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A Prototype Forest Fire Decision Support System for Uttarakhand, India

Neelesh Yadav [1], Shrey Rakholia [1], Peter Moore [2], Laura Patricia Ponce-Calderón [3], Mithun Kumar S R [4] and Reuven Yosef [5,*]

[1] Bioinformatics Center, Forest Research Institute, Dehradun 248006, Uttarakhand, India; neeleshy@gmail.com (N.Y.); rakholias@gmail.com (S.R.)
[2] NRFC Natural Resources Fire & Carbon Pty Ltd., Sydney, NSW 2000, Australia; peterfmoore.nrfc@gmail.com
[3] Department of Society and Culture, El Colegio de la Frontera Sur, San Cristóbal de las Casas 29290, Chiapas, Mexico; laponce@ecosur.edu.mx
[4] Google Maps, Google, Bangalore 560036, Karnataka, India; srmk@google.com
[5] Eilat Campus, Ben Gurion University of the Negev, P.O. Box 272, Eilat 881020, Israel
* Correspondence: ryosef60@gmail.com

Simple Summary: This study presents the development of a prototype Decision Support System (DSS) for forest fire management in Uttarakhand, India. By analyzing large datasets of fire incidents, the system provides essential spatial tools to support fire-related decision-making. The DSS includes three main components: tools for pre-fire forest visualization, during-fire terrain-based support, and post-fire restoration planning. It integrates satellite data, fire risk indices, and fire spread simulations using an open-source R Shiny framework. The system also incorporates ecological, community-based, and financial considerations, aiming to improve data-driven forest fire management and planning.

Abstract: We present a study that addresses the critical need for a prototype Decision Support System for forest fire information and management in Uttarakhand, India. The study's main objective was to carry out statistical analysis of large fire incident datasets to understand trends of fires in the region and develop essential spatial decision support tools. These tools address the necessary fire management decision-making along with comprehensive datasets that can enable a decision maker to exercise better management. Moreover, this DSS addresses three major components of forest fire decision support: (i) pre-fire (forest information visualization) tools, (ii) during-fire terrain-based spatial decision support tools, and (iii) post-fire restoration tools. The efforts to develop this DSS included satellite lidar dataset-based fuel load estimations, the Keetch–Byram Drought Index, and the integration of spatial tools that ensure better spatial decisions in fire suppression planning. In addition, based on the bibliographic literature, the study also uses ecological and community-based knowledge, including financial aspects, for fire prevention and post-fire restoration planning. The development of this DSS involves an open-source R Shiny framework, enabling any decision maker at the execution or planning level to access these key datasets and simulate the spatial solutions cost-effectively. Hence, this study aimed to internalize key decision support tools and datasets based on extensive statistical analysis for data-driven forest fire planning and management.

Keywords: GIS; forest fire; decision support systems; R Shiny

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Academic Editor: Grant Williamson

Received: 11 March 2025
Revised: 28 March 2025
Accepted: 1 April 2025
Published: 8 April 2025

Citation: Yadav, N.; Rakholia, S.; Moore, P.; Ponce-Calderón, L.P.; S R, M.K.; Yosef, R. A Prototype Forest Fire Decision Support System for Uttarakhand, India. *Fire* **2025**, *8*, 149. https://doi.org/10.3390/fire8040149

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1. Introduction

The need for Decision Support Systems (DSSs) is crucial for focusing spatial planning on fire management, conducting risk and hazard assessments, mapping forest fires, and thus carrying out fuel management, prescribed burns, monitoring, and surveillance, generating helpful information for the end user [1,2].

Historically, Canadian forest fire management agencies have been at the forefront since the early 1980s, utilizing information technology-based Decision Support Systems for forest fire behavior prediction, the monitoring of fire occurrences, and capturing terrain and fