5.1.2.5.3 Diagnostic and Stability Tests

Table 5.7: Regression Model Summary and Diagnostics

Statistic	***Value***	***Statistic***	***Value***
$R-squared$	0.888	$Mean\ dependent\ var$	9.327
$Adjusted\ R-squared$	0.837	$S.D.dependent\ var$	1.147
$S.E.of\ regression$	0.463	$Akaike\ info\ criterion$	1.559
$Sum\ squared\ resid$	4.286	$Schwarz\ criterion$	2.026
$Log\ likelihood$	-13.380	$Hannan-Quinn\ criter.$	1.708
$F-statistic$	17.556	$Durbin-Watson\ stat$	2.244
$Prob(F-statistic)$	0.000		

In table 5.7, the regression results demonstrate a strong model fit, with an R^2 of 0.888, indicating that 88.8% of the variation in the dependent variable is explained by the independent variables. The adjusted R^2 of 0.837 confirms the model's robustness, even after accounting for the number of predictors. The standard error of regression (0.463) shows that the residuals are relatively small, suggesting good

predictive accuracy. The F-statistic (17.556) and its probability value of 0.000 confirm that the overall model is statistically significant. The Durbin-Watson statistic (2.244) suggests no significant autocorrelation in the residuals, ensuring reliability in the estimates. Furthermore, the information criteria ($Akaike$: 1.5587, $Schwarz$: 2.0257, $and\ Hannan-Quinn$: 1.7081) are relatively low, indicating that the model is well-specified and efficient for comparison. Overall, the results indicate a well-fitting and statistically significant regression model with stable residuals.

In table 5.8, the stability and levels relationship of the model were assessed using the F-Bounds test, CUSUM, and CUSUM of squares tests. The F-statistic (4.254) exceeds the upper critical bound I (1) at the 5% level (3.153), confirming the presence of a levels relationship and rejecting the null hypothesis and concluding that there is relationship between dependent and independent variables. The CUSUM and CUSUM of squares graphs ($Fig\ 5.2-5.3$) show that the test statistics remain within the 5% significance boundaries, indicating model stability over the tested period and model is devoid of any structural breaks. Thus, the model is both stable and demonstrates a significant long-term relationship.

Table 5.8 - F- Bound Test

F-Bounds Test			**Null Hypothesis:** No levels relationship	
Test Statistic	**Value**	**Signif.**	**I (0)**	**I (1)**
			Asymptotic: n=1000	
F-statistic	4.253386	10%	1.85	2.85
K	8	5%	2.11	3.15

		2.5%	2.33	3.42
		1%	2.62	3.77
Actual Sample Size	30		Finite Sample: n=30	
		10%	-1	-1
		5%	-1	-1
		1%	-1	-1

Figure 5.2 – Cusum Test

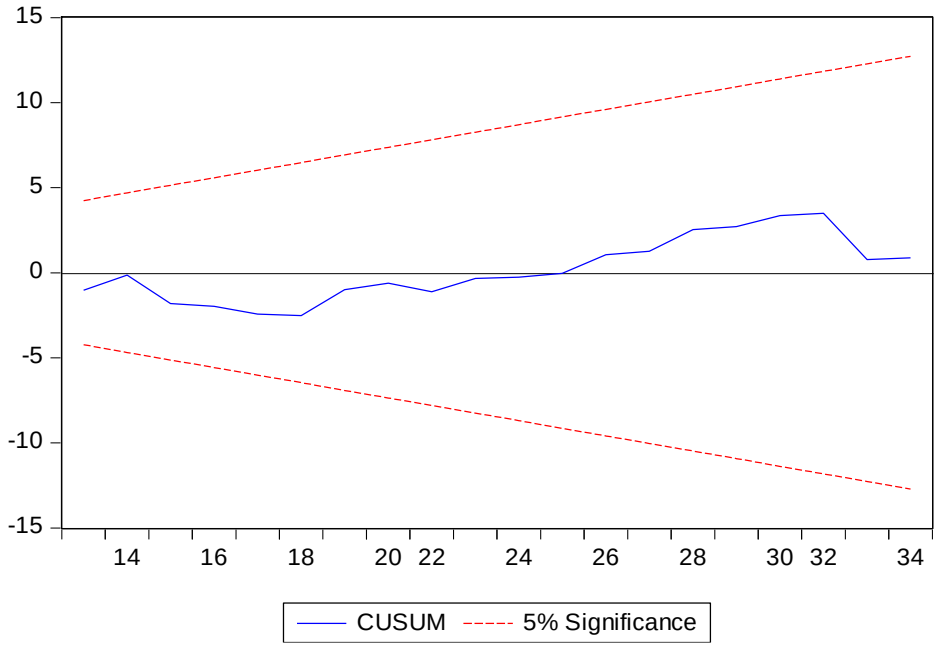
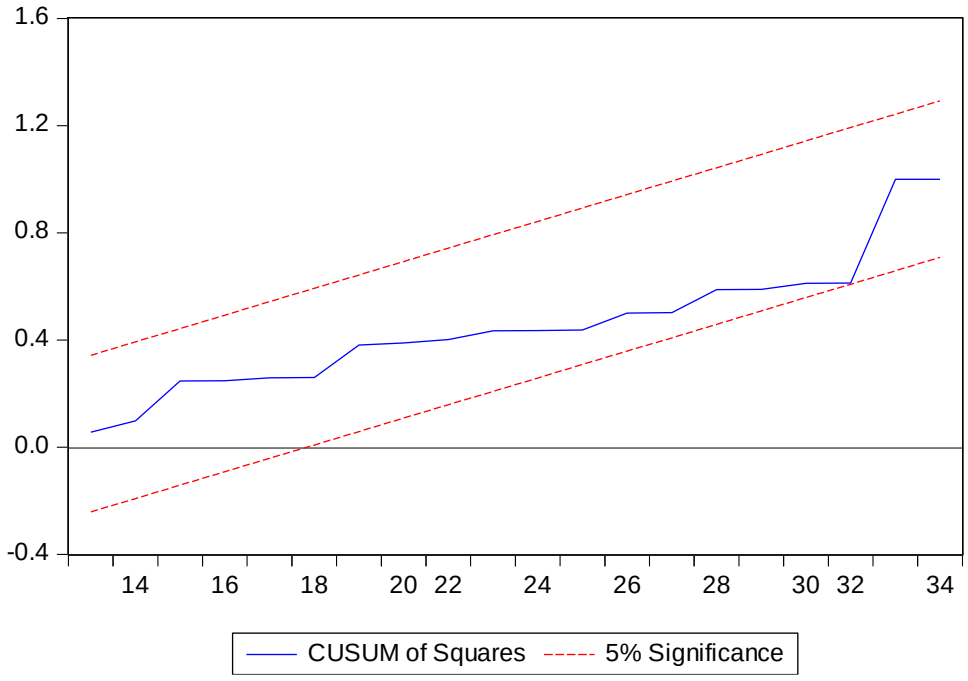


Figure 5.3 – Cusum Square Test



5.1.3. Forest fires and Environment Variables

This study explores how environmental variables like carbon emissions, airborne particulate matter, biocapacity, ecological footprint, environment policy stringent index, and average mean temperature influence forest fire incidences.

5.1.3.1. Descriptive Statistics

The descriptive statistics in the *table* 5.9, summarize key variables relevant to environmental dynamics. Forest Fire Incidences (FFI) exhibit a mean of 9.22 with moderate variability ($Std.Dev.$ 1.36), ranging from 4.95 to 10.87, indicating significant regional differences. Airborne Particulate Matter ($PM2.5$) averages 41.13 with high variability (13.55), reflecting diverse pollution levels. Carbon Emission (CE) shows a stable mean of 21.03 with moderate variation (0.51), suggesting consistent energy demands. The biocapacity ($Biocap$) is stable across

observations, with a mean of 19.81 and minimal deviation (0.14). Environment Policy Stringent Index (EPSI) is relatively narrow, averaging 1.56 with variability of 0.75. RLI has a high mean of 0.72 and very low variability (0.03), reflecting consistent governance indicators across the dataset.

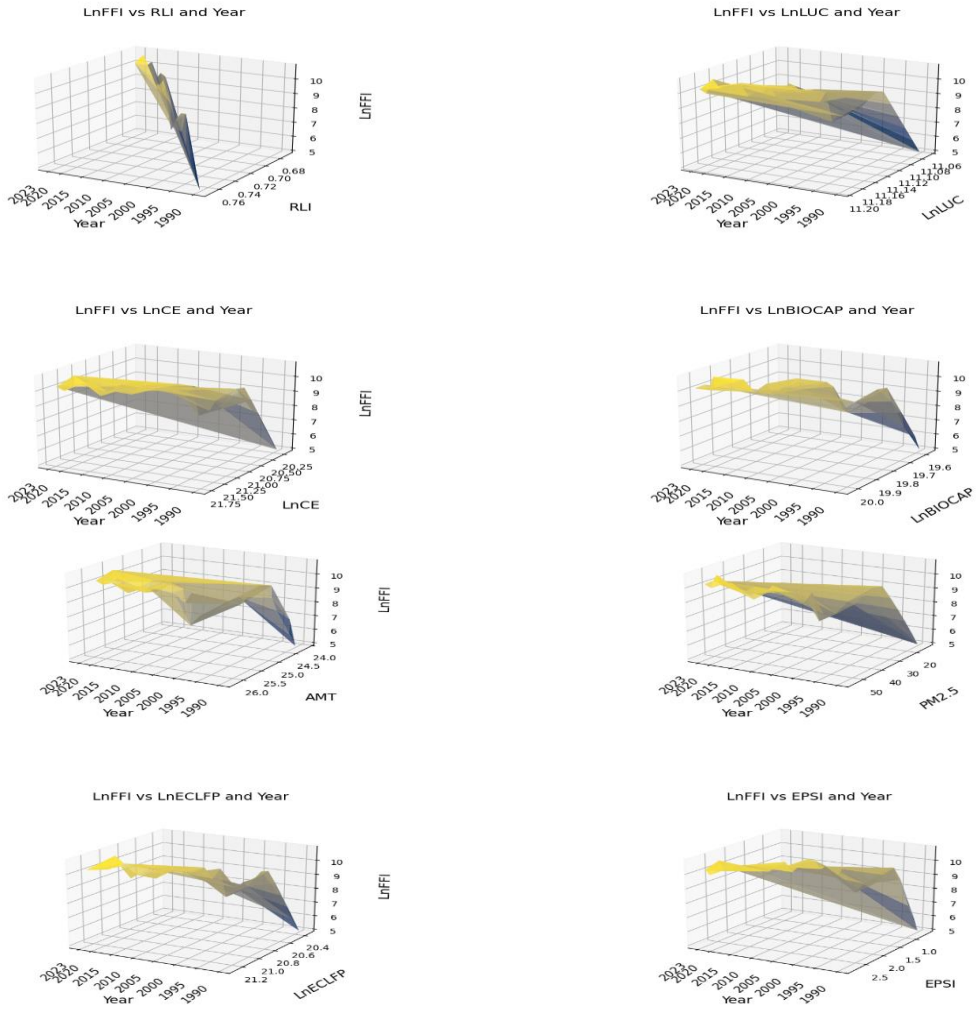
The relationships between key environmental variables and forest fire incidences ($LnFFI$) from 1990 to 2023 in *Figure* 5.4. For land use change ($LnLUC$), biodiversity loss (RLI), carbon emissions ($LnCE$), atmospheric mean temperature (AMT), ($PM_{2.5}$) levels, and ecological footprint ($LnECLFP$), an upward trend is evident. Initially, lower values (grey) in 1990 indicate minimal impact, but the transition to yellow by 2005 and beyond signifies a marked increase, suggesting that rapid land use changes, biodiversity decline, rising emissions, warming temperatures, and human activities have intensified fire occurrences. Conversely, biocapacity ($LnBIOCAP$) exhibits a negative correlation with forest fire incidences, where higher biocapacity in earlier years coincides with fewer fires, but as biocapacity declines, fire incidences rise. This implies that ecosystem degradation has reduced resilience against forest fires. Similarly, environmental policy stringency ($EPSI$) demonstrates weak effectiveness, as increasing fire incidences persist despite policy developments, highlighting gaps in forest fire management strategies.

Table 5.9: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
FFI	9.224	1.364	4.954	10.874
AMT	25.382	0.664	24.100	26.210
PM2. 5	41.129	13.549	13.474	54.900
ECLFP	20.828	0.290	20.345	21.286

EPSI	1.564	0.753	0.639	2.833
RLI	0.723	0.034	0.670	0.770
LUC	11.137	0.037	11.066	11.194
CE	21.027	0.506	20.175	21.763
BIOCAP	19.811	0.139	19.576	20.025

Figure 5.4 – Graphical Plot of Forest fires and environment variable



5.1.3.2. Normality, Autocorrelation and Heteroscedasticity Test

In table 5.10, the normality test results from the Jarque-Bera test indicate that the residuals are normally distributed, with a chi² value of 2.576 and a p-value of 0.276, which exceeds the 0.05 significance level. Thus, the null hypothesis of normality cannot be rejected. The Breusch-Godfrey LM test for autocorrelation shows a chi² value of 0.014 with a p-value of 0.907, well above 0.05, indicating the null hypothesis of no serial correlation cannot be rejected. This confirms that the residuals are free from autocorrelation. For heteroscedasticity, the White test provides a chi² value of 34.00 with a p-value of 0.419, which is greater than 0.05. Therefore, the null hypothesis of constant variance cannot be rejected, confirming the absence of heteroscedasticity and validating homoscedasticity in the model. These diagnostic tests support the reliability of the regression model's assumptions.

Table 5.10 – Normality, Autocorrelation, and Heteroscedasticity

Normality Test:			
$Jarque-Bera\ normality\ test$:		$Chi\ Square$	
2.576		0.276	
Autocorrelation*: *Breusch − Godfrey LM test			
$lags(p)$	$Chi\ Square$	df	$Prob > chi2$
1	0.014	1	0.907
White Test for Heteroscedasticity:			
$Chi\ Square$		df	$Prob > chi2$
34.00		33	0.419

5.1.3.3. Multicollinearity

The multicollinearity test using the Variance Inflation Factor (VIF) evaluates the extent of correlation between independent variables in a regression model. A VIF value under 5 typically indicates acceptable multicollinearity, meaning the variables are not excessively correlated. The VIF values of all variables are below 5. So, there is no multicollinearity issue.

Table 5.11 – VIF Values

Variable	***VIF***
CE	2.15
RLI	1.98
LUC	1.62
ECLFP	1.46
AMT	1.44
PMM2. 5	1.38
BIOCAP	1.25
EPSI	1.06

5.1.3.4. Cointegration Test

The Johansen Cointegration Test was conducted to determine whether a long-term equilibrium relationship exists among the variables in the dataset. The results indicate the presence of cointegration.

Table 5.12- Cointegration Test

$\boldsymbol{Test}$	$\boldsymbol{Hypothesized\ No.\ of\ CE(s)}$	$\boldsymbol{Statistic}$	$\boldsymbol{Critical\ Value\ (0.05)}$	$\boldsymbol{P-Value}$
$\boldsymbol{Trace\ Test}$	$None$	328.424	197.371	0.000
	$At\ most\ 1$	229.037	159.529	0.000
	$At\ most\ 2$	163.366	125.615	0.000
	$At\ most\ 3$	113.405	95.754	0.001
	$At\ most\ 4$	74.056	69.819	0.022
$\boldsymbol{Max-Eigen\ Test}$	$None$	99.387	58.433	0.000
	$At\ most\ 1$	65.670	52.362	0.001
	$At\ most\ 2$	49.961	46.231	0.019

5.1.3.5. ARDL Results

The results from the ARDL model underscore the dynamic factors of forest fire incidences explained by environmental factors in the short and long run.

Table 5.13 – ARDL Results

Variable	Coefficient	Std. Error	t − Statistic	Prob.*
		Short Run		
AMT	2.462**	0.916	2.686	0.011
$PM_{2.5}$	0.064	0.594	0.107	0.915
ECLFP	1.387***	0.508	2.730	0.010

EPSI	2.582^{***}	0.684	3.771	0.000
RLI	2.157^{***}	0.611	3.528	0.001
LUC	15.152^{***}	2.730	5.549	0.000
CE	2.045^{***}	0.709	2.885	0.007
BIOCAP	-7.156^{***}	1.561	-4.586	0.000
Long run				
AMT	2.449^{***}	0.693	3.532	0.001
$PM_{2.5}$	0.153^{***}	0.053	2.865	0.007
ECLFP	3.313^{***}	1.017	3.254	0.002
EPSI	6.162^{***}	1.350	4.557	0.000
RLI	5.148^{**}	1.960	2.625	0.014
LUC	20.814^{***}	4.597	4.527	0.000
CE	2.813^{***}	0.754	3.728	0.000
BIOCAP	-5.468^{***}	1.538	-3.554	0.001
C	-41.424	27.155	-1.525	0.142

Note: $***,**, and\ *$ represent the significance levels at 1%, 5%, and 10%, respectively. (Source: Authors' estimations and results are obtained by using EViews).

5.1.3.5.1. Short-Run Dynamics

The average mean temperature (AMT) showed a very crucial immediate and lagged effect. From here, it can be seen that with every 1% increase in AMT, forest fire incidences increase by 2.462%.Ecological Footprint, as represented by $ECLFP$, exerts a considerable positive impact whereby a 1% increase in the said factor leads to a 1.387% increase in fire incidences, thus showing clear evidence of stress produced due to unsustainable resource utilization. The stringency of

environmental policy plays a very important role as well. A 1% increase in the $EPSI$ increases fire incidences by 2.582%, which could reflect the indirect impacts of policy measures. Biodiversity loss as measured by the RLI contributes significantly; this means that when biodiversity decreases by 1%, fire risk increases by 2.157%.The most dramatic impact is exhibited by land use change, LUC, where every unit of change is driving a 15.152% increase. Therefore, the management of land is crucial when it comes to preventing fire. Carbon emissions are also showing a positive and significant impact on forest fire incidences. Biocapacity, $BIOCAP$, effectively lowers risks, a 1% increase in biocapacity reduces incidences by 7.156%. $PM_{2.5}$ is statistically insignificant in the short run.

5.1.3.5.2. Long-Run Dynamics

The mean temperature is significant only at an average significance level of 0.0786. Particulate matter, insignificant in the short run, becomes significant over time, with a 1% increase contributing to a 0.153% increase in fire incidences over a latent environmental impact. The $ECLFP$ remains one of the key drivers-every 1% increase gives a rise in fire incidences of 3.313%, underlining long resource pressures. Stringent environmental policies, $EPSI$, are found to bear a high impact, 1% increase in $EPSI$ leads to an increase in incidences by 6.162%, reflecting the complexity of the action of that relationship between policies and environmental outcomes.While for biodiversity loss, with a 1% decline in the RLI, fire risks increase by about 5.148%, LUC land use change still is the most long-term influencing factor, increasing incidences, per unit change, by the staggering rate of 20.814%, thus again referring to the urgent need for sustainable use of land. $BIOCAP$ is consistently reducing the risk, as a 1% increase reduces fire incidences by 5.468%.These results highlight interlinked climatic, and ecological interactions in the occurrences of forest fire. Key determinants include temperature, ecological footprint, change in land use, biodiversity, and biocapacity. Policymakers must

comprehensively act on these factors to take mitigative actions effectively against fire hazards considering both short-run and long-run scenarios.

5.1.3.5.3. Diagnostic and Stability Tests

In Table 5.14, the regression analysis indicates a strong model fit, with an R-squared value of 0.894, suggesting that 89.4% of the variance in the dependent variable is explained by the independent variables. The adjusted R-squared, at 0.831, confirms this robustness after accounting for the number of predictors. The low standard error of regression (0.475) and sum of squared residuals (4.506) demonstrate high predictive accuracy. The model is statistically significant, as evidenced by an F-statistic of 14.08 and a corresponding p-value (< 0.001), confirming the overall validity of the regression. Information criteria values (Akaike: 1.635, Schwarz: 2.224, Hannan-Quinn: 1.833) are favorable, supporting the model's parsimony. The Durbin-Watson statistic of 2.369 suggests no significant autocorrelation in the residuals. Overall, the model effectively captures the relationship between variables and performs well across diagnostics.

In Table 5.15, the F-Bounds test examines whether there is a long-term (levels) relationship among variables. With a test statistic of 3.860, which falls between the I(0) and I(1) critical bounds at the 5% significance level, the result is inconclusive.

In Figure 5.5-5.6, the presented CUSUM and CUSUM of Squares tests evaluate the stability of the regression coefficients over time. The CUSUM test indicates stability when the blue line remains within the 5% significance bounds. The CUSUM of Squares test further assesses stability by monitoring variance. For both tests, the model's residuals appear stable as the lines remain within the bounds, suggesting no structural breaks in the regression model. These findings collectively suggest a structurally stable model with the potential for a long-term relationship but requiring further exploration for confirmation.

Table 5.14 – Regression Model Summary & Diagnostics

Statistic	***Value***	***Statistic***	***Value***
R − squared	0.894	**Mean dependent var**	9.353
Adjusted R − squared	0.830	**S. D. dependent var**	1.153
S. E. of regression	0.474	**Akaike info criterio**	1.634
Sum squared resid	4.506	**Schwarz criterion**	2.224
Log likelihood	−13.972	**Hannan − Quinn criter.**	1.833
F − statistic	14.080	**Durbin − Watson stat**	2.220
Prob(F − statistic)	0.000		

Table 5.15 – F Bound Test

F − Bounds Test		**Null Hypothesis**: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: = 1000	
F − statistic	3.860	10%	1.85	2.85
K	8	5%	2.11	3.15
		2.5%	2.33	3.42
		1%	2.62	3.77

Actual Sample Size	33		Finite Sampl = 35	
		10%	−1	−1
		5%	−1	−1
		1%	−1	−1
			Finite Sampl = 30	
		10%	−1	−1
		5%	−1	−1
		1%	−1	−1

Figure 5.5 - Cusum

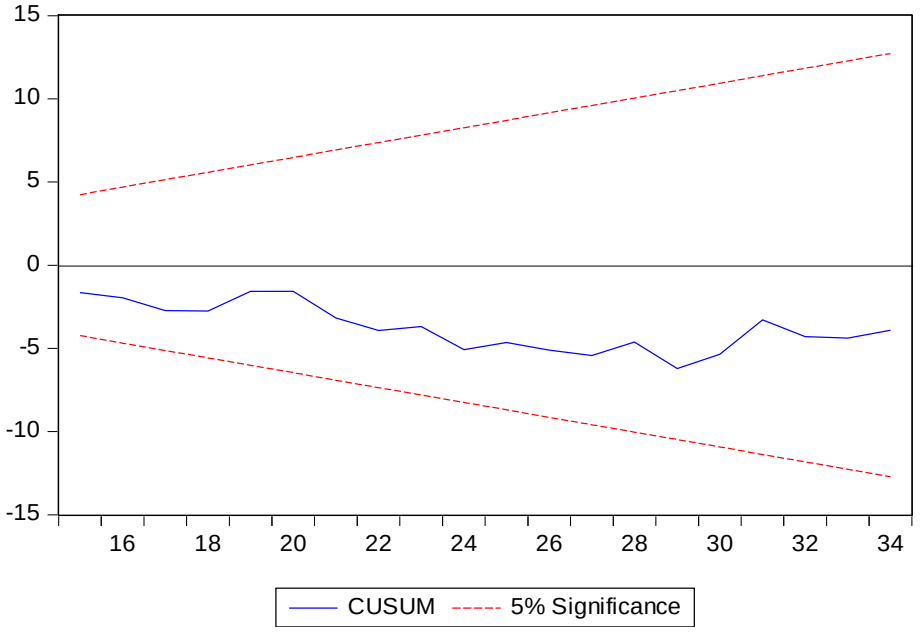
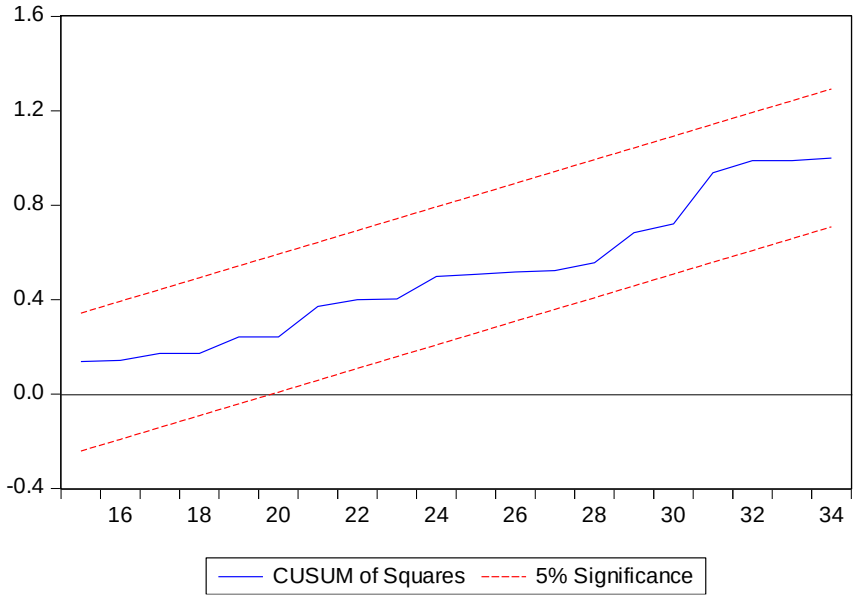


Figure 5.6 - Cusum Square



5.1.4. Forest Fires and Health

This study explores how health is affected by forest fires and other macroeconomic variables. It is crucial to understand how environmental pollution, urban management, and healthcare investments affect child mortality rates.

5.1.4.1. Descriptive Statistics

The descriptive statistics highlight key variables like forest fires and other macroeconomic variables (Table 5.16). The $Under-Five\ Mortality\ Rate\ (U5MR)$ shows significant variability with a mean of 71.714 and a range from $19.615\ to\ 126.474$, indicating disparities in child health. $LnFFI$ averages 9.22 with moderate variability, while $PM_{2.5}$ levels reflect substantial air quality differences, averaging 41.13 with a wide range. AMT is relatively consistent with a mean of 25.38. eg and urb are stable across regions, with low variability. $Emit\_ff$ show considerable differences, averaging 8.84. Hex

is moderately variable, xCE remains stable at 21.03, indicating consistent energy demands. These variations provide a comprehensive view of regional disparities and stability in key development areas.

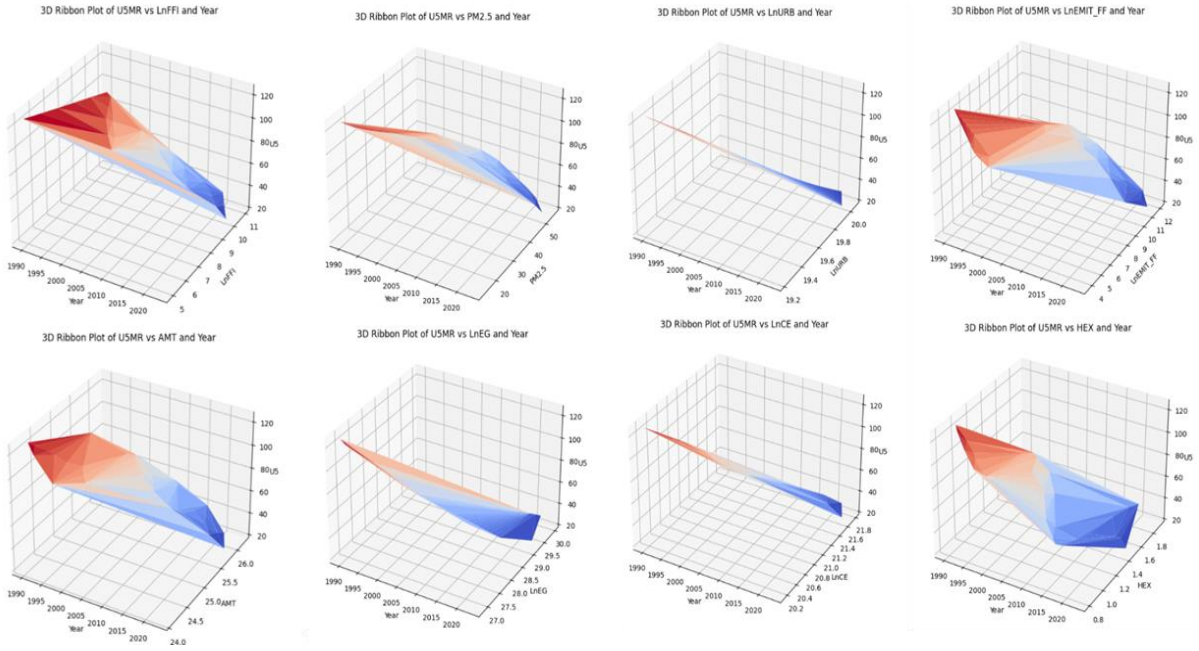
The diagrams (Figure 5.7) illustrate the relationship between under-five mortality rate ($U5MR$) and various environmental and economic factors from 1990 to 2023. The results indicate that as forest fire incidences ($LnFFI$) increase, $U5MR$ also rises, though the effect is less pronounced compared to atmospheric mean temperature (AMT), $PM_{2.5}$ levels, and urbanization ($LnURB$), which show a stronger impact on child mortality. Additionally, $U5MR$ increases with rising carbon emissions ($LnCE$), highlighting the negative health effects of pollution. However, as economic growth ($LnEG$) and health expenditure (HEX) increase, $U5MR$ declines, suggesting that improved economic conditions and higher investments in healthcare contribute to reducing child mortality.

Table 5.16- Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
U5MR	71.714	31.524	19.614	126.474
FFI	9.224	1.3637	4.953	10.874
AMT	25.382	0.664	24.100	26.210
PM2.5	41.129	13.549	13.473	54.900
EG	27.943	0.847	26.865	29.941
URB	19.662	0.255	19.219	20.046
EMIT_FF	8.839	3.223	3.787	11.911
HEX	1.184	0.279	0.81	1.9

CE	21.027	0.505	20.175	21.763

Figure 5.7 – Graphical plot of Health, forest fires, and other variables.



5.1.4.2. Normality, Autocorrelation and Heteroscedasticity Test

In Table 5.17, the normality test results from the Jarque-Bera test indicate that the residuals are normally distributed, with a chi^2 value of 0.319 and a $p - value$ of 2.287, which exceeds the 0.05 significance level. Thus, the null hypothesis of normality cannot be rejected. The Breusch-Godfrey LM test for autocorrelation shows a chi² value of 0.216 with a p-value of 0.642, well above 0.05, indicating the null hypothesis of no serial correlation cannot be rejected. This confirms that the residuals are free from autocorrelation. For heteroscedasticity, the White test provides a chi² value of 34.00 with a p-value of 0.419, which is greater than 0.05.

Therefore, the null hypothesis of constant variance cannot be rejected, confirming the absence of heteroscedasticity and validating homoscedasticity in the model. These diagnostic tests support the reliability of the regression model's assumptions.

Table 5.17 – Normality, Autocorrelation, and Heteroscedasticity

$\boldsymbol{Normality\ Test}$:			
$Jarque-Bera\ normality\ test$:		$Chi\ Square$	
2.287		0.319	
$\boldsymbol{Autocorrelation}$: $\boldsymbol{Breusch-Godfrey\ LM\ test}$			
$lags(p)$	$Chi\ Square$	df	$Prob > chi2$
1	0.216	1	0.642
$\boldsymbol{White\ Test\ for\ Heteroscedasticity}$:			
$Chi\ Square$		df	$Prob > chi2$
34.00		33	0.419

5.1.4.3. Multicollinearity

The multicollinearity test using the Variance Inflation Factor (VIF) evaluates the extent of correlation between independent variables in a regression model. A VIF value under 5 typically indicates acceptable multicollinearity, meaning the variables are not excessively correlated. The VIF values of all variables are below 5. So, there is no multicollinearity issue.

Table 5.18 – VIF values

Variable	***VIF***
CE	3.19
URB	2.51
EG	2.04
EMIT_FF	1.53
AMT	1.51
HEX	1.30
$PM_{2.5}$	1.18
FFI	1.09

5.1.4.4. Cointegration Test

The Johansen Cointegration Test was conducted to determine whether a long-term equilibrium relationship exists among the variables in the dataset. The results indicate the presence of cointegration.

Table 5.19 - Cointegration Test

Test	**Hypothesized No. of CE(s)**	**Eigenvalue**	**Statistic**	**Critical Value**	**Prob.**
Trace Test	None	0.987	447.985	197.371	0.000
	At most 1	0.952	308.839	159.529	0.000

	At most 2	0.813	211.419	125.615	0.000
	At most 5	0.635	69.665	47.856	0.000
Max-Eigenvalue Test	None	0.987	139.149	58.433	0.000
	At most 1	0.952	97.421	52.363	0.000
	At most 2	0.813	53.669	46.231	0.007
	At most 5	0.635	32.256	27.584	0.012

5.1.4.5. ARDL Results

The results from the ARDL model underscore the dynamic relation between health, forest fires, and other variables.

Table 5.20 – ARDL Results

Short Run				
Variable	**Coefficient**	**Std. Error**	**t − Statistic**	**Prob.***
FFI	0.002***	0.000	3.947	0.000
AMT	0.337***	0.059	5.656	0.000
PM2.5	0.327***	0.082	3.950	0.001
EG	−0.001	0.014	−0.096	0.923
URB	15.320***	58.737	5.216	0.000
CE	9.630***	3.152	3.055	0.007

EMIT_ff	0.002^{***}	0.000	3.115	0.004
HEX	-0.055^{*}	0.027	-2.006	0.061
		Long run		
FFI	0.010^{**}	0.004	2.312	0.027
AMT	0.837^{***}	0.267	3.125	0.006
PM2.5	0.120^{*}	0.067	1.782	0.092
EG	-0.005^{**}	0.002	-2.126	0.041
URB	17.825^{***}	5.655	3.152	0.005
CE	5.250^{*}	2.590	2.028	0.058
EMIT_ff	0.008^{***}	0.002	4.207	0.000
HEX	-0.018^{**}	0.008	-2.277	0.030
C	-0.152	0.044	-3.447	0.003

Note: $***,**, and\ *$ represent the significance levels at 1%, 5%, and 10%, respectively. (Source: Authors' estimations and results are obtained by using EViews).

5.1.4.5.1. Short Run Dynamics

The ARDL results reveal the impact of various determinants on under-five mortality rate ($U5MR$) in both the short and long run. A 1% increase in forest fire incidences ($LnFFI$) leads to a rise of 0.002 in $U5MR$ and is significant. Average mean temperature (AMT) significantly increases $U5MR$, contributing to an increase of 0.337, and its lag further adding 0.121. Similarly, a 1% rise in particulate matter ($PM_{2.5}$) results in a significant increase of 0.327 in $U5MR$, with its lagged effect contributing an additional 0.297. Urbanization (URB) has a strong influence, leading to a rise of 15.320 in $U5MR$, highly significant. Carbon emissions (CE)

have a notable impact, raising $U5MR$ by 9.631, and its lag contributing an additional 3.898. Emissions from forest fires ($EMIT\_FF$) significantly increase $U5MR$ by 0.002. Health expenditure (HEX) shows a mitigating effect, as a 1% increase reduces $U5MR$ by 0.055 in the short run, similarly as economy grows it also reduces U5MR.

5.1.4.5.2. Long Run Dynamics

In the long run, a 1% increase in average mean temperature (AMT) leads to a rise of 0.337 in $U5MR$, while a 1% increase in particulate matter ($PM_{2.5}$) raises $U5MR$ by 0.120, both highly significant. Carbon emissions (CE) and emissions from forest fires ($EMIT\_FF$) continue to contribute positively to mortality, with increases of 5.250 and 0.008, respectively, for each unit rise, emphasizing the detrimental role of environmental pollution. Urbanization (URB) has a strong long-term effect, with a 1% increase resulting in significant increases in U5MR by 17.825.Health expenditure (HEX) maintains its mitigating influence in the long run, with a 1% increase reducing $U5MR$ by 0.018 and also as EG increases it reduces $U5MR$. These results underscore the critical importance of addressing environmental pollution, urban management, and healthcare investments to achieve sustained reductions in child mortality rates.

5.1.4.5.3. Diagnostic and Stability Tests

This regression model demonstrates a strong fit with an $R-squared\ of$ 0.993, indicating that 99.3% of the variability in the dependent variable is explained by the model. The Adjusted R-squared (0.989) confirms this fit after adjusting for the number of predictors. The F-statistic (180.878) is highly significant with a p-value of 0.000, suggesting the model is statistically significant. The S.E. of regression (0.013) and low sum of squared residuals (0.003) indicate precise predictions. The

Durbin-Watson statistic (2.837) suggests minimal autocorrelation in the residuals. Overall, these metrics confirm the model's robustness and reliability. In Table 5.22, the **F-Bounds test** evaluates whether a long-term equilibrium (cointegration) relationship exists. The F-statistic is 82.78, which far exceeds the critical values for all significance levels, indicating strong evidence of cointegration. In Figure 5.8-5.9, the **CUSUM** and **CUSUM of Squares p**lots are stability tests. Since both plots remain within the 5% significance boundaries, the model is structurally stable, indicating reliable parameter estimates over time. This confirms the robustness of the regression model.

Table 5.21- Regression Model Summary & Diagnostics

Statistic	***Value***
$R-squared$	0.993
$Adjusted\ R-squared$	0.988
$S.E.of\ regression$	0.013
$Sum\ squared\ resid$	0.003
$Log\ likelihood$	102.690
$F-statistic$	180.878
$Prob(F-statistic)$	0.000
$Mean\ dependent\ var.$	−0.008
$S.D.dependent\ var.$	0.122
$Akaike\ info\ criterion$	−5.481
$Schwarz\ criterion$	−4.794
$Hannan-Quinn\ criter.$	−5.253

$Durbin - Watson\ stat$	2.237

Table 5.22- **F-Bounds Test Results**

Test Statistic	Value	Significance Levels	I(0)	I(1)
$F - statistic$	82.78	10%	1.85	2.85
		5%	2.11	3.15
		2.5%	2.33	3.42
		1%	2.62	3.77
$k\ (Number\ of\ regressors)$	8	–	–	–
$Sample\ Size\ (Actual)$	32			

Figure 5.8 – CUSUM

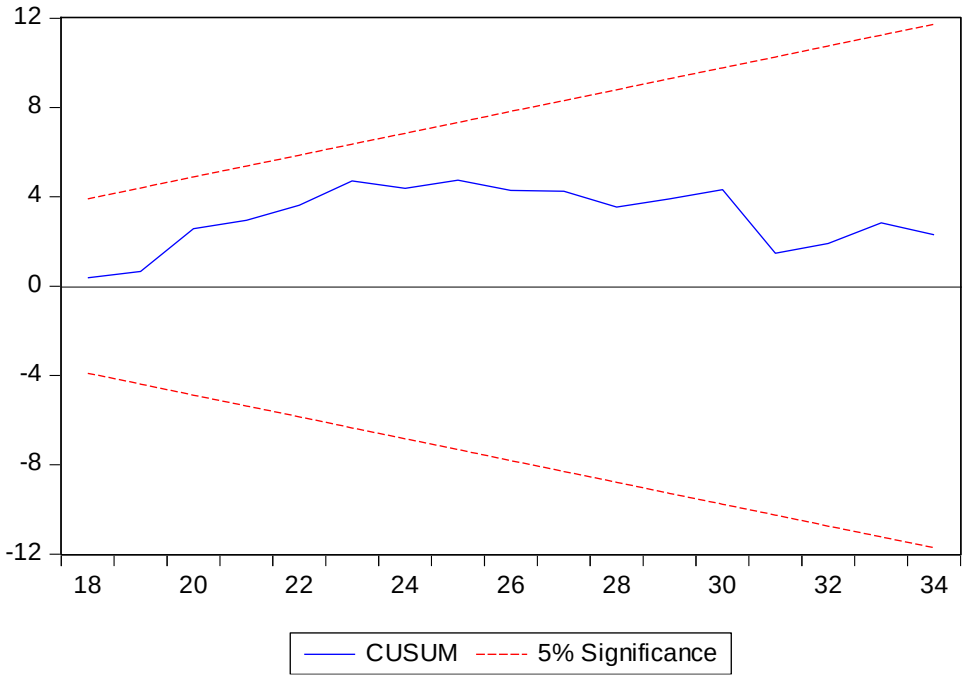
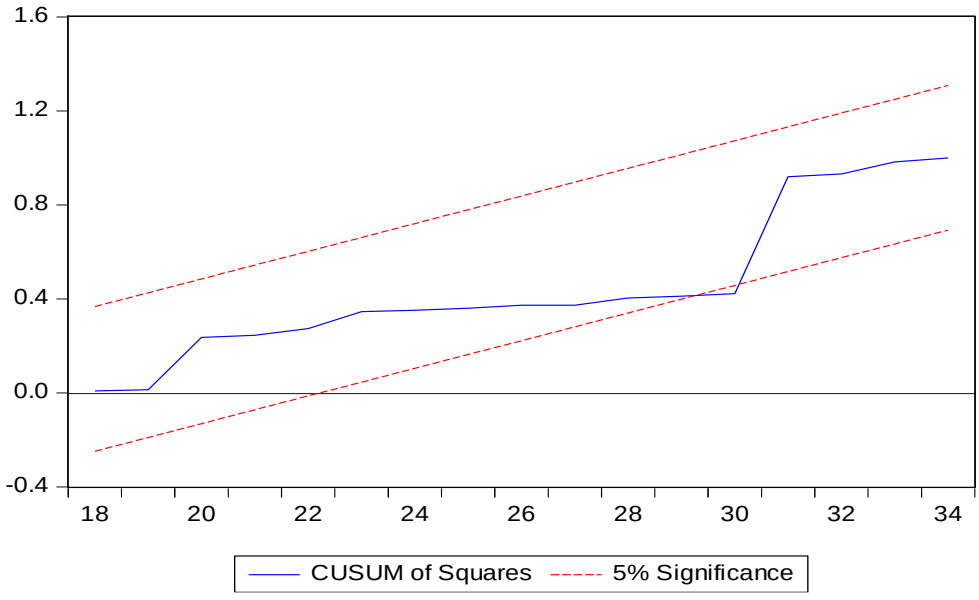


Figure 5.9. - Cusum square



5.1.5. Causality Test

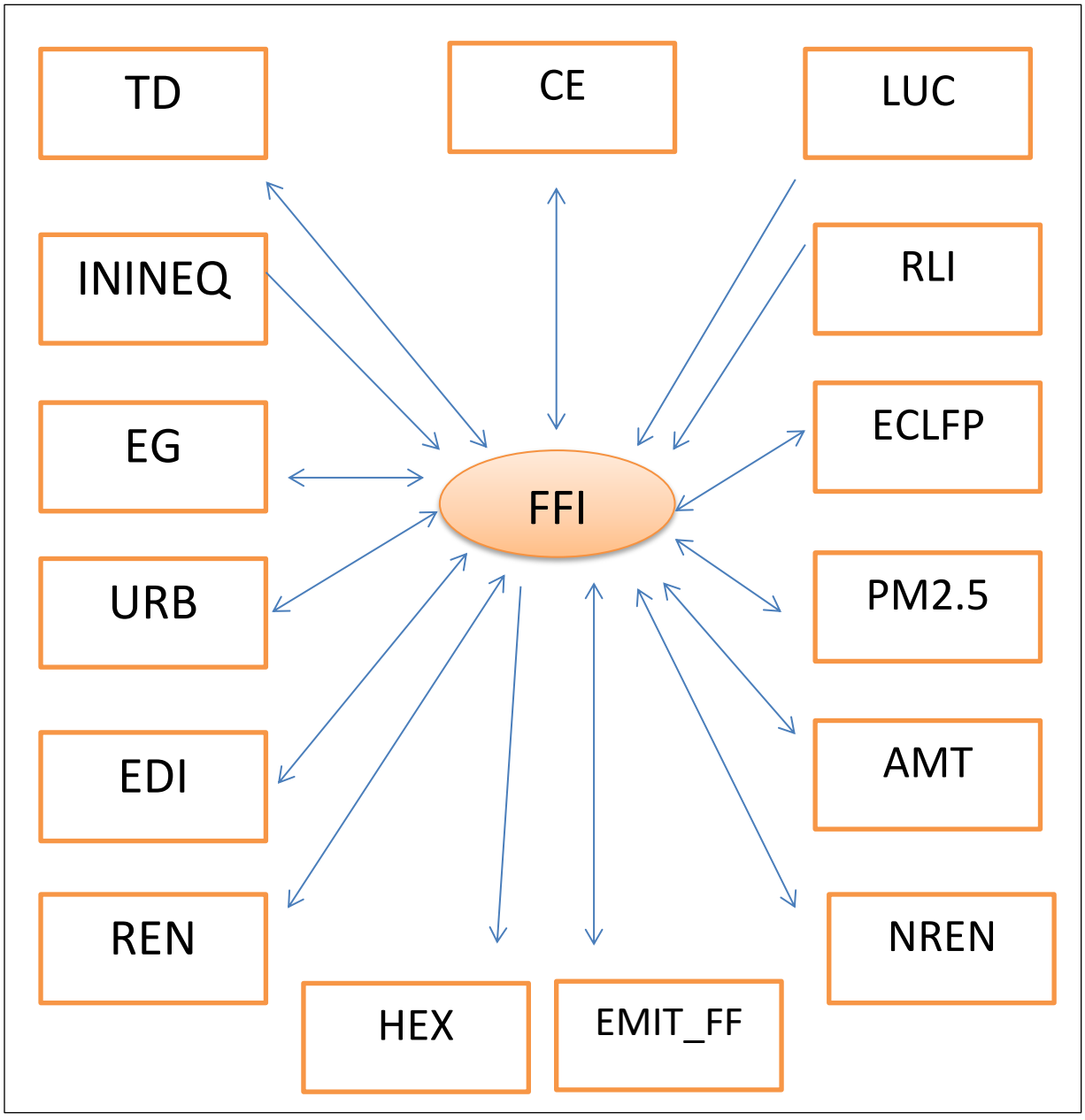
The Granger causality test evaluates whether one variable can predict another over time, establishing directional causality. In the robustness analysis, forest fires are tested against various variables. Significant causality is identified when **P-values** are below 0.05. For instance,, $LnFFI \rightarrow ININEQ$ $(P = 0.000)$ indicates a strong predictive relationship. Conversely, higher P-values, such as $LnFFI \rightarrow LnBIOCAP$ $(P = 0.134)$, suggest no causality. By examining bidirectional causality, the test ensures robust findings, confirming consistency across significant relationships while identifying asymmetries in weaker links.

Table 5.23– Granger Causality Test

Variables	chi^2	P value
LnFFI − LnTD	7.798	0.020
LnTD − LnFFI	7.020	0.030
LnFFI − ININEQ	3.030	0.220
ININEQ − LnFFI	17.226	0.000
LnFFI − LnEG	7.061	0.029
LnEG − LnFFI	14.128	0.001
LnFFI − LnURB	946.77	0.000
LnURB − LnFFI	10.155	0.006
LnFFI − EDI	15.46	0.000
EDI − LnFFI	14.67	0.000
LnFFI − LnREN	7.829	0.020
LnREN − LnFFI	12.977	0.002
LnFFI − LnNREN	5.353	0.069
LnNREN − LnFFI	7.020	0.030
LnFFI − AMT	10.14	0.006
AMT − LnFFI	10.768	0.004
LnFFI − PM2.5	6.404	0.041
PM2.5 − LnFFI	6.976	0.031
LnFFI − LnECLFP	10.974	0.004
LnECLFP − LnFFI	9.974	0.006
LnFFI − RLI	4.482	0.106
RLI − LnFFI	6.598	0.036
LnFFI − LnLUC	3.959	0.138

LnLUC – LnFFI	6.482	0.039
LnFFI – LnCE	7.482	0.023
LnCE – LNFFI	8.482	0.014
LnFFI – LnBIOCAP	4.018	0.134
LnBIOCAP – LnFFI	2.899	0.235
LnFFI – EMIT_FF	9.482	0.008
EMIT_FF – LnFFI	10.774	0.004
LnFFI – HEX	29.556	0.000
HEX – LnFFI	2.781	0.249
LnFFI – U5MR	17.706	0.000
U5MR – LnFFI	2.774	0.249

Figure 5.10- Causality Test



5.2. Objective 2 and 3 Results

5.2.1. Demographics

The study's demographics cover Uttarakhand (UK), Jammu & Kashmir (JK), and Himachal Pradesh (HP). Participants include 48% males and 52% females, with most aged 18-64. Education levels vary from non-educated to post-graduates, with UK and HP showing higher post-graduate representation. Family sizes are predominantly 1-10 members, with males and females evenly distributed across households. Economic status reveals a nearly equal BPL-APL split across regions. Caste representation includes General, OBC, SC, ST, and others, with STs being significantly lower in JK. Responses are captured using a five-point Likert scale, providing insights into perceptions related to forest fires and environmental impacts.

Table – 5.24: Descriptive Statistics

Measures	**Items**	**UK**	**JK**	**HP**
Gender	Male	248	223	240
	Female	312	127	160
Age	18-30	158	120	104
	30-42	173	85	109
	42-64	119	104	134
	64-76	110	41	53
Education	Not educated	109	108	89

	High school or below	117	88	110
	Intermediate	104	70	131
	Under-Graduate	193	67	40
	Post-Graduate or above	37	17	30
Number of Family Members	0-5	348	227	308
	5-10	190	113	82
	10-15	19	10	10
	15-20	3	0	0
Male in each Family	0-5	196	173	211
	5-10	33	41	17
	10-15	11	9	12
	15-20	8	0	0
Female in each Family	0-5	273	103	140
	5-10	27	21	11
	10-15	8	3	9
	15-20	4	0	0
Economic Status	BPL	237	180	206
	APL	323	170	194
Caste	(i) General	114	110	103
	(ii) OBC	123	115	96
	(iii) SC	103	56	93
	(iv) ST	105	40	88

	(v) Others	115	29	20
Likert scale questions				
Strongly Agree	1			
Agree	2			
Neutral	3			
Disagree	4			
Strongly Disagree	5			

5.2.2. Test of Normality

The results of a normality test show whether the samples were drawn from a normal distribution. The Kolmogorov-Smirnov and Shapiro-Wilk tests were used to determine whether the sample data were normal. The sample data coming from the normal distribution is the null hypothesis for both the Shapiro-Wilk and Kolmogorov-Smirnov tests. A significance value (p-value) higher than 0.05 is therefore taken to indicate that the data are normal. On the other hand, the sample data is not normal if the p-value is less than 0.05. Kolmogorov-Smirnov and Shapiro-Wilk test findings for the study indicate that the significance level is lower than 0.05. As a result, the sample data is not normal. The results of the normalcy tests are displayed in Table 5.25.

Table 5.25 - Tests of Normality

Tests of Normality (Uttarakhand)[1]						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
FFE 1	0.262	560	0.000	0.819	560	0.000
FFE 2	0.337	560	0.000	0.740	560	0.000
FFE 3	0.270	560	0.000	0.825	560	0.000
FFE 4	0.264	560	0.000	0.822	560	0.000
FD 1	0.280	560	0.000	0.702	560	0.000
FD 2	0.305	560	0.000	0.723	560	0.000
FD 3	0.254	560	0.000	0.763	560	0.000
HP 1	0.280	560	0.000	0.776	560	0.000
HP 2	0.266	560	0.000	0.787	560	0.000
HP 3	0.255	560	0.000	0.792	560	0.000
EP 1	0.427	560	0.000	0.592	560	0.000
EP 2	0.443	560	0.000	0.569	560	0.000
EP 3	0.419	560	0.000	0.588	560	0.000
HWI 1	0.392	560	0.000	0.617	560	0.000
HWI 2	0.412	560	0.000	0.632	560	0.000
HWI 3	0.411	560	0.000	0.635	560	0.000
HWI 4	0.411	560	0.000	0.628	560	0.000

[1] Results of Himachal Pradesh and Jammu & Kashmir are presented in Appendix A.

FFC 1	0.334	560	0.000	0.669	560	0.000
FFC 2	0.297	560	0.000	0.696	560	0.000
FFC 3	0.280	560	0.000	0.716	560	0.000
ED 1	0.273	560	0.000	0.829	560	0.000
ED 2	0.214	560	0.000	0.854	560	0.000
CI 1	0.293	560	0.000	0.788	560	0.000
CI 2	0.266	560	0.000	0.777	560	0.000
CI 3	0.288	560	0.000	0.778	560	0.000
CI 4	0.256	560	0.000	0.787	560	0.000
PR 1	0.292	560	0.000	0.784	560	0.000
PR 2	0.273	560	0.000	0.781	560	0.000
PR 3	0.276	560	0.000	0.787	560	0.000
AW 1	0.386	560	0.000	0.769	560	0.000
AW 2	0.378	560	0.000	0.761	560	0.000
AW 3	0.383	560	0.000	0.773	560	0.000
EI 1	0.377	560	0.000	0.628	560	0.000
EI 2	0.371	560	0.000	0.557	560	0.000
EI 3	0.394	560	0.000	0.674	560	0.000
EI 4	0.411	560	0.000	0.613	560	0.000
CFF 1	0.418	560	0.000	0.562	560	0.000
CFF 2	0.426	560	0.000	0.545	560	0.000
CFF 3	0.429	560	0.000	0.534	560	0.000

CFF 4	0.426	560	0.000	0.527	560	0.000
CFF 5	0.433	560	0.000	0.533	560	0.000
FH 1	0.326	560	0.000	0.698	560	0.000
FH 2	0.320	560	0.000	0.702	560	0.000
FS 1	0.424	560	0.000	0.614	560	0.000
FS 2	0.429	560	0.000	0.604	560	0.000

a. Lilliefors Significance Correction

Source: Calculated by the researcher using SPSS 29.0

5.2.3. Exploratory factor analysis

Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis (PCA) in SPSS 29.0 to uncover the constructs and associated items within the underlying model. Multivariate normality was not a prerequisite for performing PCA. The analysis employed varimax rotation and adhered to the criterion of eigenvalues exceeding 1. Following the guidelines by Hair et al. 2011, factor loadings for each item are expected to surpass 0.7. The results show a satisfactory Kaiser-Meyer Olkin (KMO) value of 0.805 (greater than 0.7), ensuring sampling adequacy for further factor analysis and a significant test of sphericity ($p<0.05$), which tests for collinearity and presence of redundancy between variables leading to fewer factors. The results of KMO and Bartlett's test of sphericity are shown in Table 5.26. Both tests ensured data fit for factor analysis.

Table 5.26 - Results of Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test of Sphericity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.805
Bartlett's Test of Sphericity	Approx. Chi-Square	147530.763
	Df	1711
	Sig.	0.000

Source: Calculated by the researcher using SPSS 29.0

5.2.4. Common Method Bias

Common Method Bias (CMB), as described by Podsakoff and Organ (1986), occurs when relationships between constructs are biased due to using the same measurement method. To address this, the researcher applied Harman's Single Factor Test. In this study, the highest variance explained by a single factor was 27.620% (Table 5.27), well below the 50% threshold, indicating CMB is not a concern, allowing further analysis.

Table -5.27 – Common Method Bias

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	16.296	27.620	27.620	16.296	27.620	27.620	4.929	8.354	8.354
2	6.170	10.458	38.078	6.170	10.458	38.078	4.777	8.097	16.451
3	4.861	8.238	46.316	4.861	8.238	46.316	4.754	8.058	24.510
4	3.493	5.920	52.237	3.493	5.920	52.237	4.469	7.575	32.084

5	3.154	5.345	57.582	3.154	5.345	57.582	4.243	7.192	39.276
6	2.268	3.844	61.426	2.268	3.844	61.426	3.824	6.482	45.758
7	2.214	3.752	65.178	2.214	3.752	65.178	3.697	6.266	52.023
8	2.049	3.472	68.651	2.049	3.472	68.651	3.530	5.984	58.007
9	1.989	3.371	72.022	1.989	3.371	72.022	3.453	5.853	63.860
10	1.512	2.563	74.584	1.512	2.563	74.584	3.183	5.394	69.254
11	1.281	2.172	76.756	1.281	2.172	76.756	2.892	4.901	74.156
12	1.141	1.934	78.690	1.141	1.934	78.690	2.675	4.534	78.690
13	0.946	1.603	80.293						
14	0.861	1.459	81.753						
15	0.818	1.386	83.139						
16	0.806	1.366	84.505						
17	0.757	1.283	85.787						
18	0.705	1.196	86.983						
19	0.632	1.071	88.054						
20	0.570	0.966	89.020						
21	0.525	0.890	89.910						
22	0.498	0.844	90.754						
23	0.453	0.768	91.522						
24	0.432	0.731	92.254						
25	0.408	0.691	92.945						
26	0.372	0.630	93.574						

27	0.349	0.591	94.165
28	0.336	0.569	94.734
29	0.324	0.550	95.284
30	0.308	0.522	95.806
31	0.288	0.489	96.295
32	0.267	0.453	96.747
33	0.253	0.429	97.176
34	0.246	0.416	97.592
35	0.230	0.389	97.982
36	0.201	0.341	98.323
37	0.189	0.321	98.643
38	0.183	0.310	98.953
39	0.142	0.240	99.193
40	0.125	0.212	99.405
41	0.090	0.153	99.558
42	0.077	0.131	99.689
43	0.073	0.124	99.813
44	0.062	0.105	99.918
45	0.048	0.082	100.000

Extraction Method: Principal Component Analysis.

5.2.5. Outer or Measurement model estimation

In Structural Equation Modeling (SEM), the outer model explains the relationship between latent variables and their observed indicators, showing how well the indicators represent the underlying constructs. The inner model, on the other hand, explains the relationships among the latent variables themselves, capturing the hypothesized causal or correlational links based on theory. Together, they provide a comprehensive understanding of measurement and structural relationships in the model. Figure 5.11 – 5.13 presents the outer model (Uttarakhand, Jammu & Kashmir, and Himachal Pradesh) with outer loadings. Using CFA, the measurement model's reliability and validity were assessed, as required in PLS-SEM.

Figure 5.11 – Outer Model – Uttarakhand

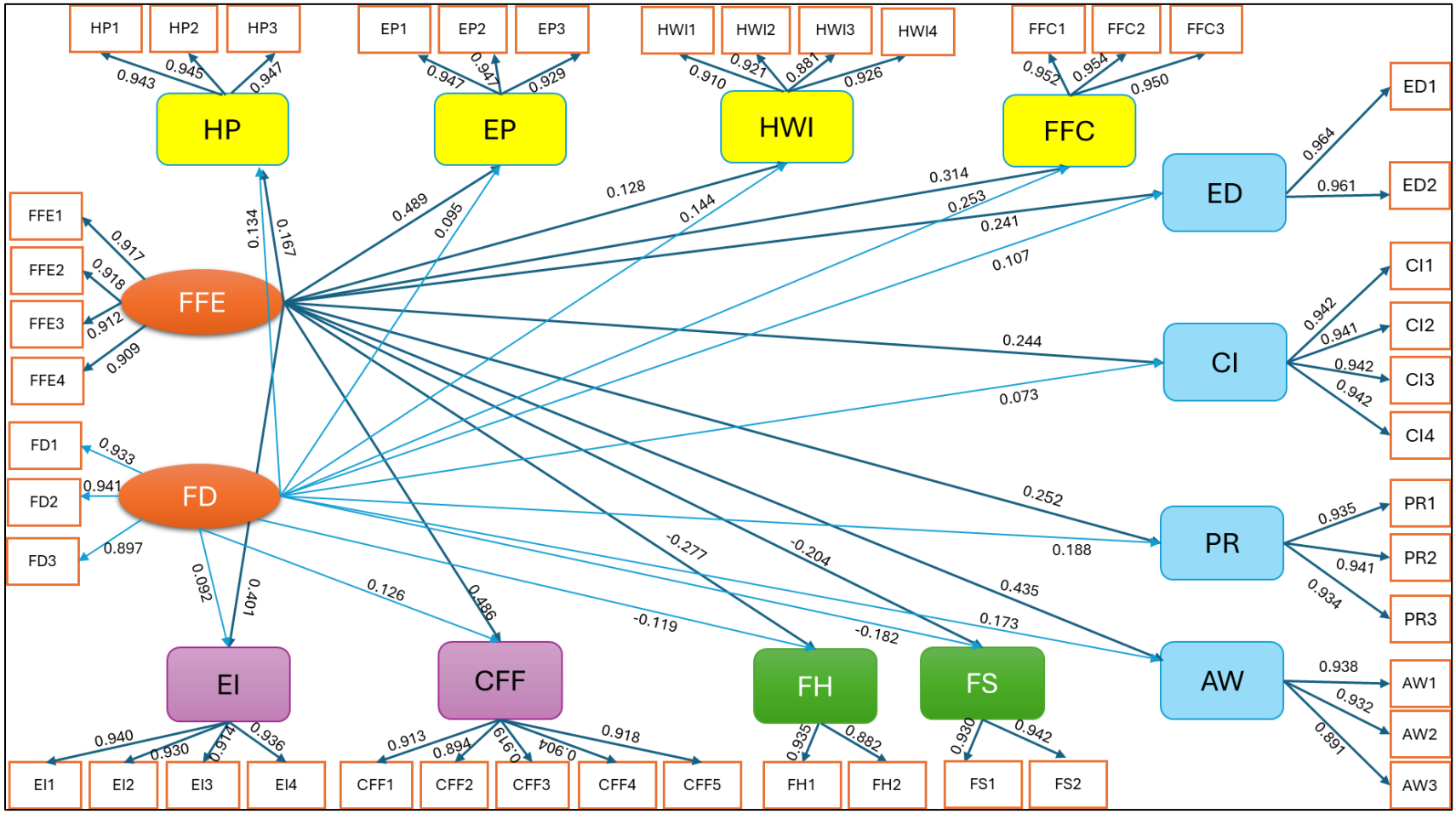


Figure 5.12 – Outer Model - Jammu & Kashmir

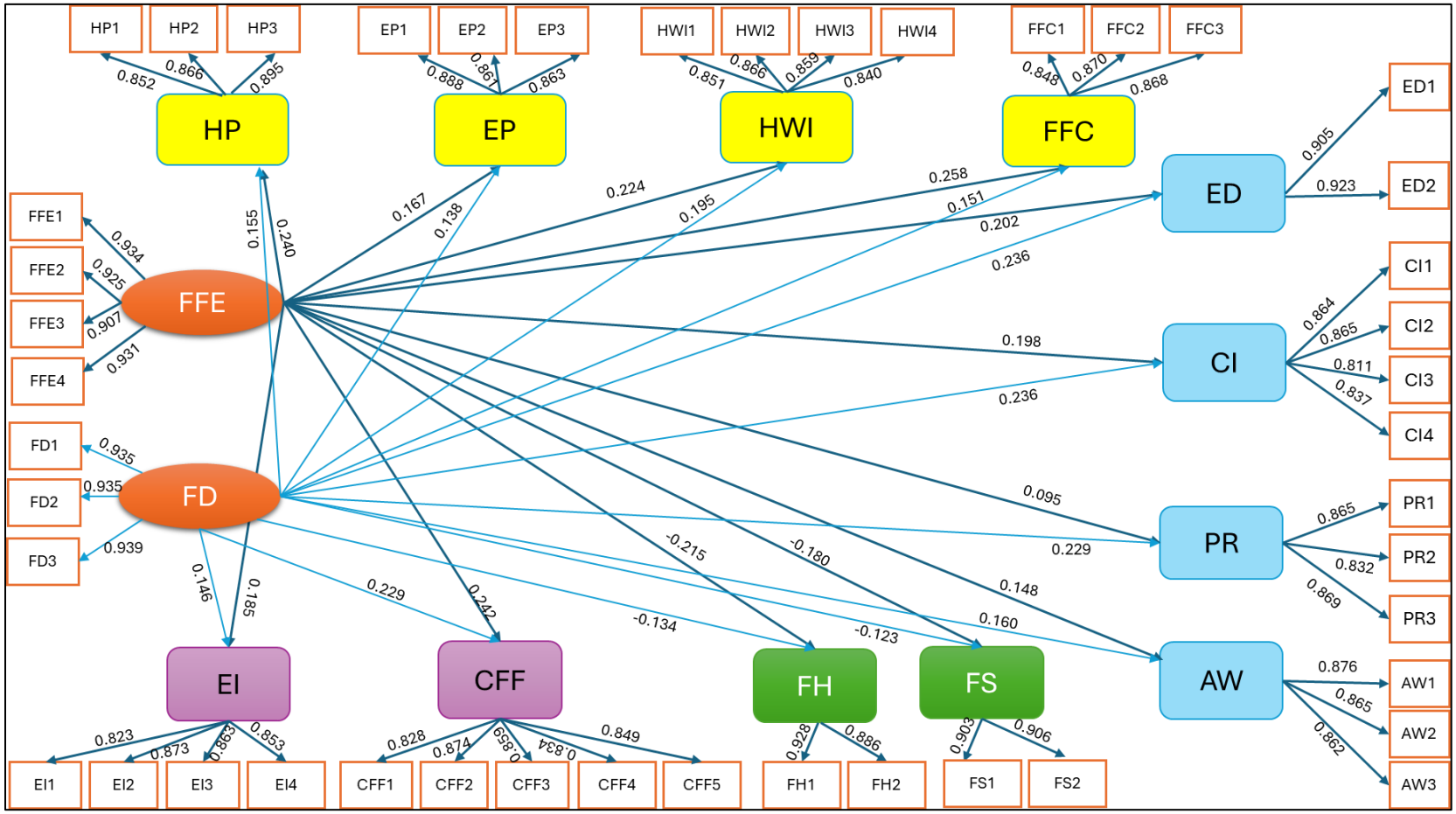
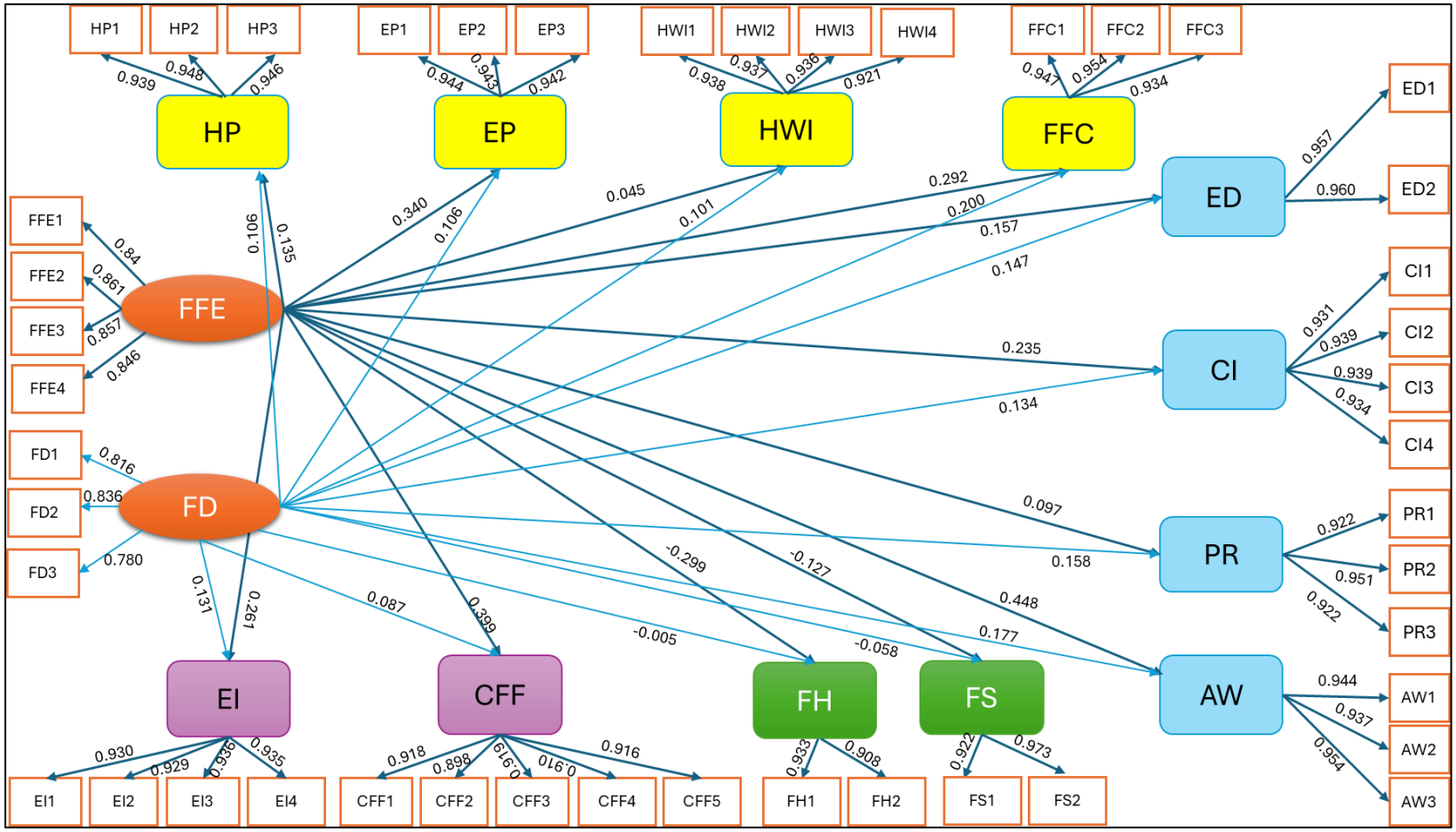


Figure 5.13 – Outer Model - Himachal Pradesh



5.2.5.1. Reliability and Convergent Validity

Reliability reflects consistency, and validity ensures accuracy. Table 5.28-5.30 presents outer loadings, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) of Uttarakhand, Jammu & Kashmir, Himachal Pradesh. All constructs have Cronbach's alpha and CR values above 0.7, as recommended by Hair et al. (1995). Factor loadings exceed 0.7, and AVE values are above 0.5, confirming convergent validity.

Table 5.28 – Results of Uttarakhand

	Uttarakhand			
	Outer loadings	**Cronbach's alpha**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
AW 1 <- AW	0.938	0.910	0.943	0.847
AW 2 <- AW	0.932			
AW 3 <- AW	0.891			
CFF 1 <- CFF	0.913	0.948	0.96	0.827
CFF 2 <- CFF	0.894			
CFF 3 <- CFF	0.919			
CFF 4 <- CFF	0.904			
CFF 5 <- CFF	0.918			
CI 1 <- CI	0.942	0.955	0.967	0.88
CI 2 <- CI	0.941			

CI 3 <- CI	0.942			
CI 4 <- CI	0.925			
ED 1 <- ED	0.964	0.921	0.962	0.926
ED 2 <- ED	0.961			
EI 1 <- EI	0.940	0.948	0.963	0.865
EI 2 <- EI	0.930			
EI 3 <- EI	0.914			
EI 4 <- EI	0.936			
EP 1 <- EP	0.947	0.935	0.959	0.885
EP 2 <- EP	0.947			
EP 3 <- EP	0.929			
FD 1 <- FD	0.933	0.915	0.946	0.854
FD 2 <- FD	0.941			
FD 3 <- FD	0.897			
FFC 1 <- FFC	0.952	0.948	0.967	0.906
FFC 2 <- FFC	0.954			
FFC 3 <- FFC	0.950			
FFE 1 <- FFE	0.917	0.934	0.953	0.835
FFE 2 <- FFE	0.918			
FFE 3 <- FFE	0.912			
FFE 4 <- FFE	0.909			
FH 1 <- FH	0.935	0.793	0.904	0.826

FH 2 <- FH	0.882			
FS 1 <- FS	0.930	0.860	0.934	0.877
FS 2 <- FS	0.942			
HP 1 <- HP	0.943	0.940	0.962	0.893
HP 2 <- HP	0.945			
HP 3 <- HP	0.947			
HWI 1 <- HWI	0.910	0.931	0.950	0.827
HWI 2 <- HWI	0.921			
HWI 3 <- HWI	0.881			
HWI 4 <- HWI	0.926			
PR 1 <- PR	0.934	0.930	0.956	0.878
PR 2 <- PR	0.941			
PR 3 <- PR	0.935			

Table- 5.29 – Results Of Jammu & Kashmir

Jammu & Kashmir				
	Outer loadings	**Cronbach's alpha**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
AW 1 <- AW	0.876	0.837	0.902	0.753

AW 2 <- AW	0.865			
AW 3 <- AW	0.862			
CFF 1 <- CFF	0.828	0.903	0.928	0.721
CFF 2 <- CFF	0.874			
CFF 3 <- CFF	0.859			
CFF 4 <- CFF	0.834			
CFF 5 <- CFF	0.849			
CI 1 <- CI	0.864	0.867	0.908	0.713
CI 2 <- CI	0.865			
CI 3 <- CI	0.811			
CI 4 <- CI	0.837			
ED 1 <- ED	0.905	0.803	0.91	0.835
ED 2 <- ED	0.923			
EI 1 <- EI	0.823	0.876	0.915	0.728
EI 2 <- EI	0.873			
EI 3 <- EI	0.863			
EI 4 <- EI	0.853			
EP 1 <- EP	0.888	0.841	0.904	0.758
EP 2 <- EP	0.861			
EP 3 <- EP	0.863			
FD 1 <- FD	0.935	0.930	0.955	0.877
FD 2 <- FD	0.935			
FD 3 <- FD	0.939			

FFC 1 <- FFC	0.848	0.828	0.897	0.743
FFC 2 <- FFC	0.870			
FFC 3 <- FFC	0.868			
FFE 1 <- FFE	0.934	0.943	0.959	0.854
FFE 2 <- FFE	0.925			
FFE 3 <- FFE	0.907			
FFE 4 <- FFE	0.931			
FH 1 <- FH	0.928	0.788	0.903	0.823
FH 2 <- FH	0.886			
FS 1 <- FS	0.903	0.778	0.900	0.818
FS 2 <- FS	0.906			
HP 1 <- HP	0.852	0.841	0.904	0.759
HP 2 <- HP	0.866			
HP 3 <- HP	0.895			
HWI 1 <- HWI	0.851	0.876	0.915	0.729
HWI 2 <- HWI	0.866			
HWI 3 <- HWI	0.859			
HWI 4 <- HWI	0.840			
PR 1 <- PR	0.865	0.817	0.891	0.732
PR 2 <- PR	0.832			
PR 3 <- PR	0.869			

Table-5.30 – Results of Himachal Pradesh

	Himachal Pradesh			
	Outer loadings	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Average variance extracted (AVE)**
AW 1 <- AW	0.944	0.940	0.947	0.893
AW 2 <- AW	0.937			
AW 3 <- AW	0.954			
CFF 1 <- CFF	0.918	0.950	0.953	0.832
CFF 2 <- CFF	0.898			
CFF 3 <- CFF	0.919			
CFF 4 <- CFF	0.910			
CFF 5 <- CFF	0.916			
CI 1 <- CI	0.931	0.953	0.956	0.876
CI 2 <- CI	0.939			
CI 3 <- CI	0.939			
CI 4 <- CI	0.934			
ED 1 <- ED	0.957	0.913	0.913	0.920
ED 2 <- ED	0.960			
EI 1 <- EI	0.930	0.950	0.950	0.869
EI 2 <- EI	0.929			
EI 3 <- EI	0.936			
EI 4 <- EI	0.935			
EP 1 <- EP	0.944	0.938	0.938	0.889
EP 2 <- EP	0.943			
EP 3 <- EP	0.942			
FD 1 <- FD	0.816	0.739	0.739	0.657

FD 2 <- FD	0.836			
FD 3 <- FD	0.780			
FFC 1 <- FFC	0.947	0.940	0.947	0.893
FFC 2 <- FFC	0.954			
FFC 3 <- FFC	0.934			
FFE 1 <- FFE	0.864	0.880	0.880	0.735
FFE 2 <- FFE	0.861			
FFE 3 <- FFE	0.857			
FFE 4 <- FFE	0.846			
FH 1 <- FH	0.933	0.821	0.834	0.847
FH 2 <- FH	0.908			
FS 1 <- FS	0.922	0.894	1.077	0.899
FS 2 <- FS	0.973			
HP 1 <- HP	0.939	0.940	0.947	0.892
HP 2 <- HP	0.948			
HP 3 <- HP	0.946			
HWI 1 <- HWI	0.938	0.951	0.975	0.870
HWI 2 <- HWI	0.937			
HWI 3 <- HWI	0.936			
HWI 4 <- HWI	0.921			
PR 1 <- PR	0.922	0.925	0.955	0.868
PR 2 <- PR	0.951			
PR 3 <- PR	0.922			

5.2.5.2. Discriminant validity

It ensures that measurements are distinct and unrelated. It is assessed using cross-loadings, the square root of AVE values (Fornell & Larcker, 1981), and the Heterotrait-Monotrait ratio (HTMT). Cross-loading analysis confirms that items load higher on their parent construct. The Fornell-Larcker criterion is satisfied as the square root of AVE values exceeds inter-construct correlations. HTMT values below 0.85 (Hair et al., 2017) also confirm construct distinctiveness. Tables 5.31–5.33 demonstrate satisfactory results.

Table: 5.31 – Uttarakhand Discriminant validity

	HTMT													
	AW	**CFF**	**CI**	**ED**	**EI**	**EP**	**FD**	**FFC**	**FFE**	**FH**	**FS**	**HP**	**HWI**	**PR**
AW														
CFF	0.272													
CI	0.225	0.232												
ED	0.255	0.229	0.251											
EI	0.245	0.223	0.281	0.319										
EP	0.291	0.29	0.23	0.222	0.339									
FD	0.062	0.028	0.037	0.05	0.031	0.041								
FFC	0.243	0.124	0.163	0.22	0.175	0.283	0.179							
FFE	0.418	0.479	0.234	0.229	0.397	0.494	0.288	0.261						
FH	0.091	0.142	0.091	0.02	0.067	0.12	0.051	0.137	0.28					
FS	0.058	0.271	0.041	0.192	0.137	0.08	0.146	0.121	0.172	0.116				

HP	0.088	0.03	0.037	0.066	0.105	0.118	0.096	0.055	0.139	0.055	0.05			
HWI	0.151	0.068	0.143	0.136	0.097	0.172	0.113	0.15	0.097	0.118	0.111	0.06		
PR	0.067	0.128	0.245	0.07	0.102	0.082	0.128	0.067	0.217	0.158	0.143	0.04	0.124	

Fornell Larcker

	AW	**CFF**	**CI**	**ED**	**EI**	**EP**	**FD**	**FFC**	**FFE**	**FH**	**FS**	**HP**	**HWI**	**PR**
AW	0.921													
CFF	0.255	0.909												
CI	0.213	0.223	0.938											
ED	0.233	0.214	0.236	0.962										
EI	0.226	0.214	0.269	0.295	0.93									
EP	0.272	0.274	0.219	0.206	0.322	0.941								
FD	0.058	-0.003	0.008	0.043	-0.014	-0.035	0.924							
FFC	0.23	0.119	0.156	0.204	0.166	0.266	0.17	0.952						
FFE	0.389	0.452	0.225	0.213	0.376	0.464	-0.266	0.246	0.914					

FH	-0.068	-0.124	-0.083	-0.013	-0.046	-0.104	-0.045	-0.125	-0.246	0.909				
FS	-0.053	-0.246	0.005	-0.171	-0.123	-0.075	-0.127	-0.111	-0.156	0.095	0.936			
HP	0.083	0	0.034	0.062	0.098	0.111	0.09	0.051	0.131	0.013	-0.045	0.945		
HWI	0.142	0.061	0.135	0.126	0.092	0.162	0.11	0.145	0.09	-0.099	-0.098	-0.056	0.91	
PR	0.062	0.12	0.232	0.064	0.096	0.078	0.121	0.063	0.202	-0.135	-0.128	0.038	0.115	0.937

Table 5.32 – Jammu & Kashmir Discriminant validity

	HTMT													
	AW	**CFF**	**CI**	**ED**	**EI**	**EP**	**FD**	**FFC**	**FFE**	**FH**	**FS**	**HP**	**HWI**	**PR**
AW														
CFF	0.151													
CI	0.068	0.093												
ED	0.127	0.111	0.036											
EI	0.061	0.072	0.051	0.082										
EP	0.049	0.093	0.098	0.141	0.098									
FD	0.174	0.244	0.142	0.27	0.158	0.152								
FFC	0.051	0.097	0.069	0.111	0.026	0.147	0.168							
FFE	0.167	0.255	0.213	0.227	0.198	0.185	0.026	0.288						
FH	0.094	0.086	0.189	0.173	0.051	0.055	0.15	0.126	0.245					
FS	0.066	0.162	0.17	0.161	0.068	0.06	0.142	0.112	0.208	0.039				
HP	0.151	0.161	0.046	0.087	0.123	0.073	0.17	0.127	0.267	0.088	0.039			

HWI	0.193	0.075	0.073	0.084	0.076	0.134	0.246	0.115	0.21	0.04	0.053	0.252		
PR	0.059	0.1	0.137	0.074	0.083	0.036	0.105	0.084	0.258	0.225	0.088	0.093	0.116	

Fornell Larcker

	AW	**CFF**	**CI**	**ED**	**EI**	**EP**	**FD**	**FFC**	**FFE**	**FH**	**FS**	**HP**	**HWI**	**PR**
AW	0.868													
CFF	0.136	0.849												
CI	0.014	0.084	0.844											
ED	0.104	0.095	0.023	0.914										
EI	0.032	0.065	-0.027	0.063	0.853									
EP	0.023	0.084	0.087	0.113	0.086	0.871								
FD	0.158	0.226	0.131	0.234	0.143	0.135	0.936							
FFC	0.022	0.085	0.041	0.09	-0.009	0.124	0.148	0.862						
FFE	0.145	0.239	0.196	0.199	0.183	0.165	-0.014	0.255	0.924					
FH	-0.077	-0.073	-0.158	-0.134	0.042	-0.048	-0.131	-0.104	-0.213	0.907				
FS	-0.053	-0.136	-0.139	-0.128	-0.055	-0.036	-0.121	-0.091	-0.178	-0.016	0.905			

HP	0.124	0.139	0.03	0.073	0.112	0.04	0.152	0.107	0.238	-0.071	-0.016	0.871		
HWI	0.164	0.063	0.055	0.073	0.058	0.115	0.221	0.098	0.192	-0.033	-0.042	0.216	0.854	
PR	0.049	0.086	0.115	0.06	0.053	0.004	0.092	0.068	0.228	-0.18	-0.071	0.079	0.101	0.855

Table 5.33- Himachal Pradesh Discriminant Validity

	HTMT													
	AW	**CFF**	**CI**	**ED**	**EI**	**EP**	**FD**	**FFC**	**FFE**	**FH**	**FS**	**HP**	**HWI**	**PR**
AW														
CFF	0.181													
CI	0.161	0.101												
ED	0.125	0.059	0.05											
EI	0.153	0.077	0.173	0.159										
EP	0.186	0.148	0.067	0.041	0.148									
FD	0.108	0.04	0.105	0.141	0.097	0.052								
FFC	0.211	0.065	0.152	0.075	0.027	0.16	0.17							
FFE	0.452	0.415	0.227	0.143	0.257	0.352	0.241	0.277						
FH	0.158	0.204	0.016	0.063	0.036	0.137	0.075	0.115	0.349					

FS	0.033	0.055	0.03	0.128	0.04	0.027	0.055	0.086	0.124	0.024				
HP	0.037	0.032	0.041	0.028	0.115	0.024	0.095	0.039	0.125	0.031	0.017			
HWI	0.041	0.059	0.102	0.019	0.038	0.03	0.105	0.103	0.042	0.057	0.1	0.027		
PR	0.043	0.015	0.089	0.049	0.054	0.089	0.165	0.023	0.072	0.021	0.049	0.053	0.101	

Fornell Larcker

	AW	**CFF**	**CI**	**ED**	**EI**	**EP**	**FD**	**FFC**	**FFE**	**FH**	**FS**	**HP**	**HWI**	**PR**
AW	0.945													
CFF	0.172	0.912												
CI	0.153	0.097	0.936											
ED	0.117	0.056	0.045	0.959										
EI	0.146	0.074	0.164	0.148	0.932									
EP	0.175	0.139	0.062	0.025	0.14	0.943								
FD	0.09	0.01	0.088	0.116	0.08	0.039	0.811							
FFC	0.201	0.063	0.144	0.07	0.025	0.15	0.143	0.945						

FFE	0.413	0.382	0.209	0.128	0.236	0.32	-0.194	0.253	0.857					
FH	-0.141	-0.178	0.011	-0.057	-0.014	-0.12	0.053	-0.102	-0.298	0.92				
FS	-0.032	-0.049	0.03	-0.119	-0.017	0.009	-0.033	-0.086	-0.116	0.007	0.948			
HP	-0.034	-0.025	0.029	-0.008	0.108	0.003	0.08	0.026	0.114	0.021	0.014	0.944		
HWI	-0.006	-0.056	-0.097	0.006	0.034	-0.02	0.092	-0.094	0.025	-0.045	-0.084	-0.001	0.933	
PR	0.041	0.005	0.085	-0.045	-0.051	-0.081	0.139	-0.002	0.067	0.013	-0.043	-0.046	-0.095	0.932

5.2.5.3. Measurement model assessment for Collinearity issues

The Variance inflation factor (VIF) is often used to evaluate collinearity. Ideally, the VIF values should be close to 5 and lower. Table 5.34 shows the VIF values of outer model and all values are below 5 for each state and union territory.

TABLE: 5.34 – VIF VALUES

	Jammu & Kashmir	Uttarakhand	Himachal Pradesh
	VIF	**VIF**	**VIF**
AW 1	1.886	3.394	3.98
AW 2	2.080	3.565	4.225
AW 3	1.935	2.609	4.886
CFF 1	2.171	4.048	4.219
CFF 2	2.537	3.812	3.782
CFF 3	2.390	4.346	4.278
CFF 4	2.287	3.729	3.779
CFF 5	2.446	4.454	4.338
CI 1	2.024	4.857	4.276
CI 2	2.205	4.908	4.908
CI 3	1.981	4.759	4.600
CI 4	2.108	4.583	4.728
ED 1	1.820	3.667	3.383
ED 2	1.820	3.667	3.383
EI 1	2.052	4.646	4.212
EI 2	2.223	4.467	4.291
EI 3	2.276	3.633	4.649
EI 4	2.140	4.644	4.500
EP 1	2.244	4.167	4.133
EP 2	2.015	4.254	4.133
EP 3	1.831	3.711	4.172
FD 1	3.822	3.411	1.523
FD 2	3.588	3.676	1.602
FD 3	3.798	2.780	1.358
FFC 1	1.801	4.991	4.301
FFC 2	2.032	4.651	4.721

FFC 3	1.867	4.979	4.007
FFE 1	4.500	3.578	2.279
FFE 2	4.082	3.689	2.289
FFE 3	3.379	3.534	2.251
FFE 4	4.218	3.328	2.072
FH 1	1.730	1.758	1.938
FH 2	1.730	1.758	1.938
FS 1	1.683	2.315	2.895
FS 2	1.683	2.315	2.895
HP 1	1.907	4.429	4.271
HP 2	2.003	4.104	4.207
HP 3	2.095	4.328	4.268
HWI 1	2.177	3.037	4.164
HWI 2	2.382	3.766	4.905
HWI 3	2.168	3.001	4.416
HWI 4	2.037	4.547	4.411
PR 1	1.804	3.752	3.322
PR 2	1.770	3.950	3.864
PR 3	1.873	3.609	3.495

5.2.6. Inner or Structural model estimation

The next step is to test the hypothesized relationships using confirmatory factor analysis for assessing the structural model. This was done via bootstrapping with 5000 subsamples at 95% confidence interval in Smart PLS4. The four hypotheses in this study were tested across 3 different regions – Uttarakhand, Jammu & Kashmir and Himachal Pradesh (Table 5.35)

Table 5.35 - Hypothesis Test

	PATH COEFF.	Standard deviation (STDEV)	T statistics	P values	Results
Uttarakhand					
FF -> ECONOMIC	0.547	0.030	18.006	0	Supported
FF -> ENVIRONMENT	-0.329	0.035	9.334	0	Supported
FF -> HEALTH	0.522	0.032	16.479	0	Supported
FF -> SOCIAL	0.505	0.035	14.556	0	Supported
Jammu & Kashmir					
FF -> ECONOMIC	0.392	0.040	9.733	0	Supported
FF -> ENVIRONMENT	-0.333	0.046	7.198	0	Supported
FF -> HEALTH	0.469	0.041	11.538	0	Supported
FF -> SOCIAL	0.461	0.038	12.099	0	Supported
Himachal Pradesh					
FF -> ECONOMIC	0.453	0.041	11.160	0	Supported
FF -> ENVIRONMENT	-0.303	0.046	6.635	0	Supported
FF -> HEALTH	0.457	0.046	10.041	0	Supported
FF -> SOCIAL	0.506	0.044	11.546	0	Supported

- **For Region Uttarakhand –**

H_1 evaluates whether Forest fires significantly affect Economic Costs.

The results reveal that forest fires have a significant impact on the economy ($\beta = 0.547\ ;\ t = 18.006, p - value < 0.05$). Hence, H_1 was supported.

H_2 evaluated whether Forest fires significantly degrade the environment.

The results reveal that forest fires have a significant impact on environmental degradation ($\beta = -0.329;\ t = 9.334, p - value < 0.05$). Hence, H_2 was supported.

H_3 evaluated whether Forest fires significantly affect Human Health.

The results reveal that forest fires have a significant impact on health ($\beta = 0.522;\ t = 1.479, p - value < 0.05$). Hence, H_3 was supported.

H_4 evaluated whether Forest fires adversely affect social well-being, leading to displacement, psychological stress, and weakened community cohesion.

The results reveal that forest fires have a significant impact on social ($\beta = 0.505;\ t = 14.556, p - value < 0.05$). Hence, H_4 was supported.

- **For Region Jammu & Kashmir –**

H_1 evaluates whether Forest fires significantly affect Economic Costs.

The results reveal that forest fires have a significant impact on the economy ($\beta = 0.392;\ t = 9.733, p - value < 0.05$). Hence, H_1 was supported.

H_2 evaluated whether Forest fires significantly degrade the environment.

The results reveal that forest fires have a significant impact on environmental degradation ($\beta = -0.333;\ t = 7.198, p - value < 0.05$). Hence, H_2 was supported.

H_3 evaluated whether Forest fires significantly affect health problems.

The results reveal that forest fires have a significant impact on health ($\beta = 0.469;\ t = 11.538, p - value < 0.05$). Hence, H_3 was supported.

H_4 evaluated $w_h$ether Forest fires adversely affect social well-being, leading to displacement, psychological stress, and weakened community cohesion.

The results reveal that forest fires have a significant impact on social ($\beta = 0.461;\ t = 12.099, p - value < 0.05$). Hence, H_4 was supported.

- **For Region Himachal Pradesh–**

H_1 evaluates whether Forest fires significantly affect Economic Cost.

The results reveal that forest fires have a significant impact on the economy ($\beta = 0.453\,;\ t = 11.160\,, p - value < 0.05$). Hence, H_1 was supported.

H_2 evaluated whether Forest fires significantly degrade the environment.

The results reveal that forest fires have a significant impact on environmental degradation ($\beta = -0.303;\ t = 6.635, p - value < 0.05$). Hence, H_2 was supported.

H_3 evaluated whether Forest fires significantly affect health problems.

The results reveal that forest fires have a significant impact on health ($\beta = 0.457;\ t = 10.041, p - value < 0.05$). Hence, H_3 was supported.

H_4 evaluated whether Forest fires adversely affect social well-being, leading to displacement, psychological stress, and weakened community cohesion.

The results reveal that forest fires have a significant impact on social ($\beta = 0506.;\ t = 11.546\,, p - value < 0.05$). Hence, H_4 was supported. The results of hypothesis testing are shown in Figures 5.14-5.16.

Figure 5.14 - Path coefficients of Uttarakhand

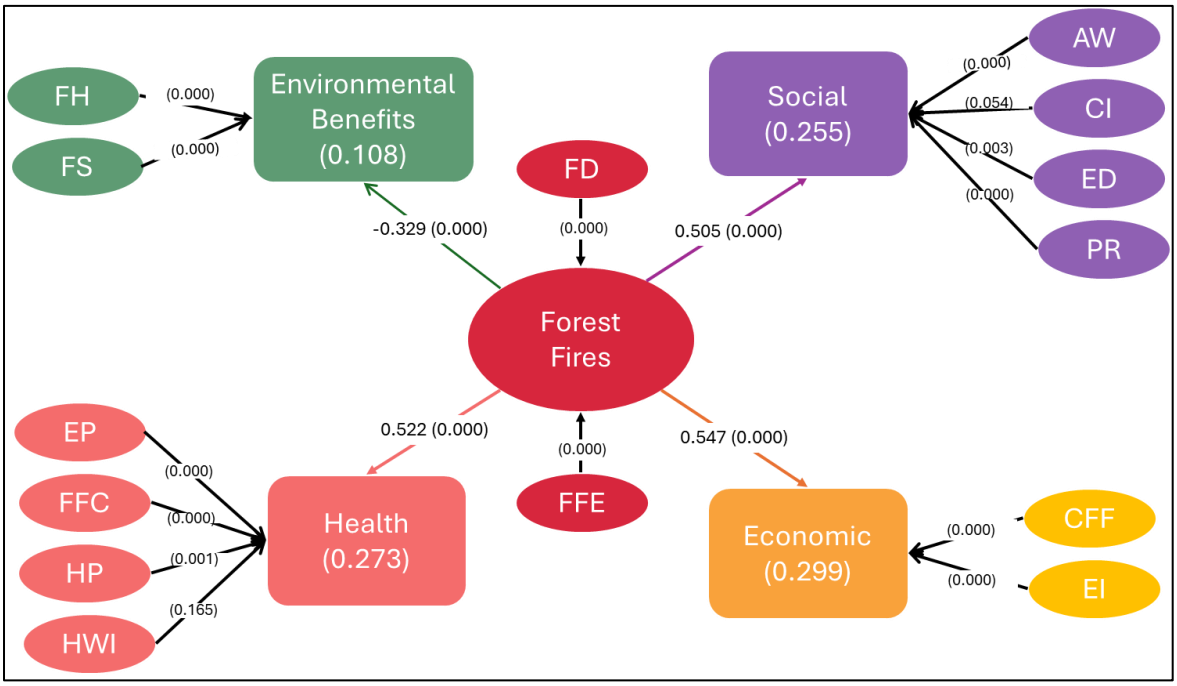


Figure 5.15 – Path coefficients of Jammu & Kashmir

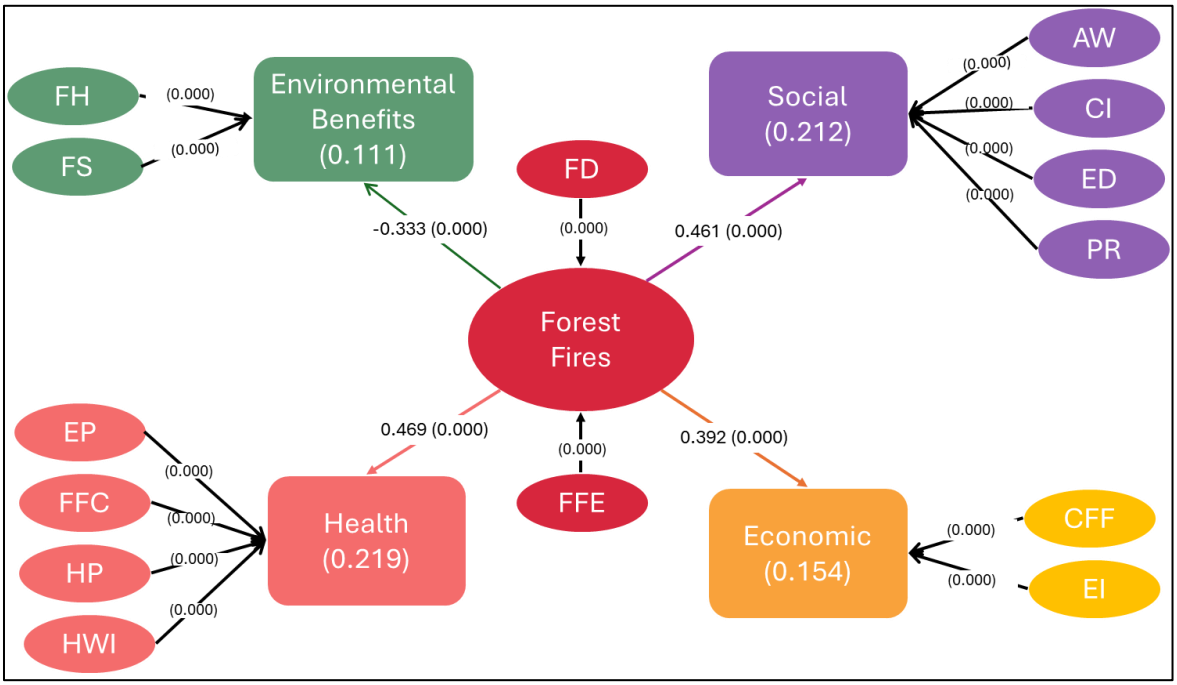
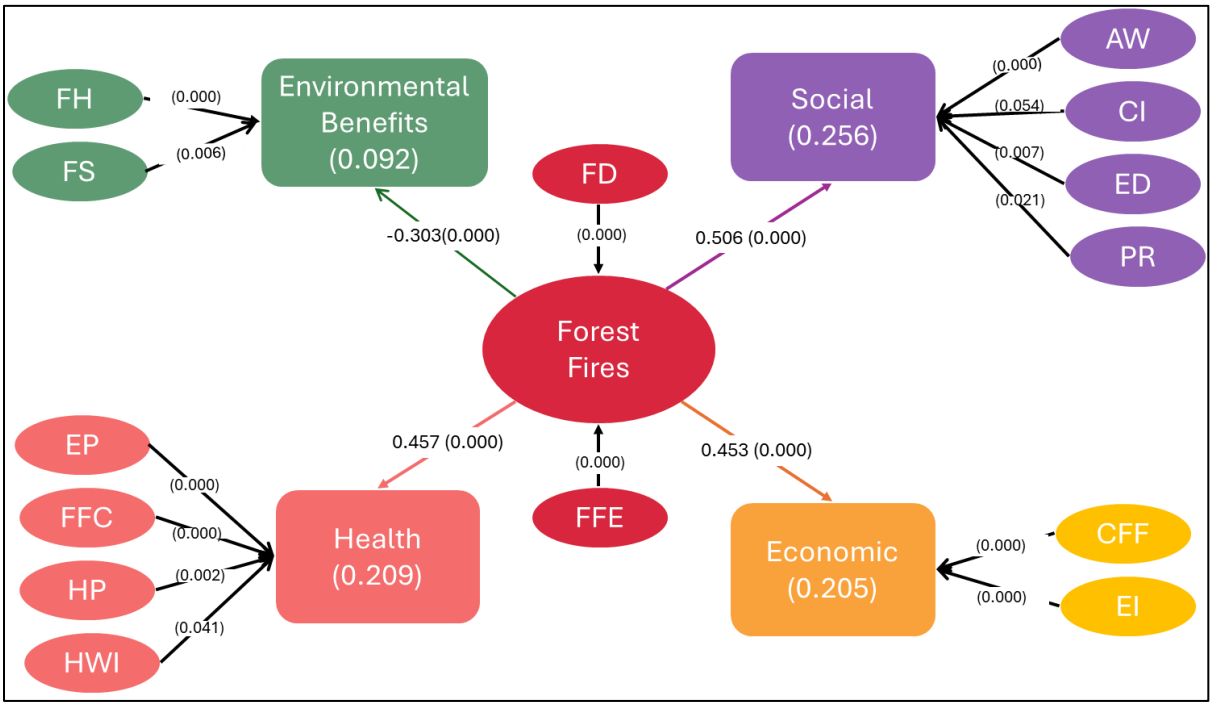


Figure 5.16 – Path coefficient of Himachal Pradesh



5.2.6.1. Predictive Relevance of Inner Model

Assessing a model's predictive relevance is a crucial aspect of the study, as it demonstrates the model's ability to predict outcomes beyond the sample data, highlighting its out-of-sample predictive accuracy. The predictive relevance and explanatory power of the model were assessed across the states of Uttarakhand, Jammu & Kashmir, and Himachal Pradesh for economic, environmental, health, and social dimensions. The Q^2 values demonstrate the model's out-of-sample predictive accuracy, while R^2 reflects the explained variance within the sample. These findings highlight variations in predictive accuracy and explanatory strength across regions and dimensions.

Table 5.36 – R^2, Q^2 Values

	Uttarakhand		Jammu & Kashmir		Himachal Pradesh	
	Q^2predict	**R^2**	**Q^2predict**	**R^2**	**Q^2predict**	**R^2**
ECONOMIC	0.293	0.299	0.144	0.154	0.194	0.205
ENVIRONMENT	0.101	0.108	0.102	0.111	0.082	0.092
HEALTH	0.261	0.273	0.203	0.219	0.189	0.209
SOCIAL	0.240	0.255	0.192	0.212	0.239	0.205

Table 5.37– VIF Values

CONSTRUCTS	**UK**	**J&K**	**HP**
AW	1.088	1.013	1.038
CFF	1.048	1.004	1.006
CI	1.144	1.014	1.032
ED	1.100	1.014	1.017
EI	1.048	1.004	1.006
EP	1.108	1.027	1.023
FD	1.076	1.000	1.039
FFC	1.090	1.031	1.033
FFE	1.076	1.000	1.039

FH	1.009	1.000	1.000
FS	1.009	1.000	1.000
HP	1.019	1.057	1.001
HWI	1.045	1.066	1.009
PR	1.057	1.019	1.011

5.2.7. Testing of the structural model

To assess the model fit or predictive relevance of the model, the researcher has used SRMR values. The Standardized Root Mean Square Residual (SRMR) measures model fit by comparing the observed and estimated correlation matrices. An SRMR value below 0.10 indicates a good fit (Hu & Bentler, 1999), and the model's SRMR of 0.046 for Jammu and Kashmir, 0.065 for Uttarakhand, 0.050 for Himachal Pradesh confirms this.

5.3. Conclusion

Chapter 5 presents a comprehensive analysis of the research objectives through the application of ARDL (Autoregressive Distributed Lag) and SEM (Structural Equation Modeling) methodologies. The findings robustly addressed Objectives 1, 2, and 3, providing empirical validation for the proposed hypotheses. The ARDL analysis demonstrated both short-term and long-term dynamics, confirming the significance of the relationships between key variables under study. Similarly, SEM provided insights into the structural relationships, highlighting the effects of forest fires. Collectively, these results not only substantiate the hypotheses but also contribute to a nuanced understanding of the underlying phenomena, thereby enriching the field's theoretical and practical knowledge.

Chapter VI
CONCLUSIONS: FINDINGS AND POLICY IMPLICATIONS

This Chapter synthesizes the key findings of this study, guided by three specific research objectives, this study aims to explore the diverse effects of forest fires on environmental, economic, social, and health domains in India especially in the Northern Indian Himalayan Region in an exploratory and descriptive manner. Using secondary and primary data, this study delivers a comprehensive view of forest fire dynamics at the national level and in the Northern Himalayan Region in India, providing a vital perspective on how forest fires affect different sectors of society and the environment. The chapter further explores the practical and theoretical implications of the research, emphasizing its relevance to policymaking, environmental conservation, and future academic pursuits. By addressing these elements, it aims to offer a holistic perspective on the study's contributions and areas for further exploration.

6.1. Findings

The findings of the study reveal a multidimensional impact of forest fires on India's environment, socio-economy, and public health, emphasizing the urgent need for integrated and sustainable strategies to mitigate these effects. The *first objective*, which focuses on the assessment of forest fires at the national level, highlights the profound short-term and long-term consequences on India's socio-economic and environmental conditions. One of the significant findings is the rejection of the Environmental Kuznets Curve (EKC) hypothesis in the Indian context. The EKC theory, which suggests that environmental degradation initially worsens with economic growth but declines once a country reaches a certain level of

development (Grossman & Krueger, 1995), does not hold true in India. Instead, the study finds a persistent rise in environmental damage alongside economic growth, reflecting an unsustainable development trajectory. This result aligns with previous research conducted in other developing economies (Destek & Sinha, 2019, Katircioğlu & Katircioğlu, 2017), which also failed to observe an inverted U-shaped relationship between economic growth and environmental quality. In India, rapid urbanization, growing demand for energy, and unsustainable tourism practices are identified as key drivers exacerbating forest fire risks and amplifying environmental degradation. This persistent rise in ecological damage supports the argument that economic growth without adequate environmental regulations contributes to long-term ecological harm (Jie et al., 2023).

The study's findings emphasize the need for progressive and sustainable policies to reverse this trend. Policies aimed at decoupling economic growth from environmental degradations such as promoting clean energy, sustainable land use planning, and stricter forest protection measures—are crucial for achieving this balance. Other studies (Aguilar & Wen, 2021; Cochrane & Bowman, 2021) have similarly stressed the importance of integrated environmental policies in mitigating the adverse effects of economic activities on the environment.

This study delves into the relationship between forest fire incidences and various environmental variables, such as temperature, particulate matter concentrations, ecological footprint, land-use change, carbon emissions, biocapacity, biodiversity loss, and urbanization. The findings reveal a strong positive association between forest fire frequency and environmental variables like temperature, carbon emissions, and land-use changes, indicating that forest fires act as both a driver and a consequence of environmental degradation. Studies such as Zhong et al., 2021; Abram et al., 2021 have previously documented how rising temperatures and land-use changes increase the frequency and intensity of forest fires. Similarly, the study

confirms that higher temperatures and increased particulate matter concentrations (PM2.5) enhance the likelihood of forest fires, contributing to further carbon emissions and ecological degradation. This positive feedback loop amplifies environmental fragility and reduces the resilience of affected ecosystems.

One notable finding is that increasing biocapacity reduces the likelihood of forest fires. Biocapacity refers to an ecosystem's ability to regenerate resources and absorb waste, particularly carbon emissions. This finding is consistent with earlier studies (Zaman, 2021; Wunder et al., 2021), which argue that strengthening ecosystems through sustainable management practices, afforestation, and biodiversity conservation can improve their resilience against environmental shocks like forest fires. The study suggests that enhancing biocapacity through targeted policies such as restoring degraded land, preserving biodiversity, and promoting sustainable agricultural practices can play a crucial role in mitigating forest fire risks and their associated impacts.

This research explores the relationship between forest fires and public health, with a specific focus on under-5 mortality rates. The study identifies a strong association between forest fire activity and adverse health outcomes, particularly for vulnerable populations such as children under five. Forest fires release significant amounts of particulate matter ($PM_{2.5}$ and other toxic pollutants that degrade air quality and contribute to respiratory and cardiovascular diseases (Park et al., 2023). The results indicate that regions experiencing frequent forest fires have higher under-5 mortality rates, as the pollutants exacerbate respiratory infections and malnutrition. This is consistent with studies by Roberts & Wooster, 2021 and Requia et al., 2021, which show that exposure to air pollutants from wildfires is directly linked to increased hospital admissions and mortality among children. Additionally, the findings reveal that health expenditure plays a critical role in mitigating the health impacts of forest fires. Increased investment in healthcare systems and preventive

measures significantly reduces child mortality, particularly in vulnerable regions. This result aligns with the work of Simmons et al., 2021, this study emphasizes the importance of healthcare accessibility and public health infrastructure in reducing the health burden of environmental disasters. The study highlights the necessity of scaling up investments in healthcare and preventive services, especially in rural and fire-prone regions, to reduce mortality rates and improve long-term health outcomes. The findings also show that urbanization and forest fire emissions are strongly linked, with unsustainable urban expansion contributing to higher health risks through increased exposure to pollutants and degraded air quality. This observation resonates with previous research (Zhan et al., 2023), which found that rapid urbanization without adequate environmental planning can exacerbate health risks by concentrating populations in areas with poor air quality and limited access to healthcare services.

Overall, this study underscores the interconnected nature of forest fire impacts on India's environment, economy, and public health. The persistent rise in environmental degradation alongside economic growth, the strong links between forest fire frequency and environmental variables, and the significant health burden associated with fire emissions all highlight the urgent need for integrated policies. These policies should address the socio-economic and environmental drivers of forest fires, promote sustainable land use, and strengthen healthcare systems to reduce their adverse effects on public health. Sustainable economic development strategies, focusing on increasing biocapacity, protecting biodiversity, and improving healthcare services, are essential for decoupling economic growth from environmental degradation and ensuring long-term resilience. Future research should focus on developing region-specific strategies and enhancing community resilience through participatory planning and local capacity building.

The second and third objectives of this study examine the diverse impacts of forest fires on health, social, economic, and environmental dimensions in the Northern Indian Himalayan Region (NIHR), focusing on Uttarakhand (UK), Jammu & Kashmir (J&K), and Himachal Pradesh (HP). The findings reveal that forest fires have disproportionate impacts across sectors, causing long-term deterioration of environmental benefits and posing significant challenges to sustainable development. The primary data analysis highlights how forest fires adversely affect public health, particularly through increased rates of respiratory diseases caused by smoke and particulate matter (PM2.5) exposure. Health issues such as respiratory distress, asthma, and other lung conditions show a marked rise during the fire season, especially among vulnerable groups like children, the elderly, and individuals with pre-existing conditions. These findings align with studies by Aguilera et al., 2021 and Douglas-Vail et al., 2023, which show that forest fire smoke contributes to increased hospital admissions for respiratory diseases. Additionally, prolonged exposure to high temperatures during forest fires exacerbates heat wave-induced illnesses such as dehydration, heat exhaustion, and heatstroke, placing added pressure on local healthcare systems. Psychological distress is another significant health consequence, as the displacement and uncertainty caused by fires lead to anxiety, trauma, and, in some cases, post-traumatic stress disorder (PTSD). These impacts highlight the urgent need for improved emergency medical services (EMS), mental health support, and community-based health interventions to reduce the health burden in fire-prone areas.

Social impacts are equally pronounced. Forest fires disrupt social cohesion and community stability, particularly in rural areas where social networks are crucial to recovery. Evacuations and temporary relocations often result in the loss of community ties and cultural heritage, leaving families in a state of uncertainty and vulnerability. Studies such as Fernandes et al., 2018 and (Sadri et al., 2017) have

shown that communities with strong social networks recover more quickly from disasters, while displaced populations face prolonged recovery times. However, many communities in the NIHR lack adequate education, programming, and training on fire prevention and emergency response, further reducing their resilience. Strengthening social networks and building community capacity through education, awareness programs, and participatory disaster planning are essential steps in enhancing long-term recovery and preparedness.

Economically, forest fires cause substantial damage across key sectors, particularly agriculture, forestry, and tourism—industries vital to the economies of Uttarakhand, Jammu & Kashmir, and Himachal Pradesh. Agriculture is highly vulnerable to fire-induced soil degradation, which reduces fertility and increases erosion, lowering crop yields and destabilizing rural livelihoods. This finding is consistent with Van Wees et al., 2021, who documented similar effects of fire-induced soil degradation on agricultural productivity. Forest-based tourism, a critical income source for these scenic states, is also significantly affected, as fires force the closure of tourist destinations, leading to revenue losses and unemployment in tourism-dependent communities. Firefighting efforts themselves impose a financial burden on state budgets, requiring significant expenditures for personnel, equipment, and post-fire rehabilitation. Moreover, the destruction of homes, infrastructure, and forest resources compounds economic losses, shrinking household incomes and increasing poverty levels. Similar patterns have been observed globally in regions affected by frequent forest fires, as highlighted by studies such as Wang et al., 2020 and Meier et al., 2023. Mitigating these impacts requires the implementation of sustainable forest management practices and financial support programs for affected communities.

The long-term environmental consequences of forest fires are perhaps the most significant. The loss of forests leads to the destruction of vital ecosystems, endanger

biodiversity, and forces species displacement. Soil health is adversely affected, with fires reducing soil fertility and increasing erosion, which further threatens agricultural productivity and rural livelihoods. Kumar et al., 2024 have similarly highlighted how fire-induced soil degradation can have lasting effects on ecosystems and food security. Additionally, the release of large amounts of carbon dioxide and other greenhouse gases during forest fires contributes to global warming and accelerates climate change. The study emphasizes the importance of increasing biocapacity an ecosystem's ability to regenerate resources and absorb carbon emissions as a key strategy for mitigating fire risks and enhancing ecological resilience. This aligns with Souza-Alonso et al., 2022, who argue that restoring degraded ecosystems and preserving biodiversity can significantly reduce the likelihood and severity of future forest fires.

Forest fires have significant short-term impacts on health, social and economic outcomes, but their worst long-term consequence is the degradation of environmental benefits. The loss of forests removes vital ecosystems, endangering biodiversity and forcing species displacement. Fire has long-term negative effects on soil health and agricultural productivity: soil degradation triggered by fires reduces fertility and increases erosion, thereby impacting crop yields and further destabilizing rural livelihoods. Much of the forest lost to development is never recovered; it simply cannot sequester carbon naturally, releasing this carbon back into the atmosphere and driving climate change.

The findings offer significant theoretical contributions, particularly in refining and expanding the Environmental Kuznets Curve (EKC) and Tragedy of the Commons (TOC) theories. In the context of the first objective, the results challenge the traditional EKC hypothesis by revealing The findings from the first objective challenge the traditional Environmental Kuznets Curve (EKC) hypothesis in the Indian context. Contrary to the inverted U-shaped relationship predicted by EKC,

this study finds no evidence of a turning point where economic growth reduces environmental degradation. Instead, economic expansion in India continues to escalate environmental harm due to unregulated urbanization, tourism development, and rising energy demand. This divergence highlights that economic growth alone cannot ensure environmental recovery, emphasizing the need for governance, sustainable policies, and ecological capacity as critical determinants of environmental quality. The study calls for refining the EKC model to include these factors, shifting the focus from growth-centric to governance-centric solutions.

The second and third objectives contribute to the Tragedy of the Commons (TOC) theory by illustrating how unregulated forest resource use and poor fire management deplete shared resources, exacerbating environmental degradation in the Northern Indian Himalayan Region. Forest fires emerge as both a driver and outcome of this degradation, reflecting the classic commons dilemma. The findings align with Ostrom's perspective, showing that collective action, local knowledge, and participatory governance can mitigate these risks. The study emphasizes that community-based resource management can prevent resource depletion and build resilience. By integrating adaptive management strategies, the research offers a pathway to extend and refine TOC theory while providing practical insights for sustainable resource management in fire-prone regions.

The results highlight notable regional variations in the impacts of forest fires across Himachal Pradesh, Uttarakhand, and Jammu & Kashmir due to distinct geographical, climatic, and socio-economic factors unique to each state. The health impact of forest fires is particularly severe in Himachal Pradesh, where the rugged mountainous terrain and deep valleys act as natural traps for smoke, gases, and particulate matter. Temperature inversion events further prevent their upward dispersal, causing pollutants such as volatile organic compounds (VOCs), carbon

monoxide (CO), and fine particulate matter (PM2.5)to accumulate in valleys during fire-prone months. This prolonged pollutant trapping leads to severe respiratory issues, reduced lung function, cardiovascular damage, and eye irritation, disproportionately affecting vulnerable groups such as children, the elderly, and those with pre-existing conditions. The fire-prone lower-altitude regions of Himachal Pradesh also experience intense heat, exacerbating dehydration and heat-related illnesses. In comparison, Uttarakhand's broader valleys allow for better pollutant dispersion, while Jammu & Kashmir's cooler alpine climate and less flammable vegetation reduce fire intensity and its associated health risks. However, limited healthcare access in Himachal Pradesh's remote areas further amplifies these challenges, emphasizing the need for targeted interventions in fire-prone regions.

The economic impact of forest fires is highest in Uttarakhand due to its high population density and heavy reliance on forest-based livelihoods. Frequent fires disrupt agriculture, livestock, tourism, and local businesses, causing significant financial losses. Himachal Pradesh, while also dependent on forest resources, experiences fewer and less intense fires, and its more dispersed population reduces the overall economic impact. However, the state's rugged terrain hampers firefighting and recovery efforts, prolonging the economic strain. In contrast, Jammu & Kashmir experiences the least economic impact due to its lower fire frequency, diversified economy, and lower population density in forest-adjacent areas, which help mitigate financial losses.

The social impact is also most pronounced in Uttarakhand, which has the highest incidence of forest fires within the Northern Indian Himalayan Region. Limited awareness, inadequate preparedness, and frequent evacuations in densely populated fire-prone areas disrupt community bonds and place immense strain on local populations. Himachal Pradesh shows relatively better awareness and

preparedness, but isolated communities in valleys still face challenges during evacuations and in dealing with the aftermath of fires. Jammu & Kashmir, on the other hand, experiences minimal social disruption due to its lower population density, better preparedness, and resilient communities, which help maintain social cohesion and reduce the overall impact.

The environmental impact of forest fires is the most severe in Uttarakhand, which has extensive forest cover, particularly the highly flammable Chir Pine forests. These forests release large amounts of carbon and particulate matter during fires, leading to significant forest degradation, habitat loss, and soil erosion. In Himachal Pradesh, while fires are less frequent and intense than in Uttarakhand, the state's dense pine forests and rugged terrain still contribute to environmental degradation, including vegetation loss, soil erosion, and reduced air quality. Jammu & Kashmir experiences the least environmental damage due to its lower fire frequency, cooler climate, and more resilient vegetation, which help limit degradation. The state's diversified ecosystem and less reliance on fire-prone forests further mitigate environmental losses. These findings underscore the critical need for region-specific strategies to address the multifaceted impacts of forest fires across the Northern Indian Himalayan Region.

The results from Uttarakhand, Jammu & Kashmir, and Himachal Pradesh indicate that forest fires have significant positive association to health, social and economic variables, while significant negative impact is seen on environmental benefits. Frequent incidence of forest fires disrupts regional ecosystems, livelihoods and wellbeing of the vulnerable inhabitants. With the new challenges presented by COVID-19, these states will require holistic policies that combine health interventions, community preparedness, economic support and environmental conservation. Through enhanced regional resilience and sustainable forest

management, these states will be able to reduce the harmful impacts of forest fires and protect their socio-economic and ecological future.

6.2. Implications

6.2.1. Theoretical Implications

Integrating two major theoretical frameworks — the Tragedy of the Commons and the Environmental Kuznets Curve (EKC), this study adds to the larger debate concerning environmental economics and ecological sustainability. Using these theories, we analyze the regional and national level impact of forest fires in India by writing detailed analysis of socio-economic and environmental impact of this growing phenomenon**.**

6.2.1.1. Tragedy of the Commons

The Tragedy of the Commons (Hardin, 1968) describes how shared resources are overexploited and degraded when individuals act out of self-interest without consideration for the collective benefits. Forests in states like Uttarakhand, Himachal Pradesh and Jammu & Kashmir are treated as common property resources that have very little wastage & accountability for sustainable use. The unregulated grazing, breaking of forest land, and change in land use for human activities and consumptions, with the added pressure of tourism and urbanization, are responsible for the over-exploitation of forest ecosystems. Non-unified community action along with weak law enforcement are increasing the risks of forest fire, which leads to loss of habitat and biodiversity decline, and reduces environmental services provided by forest. This corresponds with the “Tragedy” scenario, namely that short-term benefit to an individual or sector (e.g. tourism

revenue or agricultural expansion) leads to long-term environmental pollution harming the larger community.

6.2.1.2. Environmental Kuznets Curve (EKC)

EKC hypothesis holds an inverted U-shaped association between economic development and environmental degradation such that environmental quality deteriorates in early stages of development and begins to recover at higher income levels. This study questions the EKC hypothesis for India by showing that growth in the economy does not always lead to growth for the environment. The results show that with the increase of GDP per capita the incidence of environmental degrading variables has also risen, which suggests that India is still on the ascending side of the EKC. Economic activities that are not sustainable, including deforestation allowed for urbanization, energy consumption, and industrial expansion, grow faster than the ability of the ecosystem to regenerate. The absence of a turning point in India shows that growth, at the moment, increases environmental harm with no sign of abatement. If India is to be transitioned towards a sustainable growth path, it needs proactive environmental policies that address the root causes of catastrophe such as forest fires. More robust forest management, sustainable tourism development, and renewable energy subsidies may help to reverse environmental trajectories. In the absence of said interventions, the EKC hypothesis remains irrelevant, and sustained economic growth will continue to push for environmental degradation.

6.2.1.3. Synthesis of Theoretical Implications

Thus, by merging TOC and EKC frameworks, this study provides a dual lens to understand the reciprocal interrelationship between economic activities and the extraction of resources leading to environmental damage manifested in forest fire. The Tragedy of the Commons exposes the influence of local resource

mismanagement, complemented by weak regional governance. At a national scale, the EKC framework illustrates how economic growth, in the absence of proper environmental regulations, only leads to a continuation of environmental harm. Collectively, these theories highlight the importance of balancing economic growth with sustainable resource use. Dealing with forest fires in India has to be done through integrated solutions through communal accountability, stringent environmental regulations and long-term economic policies that take an economic yield and environmental preservation as equally contributive to progress.

6.2.2. Scientific Implications

The present study is of considerable scientific importance as it provides an improved knowledge of the diverse health, socio-economic and environmental sustainability impacts of forest fires in India. It will advance environmental science by showing how forest fires drive habitat loss, loss of biodiversity, soil degradation and carbon emissions which will make forest fires a self-reinforcing factor for climate change. In public health, the study also connects forest fires to respiratory illnesses, psychological distress and heat-related conditions, asking for more research into the long-term health effects of air pollution on at-risk populations. From a socio-economic standpoint, it chronicles the direct and indirect costs resulting from forest fires, including job losses and disruptions, tourism losses and property destruction, providing a basis for disaster economics and the valuation of ecosystem services. It also poses a challenge on Environmental Kuznets Curve (EKC) hypothesis which posits that initial phases of economic growth produce environmental degradation but leads to improvement in quality over time, as shown for developed countries and hence new models are required for developing economies. Regional considerations from the Northern Indian Himalayan Region demonstrate how local factors of change and community preparedness affect fire risks and provide critical ingredients for future climate adaptation and mountainous

ecosystem research and forest management. The results pave the way for interdisciplinary approaches that can inform policymakers and communities to initiate environmental, public health, and socio-economic interventions to mitigate the risk of forest fires and their associated impacts.

6.2.3. Local Community Implications

The local impact of forest fires can be intense especially for fire-prone areas such as Northern Indian Himalayan states which include Uttarakhand, Himachal Pradesh and Jammu & Kashmir. Immediate effects range from displacement and evacuation, forcing families to leave their homes, to interrupting their livelihoods. History has shown that such things usually lead to long-term social instability and the weakening of community and traditional support networks. Local businesses, especially those involved with tourism and forestry, also feel the economic impact with reduced income and property damage, high recovery costs while impoverishment and unemployment are aggravated in the area. Health consequences are serious too, including more cases of respiratory ailments, heat stroke and psychological stress , all placing a significant strain on local health care systems. In addition to air pollution, environmental destruction from forest fires, such as loss of biodiversity, habitat destruction, and soil erosion, further reduces the natural resources otherwise relied upon by communities for agriculture, livestock, and daily living. This degradation endangers food security and water availability, increases risk to future disasters, and drives displacement. There is therefore an urgent need for local communities to have greater awareness and preparedness mechanisms, as well as disaster systems in place, such as early warning systems, sustainable land use practices and forest management regimes led by communities. Measures of empowering communities in this process help, in the long term, to reduce the socio-economic and environmental consequences of forest fires.

6.2.3. Implications for Policy Makers

This study highlights important policy implications for better management of forest fire risk across India. There is a need for policy makers to embrace integrated forests management approaches that synergize sustainable development and environmental conservation. National-level policies must deal with these large-scale drivers of forest fires, like unsustainable tourism, growth of cities, industrialization and land use change by promoting tourism with less impact on the environment, adopting stricter land-use policies alongside sustainable energy practices. Implemented solutions like building local powers through community forest governance, giving the ability and the resources to local people to manage and protect forest ecosystems will be crucial in the case of fragile ecosystems in places like the Northern Indian Himalayas. Fire-related respiratory problems, psychological problems, and illnesses caused by high temperatures will require enhanced health policies like higher investment in healthcare infrastructure. Such efforts include deploying mobile health units in remote fire-prone regions and integrating disaster response into public health preparedness plans. Economically, policy will offer measures to help build resilience including financial support for affected communities, incentive schemes for the insurance industry to cover losses associated with fire-events, and taxation/rates incentives for businesses that adopt fire-resilient practices. Policies to counter environmental degradation should prioritize restoration and reforestation programs that will strengthen biodiversity conservation and the restoration of degraded lands. Policy makers should focus their efforts in campaigns for education and awareness about fire prevention, encouraging proactive public involvement. Investment in new firefighting technology and climate-resilient farming practices is another key area of focus for policy makers in preventing rural livelihoods from bearing the brunt of climate impacts even further. To mitigate the long-term consequences of forest fires and building sustainable, resilient communities, there is a need for a multi-sectoral

policy approach that encompasses economic, social, health, and environmental determinants.

6.2.5. State- Wise Policy Recommendations

The diverse impacts of forest fires in the Northern Indian Himalayan Region (NIHR) necessitate state-specific policy responses rather than a uniform approach. While Himachal Pradesh, Uttarakhand, and Jammu & Kashmir share common challenges related to forest fires, the intensity, frequency, and consequences of these events differ significantly, requiring tailored solutions. Himachal Pradesh's mountainous terrain and natural pollutant traps exacerbate health risks, while Uttarakhand faces the most severe socio-economic and environmental consequences due to its high population density and extensive forest cover. In contrast, Jammu & Kashmir experiences fewer forest fires, but proactive policies are essential to prevent future risks, especially with growing climate variability. Health, social stability, economic security, and environmental conservation must be at the core of these region-specific policy recommendations.

6.2.5.1. Policy Recommendations for Himachal Pradesh

In Himachal Pradesh, the primary policy focus should be on addressing health vulnerabilities caused by the state's rugged terrain and natural pollutant-trapping valleys, which result in prolonged exposure to high concentrations of particulate matter ($PM_{2.5}$ and PM10), carbon monoxide, and volatile organic compounds (VOCs). Mobile healthcare units should be established in remote areas to provide medical services during the fire season. Early warning systems for air quality monitoring must be implemented to alert at-risk populations, particularly vulnerable groups such as children, the elderly, and those with respiratory conditions. Public health campaigns should focus on distributing protective equipment like masks, raising awareness about respiratory protection, and

providing information on managing heat-related illnesses. On the economic front, policies should focus on fire-resilient livelihoods. Promoting sustainable agroforestry systems that incorporate fire-resistant crops can help reduce the economic dependence on vulnerable forest resources. Aerial firefighting units and advanced geospatial fire monitoring systems should be adopted to improve firefighting capabilities in the state's difficult terrain. Given the environmental impact of forest fires, afforestation programs using native fire-resistant species can help restore degraded forests and reduce future fire risks. Soil stabilization projects should also be prioritized to mitigate erosion and protect agricultural productivity in fire-affected areas. Additionally, community-based disaster management programs must be strengthened. Local communities should be trained in fire prevention, risk mitigation, and evacuation protocols to improve preparedness and response. Establishing fire volunteer brigades in high-risk areas can enhance first-response capacity.

6.2.5.2. Policy Recommendations for Uttarakhand

Uttarakhand experiences the most severe impacts from forest fires, particularly in terms of economic disruption, social instability, and environmental degradation. Policies should prioritize community-level preparedness and strengthen emergency response systems. Expanding and upgrading healthcare infrastructure in fire-prone regions is critical, along with training healthcare professionals to handle respiratory and heat-related illnesses more effectively. Establishing dedicated emergency medical centers in vulnerable districts will help reduce the health burden during peak fire seasons. Economic policies should focus on building resilience in agriculture, forestry, and tourism. Diversifying the local economy through eco-friendly tourism and value-added agricultural practices can reduce economic vulnerability. Reforestation programs should prioritize mixed-species forests to reduce flammability and enhance biodiversity. Sustainable tourism practices that

incorporate fire risk management should be promoted to ensure the continuity of tourism activities even in fire-prone areas.

Uttarakhand high population density necessitates a robust social preparedness strategy. Community-based disaster risk reduction programs should be scaled up, focusing on improving local knowledge of fire risks, evacuation procedures, and first-response training. School-based education programs can increase awareness among younger generations. Collaborating with local leaders and forest-dependent communities will ensure that these interventions are culturally appropriate and widely accepted. Investment in fire-resilient infrastructure and advanced fire detection systems will further strengthen the state's capacity to manage forest fires effectively.

6.2.5.3. Policy Recommendations for Jammu & Kashmir

Although Jammu & Kashmir experiences fewer forest fires compared to other states, climate variability and changing land-use patterns may increase future risks. Policies in J&K should focus on preventive measures and ecosystem-based management to minimize fire hazards. Enhancing early warning systems and regional coordination with firefighting units is essential for improving response capacity. Promoting sustainable grazing and agricultural practices can help reduce the accumulation of fire fuel loads in fire-prone areas. Environmental policies should prioritize biodiversity conservation and climate adaptation strategies. Protecting the state's unique ecosystems through integrated forest management plans will reduce long-term fire risks and maintain ecological stability. Agroforestry systems that promote diversified crops and sustainable land use can increase rural resilience. Public education campaigns on fire risks, particularly in the southern districts, will enhance awareness and preparedness among local populations. In addition, forest restoration projects focused on climate-resilient species can help maintain the region's carbon sequestration potential and reduce

the overall environmental impact of fires. Socially, Jammu & Kashmir's relatively low population density and strong community networks present an opportunity for preventive policies. Establishing community forest management groups can strengthen local resilience and improve resource management. Collaborating with civil society organizations and community leaders will help build capacity for managing future fire risks while preserving traditional knowledge and practices.

The impacts of forest fires across Himachal Pradesh, Uttarakhand, and Jammu & Kashmir are highly variable, requiring tailored policy responses rather than a one-size-fits-all solution. Himachal Pradesh must focus on healthcare expansion, air quality monitoring, and sustainable agroforestry, while Uttarakhand needs to prioritize community preparedness, sustainable tourism, and mixed-species reforestation. Jammu & Kashmir should concentrate on preventive measures, biodiversity conservation, and climate adaptation strategies. These state-specific policies will help reduce the adverse impacts of forest fires, protect vulnerable communities, and ensure long-term socio-economic and ecological sustainability in the Northern Indian Himalayan Region.

6.3. Limitations

Although this study offers important insights into the social, health, economic and environmental impacts of forest fires in India, many limitations should be acknowledged. Even though primary data from Northern Indian Himalayan Region is rich in local insights, the implications of our findings may not be fully generalizable to other forested ecosystems of India like for Western Ghats or central Indian forests due to disparities in ecological, socio-economic and climatic conditions. This study deals with health, social, economic, and environmental consequences of forest fires, however, there is lack of long-term health impact,

cultural, indirect economic loss and broader environmental impact, climate and water cycle. Future research should take a wider angle for more needs to be better mitigated and policies to be developed.

6.4. Future Directions

Overcoming these limitations will allow for increased validity and generalizability in future studies. Using wealthier longitudinal datasets, adopting sophisticated econometric techniques to uncover causation, and encompassing more environmental and health indicators will greatly add to future analyses. In addition, future research on forest fires in the Northern Indian Himalayan region should prioritize understanding their impact on ecosystem services, including carbon sequestration, air and water purification. Studies should also examine how tourism development and urbanization contribute to the frequency and intensity of forest fires. The effects of forest fires on biodiversity, particularly the loss of endemic and endangered species, require detailed investigation to assess long-term ecological consequences. Furthermore, the influence of forest fires on water cycles, including reduced water retention and altered streamflow, and their potential role in exacerbating vector-borne diseases, deserves attention. Ground-level research involving field surveys, community engagement, and geospatial technologies is essential to address these gaps and develop localized, data-driven fire management strategies tailored to the region's unique ecological and socio-economic conditions.

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Research Publication

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Research Paper 1

Soontha, L., Shahzeb, S. M., Bhat, M. Y., Ganie, J. A., & Gupta, S. (2024). Fiery trails: tourism's forest fire dance. *Current Issues in Tourism*, 1–25. https://doi.org/10.1080/13683500.2024.2336119

ABDC Ranking: A
Scopus Quartile: Q1
Impact Factor: 5.7

Research Paper 2

Soontha, L., & Bhat, M. Y. (2023). Preserving health, protecting economies: Mitigating the impact of forest fires on healthcare expenditure and environmental sustainability. *Sustainable Development*, *32*(3), 2066–2084. https://doi.org/10.1002/sd.2764

ABDC Ranking: C
Scopus Quartile: Q1
Impact Factor: 9.9

APPENDICES

Appendix A1

Survey Questionnaire: Primary Data Collection Tool

Dear Participant,

We appreciate your participation in this household survey. The information you provide will be used solely for academic research and will be kept confidential. This survey is a part of our research study titled "**Dynamic Linkages of Forest Fires in Northern Indian Himalayan Region: An Empirical Analysis."**
The following points are intended to brief you on the context of the questionnaire:

1. The questionnaire is designed to understand the perceptions, experiences, and coping strategies of rural households that are directly or indirectly affected by forest fires in forest fringe areas of the Northern Indian Himalaya.
2. The questionnaire comprises a total of **6 sections**.
3. **Section A** is designed to collect the participants' demographic and socio-economic information, while **Sections B to F** focus on the core research questions.

Note:
Household in this context refers to individuals or families residing in rural or forest-adjacent villages who depend on forest resources for their livelihood, food, fuel, fodder, or income. The term *forest fire* refers to uncontrolled burning of forests or grasslands, whether caused by natural or anthropogenic sources, that results in environmental and socio-economic consequences.

Impacts include, but are not limited to damage to crops, houses, forest-based livelihoods, biodiversity loss, air pollution, and health problems due to smoke or particulate exposure

Section A: Socio-Demographic Information

Measure	**Items**
Gender	☐ Male ☐ Female
Age	☐ 18–30 ☐ 30–42 ☐ 42–64 ☐ 64–76
Education	☐ Not educated ☐ High school or below ☐ Intermediate ☐ Under-Graduate ☐ post-graduate or above
Number of Family Members	☐ 0–5 ☐ 5–10 ☐ 10–15 ☐ 15–20
Male Members in Family	☐ 0–5 ☐ 5–10 ☐ 10–15 ☐ 15–20
Female Members in Family	☐ 0–5 ☐ 5–10 ☐ 10–15 ☐ 15–20
Economic Status	☐ BPL (Below Poverty Line) ☐ APL (Above Poverty Line)
Caste	☐ General ☐ OBC ☐ SC ☐ ST ☐ Others

Section B: Forest Fires Exposure and Forest Dependency

Statement	Response (Tick One)
I have witnessed a forest fire in my area.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires are common near my residence.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
My family has been directly affected by a forest fire.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
I have seen forest fire smoke in my locality.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
My family depends on forests for livelihood.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
We collect forest products for daily use.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forests are our main source of fuel, fodder, or food.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Section C: Health Impact

Forest fires have caused health problems in my family.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
We face breathing difficulties during forest fires.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Elderly or children suffer more during forest fires.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires cause stress or anxiety.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
My family fears forest fire seasons.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
I feel mentally disturbed when forest fires occur.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Heatwaves are becoming more frequent in my area.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires increase the heat intensity.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree

	☐ Strongly Disagree
Our daily activities are affected by heat during fire events.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
I avoid going outside due to high temperatures during fire seasons.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires often lead to physical harm or trauma for people nearby.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires pose a significant threat to the safety of nearby communities.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
People living near forests are at higher risk of injuries during fire outbreaks.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Section D: Social Impact

I have had to evacuate my home due to a forest fire.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Forest fires have displaced people from my village or town.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires affect our community's safety.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Community resources are damaged by forest fires.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires disrupt local economy and schooling.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
We unite as a community during forest fires.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
I feel prepared to face a forest fire.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
My community has a forest fire action plan.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Authorities provide training or information about forest fire preparedness.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
I am aware of forest fire prevention methods.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
I understand the causes of forest fires.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

I know whom to contact in case of a forest fire emergency.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Section E: Environmental Impact

Statement	**Response (Tick One)**
Forest fires degrade soil quality.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Soil erosion increases after forest fires.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires reduce forest biodiversity.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires result in the death of many wild animals.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Section F: Economic Impact

Forest fires damage homes and infrastructure.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires reduce tourism income.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Livelihood losses are high during forest fires.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Fire control operations are expensive.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fire losses are not adequately compensated.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires disrupt daily wage work.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Local businesses are impacted during fire seasons.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Transport and market access are hindered by forest fires.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree
Forest fires lead to loss of forest-based income.	☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

Appendix-A2

Himachal Pradesh

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
FFE1	0.281	400	0.000	0.836	400	0.000
FFE2	0.261	400	0.000	0.841	400	0.000
FFE3	0.281	400	0.000	0.831	400	0.000
FFE4	0.272	400	0.000	0.845	400	0.000
FD1	0.285	400	0.000	0.831	400	0.000
FD2	0.278	400	0.000	0.835	400	0.000
FD3	0.265	400	0.000	0.835	400	0.000
HP1	0.307	400	0.000	0.702	400	0.000
HP2	0.280	400	0.000	0.712	400	0.000
HP3	0.302	400	0.000	0.675	400	0.000
EP1	0.241	400	0.000	0.869	400	0.000
EP2	0.235	400	0.000	0.865	400	0.000
EP3	0.235	400	0.000	0.864	400	0.000
HW1	0.261	400	0.000	0.775	400	0.000
HW2	0.285	400	0.000	0.762	400	0.000
HW3	0.278	400	0.000	0.771	400	0.000
HW4	0.278	400	0.000	0.778	400	0.000
FFC1	0.230	400	0.000	0.845	400	0.000
FFC2	0.250	400	0.000	0.798	400	0.000
FFC3	0.261	400	0.000	0.784	400	0.000
ED1	0.244	400	0.000	0.883	400	0.000
ED2	0.223	400	0.000	0.877	400	0.000
CI1	0.186	400	0.000	0.898	400	0.000
CI2	0.162	400	0.000	0.890	400	0.000
CI3	0.182	400	0.000	0.895	400	0.000
CI4	0.171	400	0.000	0.899	400	0.000
PR1	0.228	400	0.000	0.888	400	0.000
PR2	0.204	400	0.000	0.882	400	0.000
PR3	0.227	400	0.000	0.883	400	0.000

AW1	0.323	400	0.000	0.828	400	0.000
AW2	0.304	400	0.000	0.841	400	0.000
AW3	0.308	400	0.000	0.838	400	0.000
EI1	0.235	400	0.000	0.812	400	0.000
EI2	0.257	400	0.000	0.785	400	0.000
EI3	0.261	400	0.000	0.794	400	0.000
EI4	0.270	400	0.000	0.786	400	0.000
CFF1	0.270	400	0.000	0.804	400	0.000
CFF2	0.266	400	0.000	0.807	400	0.000
CFF3	0.258	400	0.000	0.816	400	0.000
CFF4	0.279	400	0.000	0.806	400	0.000
CFF5	0.278	400	0.000	0.822	400	0.000
FH1	0.291	400	0.000	0.698	400	0.000
FH2	0.282	400	0.000	0.697	400	0.000
FS1	0.456	400	0.000	0.530	400	0.000
FS2	0.447	400	0.000	0.567	400	0.000
a. Lilliefors Significance Correction						

Jammu & Kashmir

Tests of Normality						
	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	df	Sig.	Statistic	df	Sig.
FFE1	0.266	350	0.000	0.755	350	0.000
FFE2	0.250	350	0.000	0.817	350	0.000
FFE3	0.237	350	0.000	0.821	350	0.000
FFE4	0.320	350	0.000	0.703	350	0.000
FD1	0.304	350	0.000	0.711	350	0.000
FD2	0.304	350	0.000	0.699	350	0.000
FD3	0.249	350	0.000	0.811	350	0.000
HP1	0.263	350	0.000	0.745	350	0.000

HP2	0.272	350	0.000	0.728	350	0.000
HP3	0.283	350	0.000	0.689	350	0.000
EP1	0.183	350	0.000	0.891	350	0.000
EP2	0.179	350	0.000	0.889	350	0.000
EP3	0.148	350	0.000	0.891	350	0.000
HW1	0.240	350	0.000	0.806	350	0.000
HW2	0.217	350	0.000	0.816	350	0.000
HW3	0.212	350	0.000	0.818	350	0.000
HW4	0.231	350	0.000	0.809	350	0.000
FFC1	0.189	350	0.000	0.890	350	0.000
FFC2	0.186	350	0.000	0.896	350	0.000
FFC3	0.162	350	0.000	0.896	350	0.000
ED1	0.284	350	0.000	0.846	350	0.000
ED2	0.291	350	0.000	0.863	350	0.000
CI1	0.338	350	0.000	0.767	350	0.000
CI2	0.338	350	0.000	0.767	350	0.000
CI3	0.340	350	0.000	0.760	350	0.000
CI4	0.339	350	0.000	0.765	350	0.000
PR1	0.193	350	0.000	0.896	350	0.000
PR2	0.197	350	0.000	0.896	350	0.000
PR3	0.178	350	0.000	0.897	350	0.000
AW1	0.214	350	0.000	0.884	350	0.000

AW2	0.224	350	0.000	0.882	350	0.000
AW3	0.214	350	0.000	0.884	350	0.000
EI1	0.213	350	0.000	0.844	350	0.000
EI2	0.247	350	0.000	0.822	350	0.000
EI3	0.228	350	0.000	0.835	350	0.000
EI4	0.260	350	0.000	0.776	350	0.000
CFF1	0.234	350	0.000	0.867	350	0.000
CFF2	0.256	350	0.000	0.860	350	0.000
CFF3	0.248	350	0.000	0.866	350	0.000
CFF4	0.278	350	0.000	0.851	350	0.000
CFF5	0.257	350	0.000	0.862	350	0.000
FH1	0.192	350	0.000	0.890	350	0.000
FH2	0.218	350	0.000	0.877	350	0.000
FS1	0.230	350	0.000	0.860	350	0.000
FS2	0.209	350	0.000	0.862	350	0.000
AW	0.217	350	0.000	0.898	350	0.000
CFF	0.133	350	0.000	0.913	350	0.000
CI	0.338	350	0.000	0.765	350	0.000
ED	0.267	350	0.000	0.852	350	0.000
EI	0.077	350	0.000	0.947	350	0.000
EP	0.065	350	0.002	0.972	350	0.000
FD	0.213	350	0.000	0.846	350	0.000

FFC	0.090	350	0.000	0.963	350	0.000
FFE	0.184	350	0.000	0.887	350	0.000
FH	0.135	350	0.000	0.939	350	0.000
FS	0.194	350	0.000	0.881	350	0.000
HP	0.221	350	0.000	0.756	350	0.000
HW	0.179	350	0.000	0.844	350	0.000
PR	0.164	350	0.000	0.926	350	0.000
a. Lilliefors Significance Correction						

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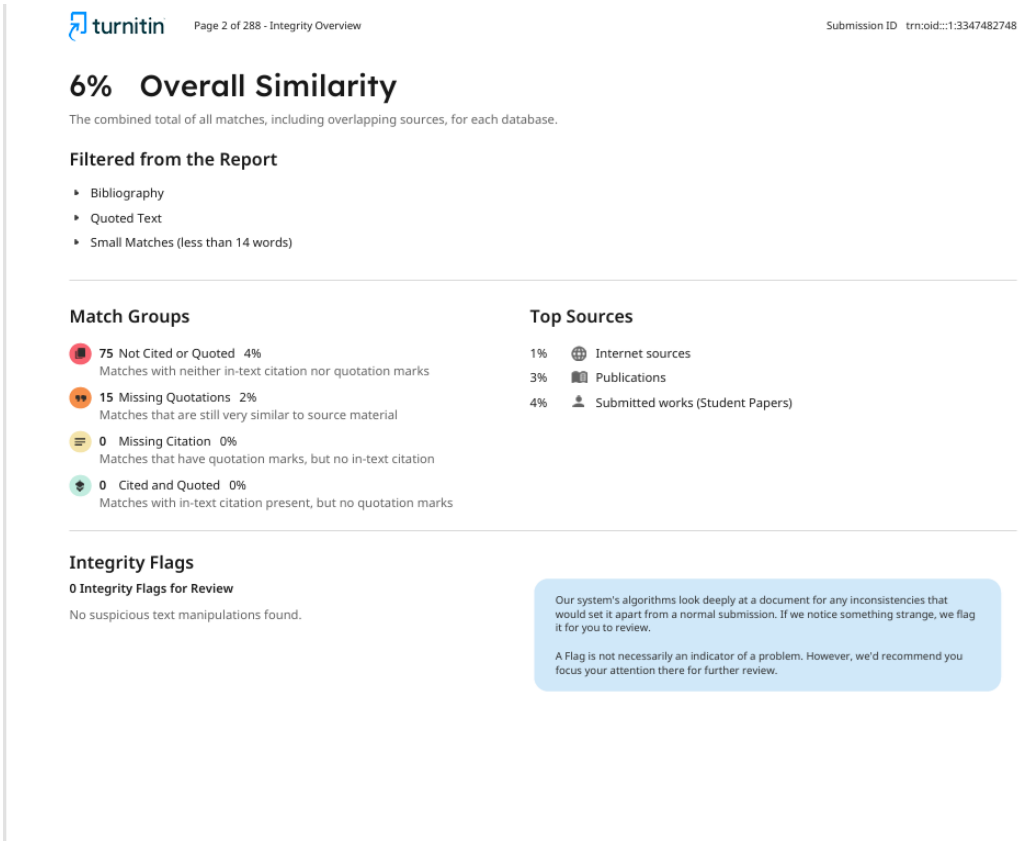


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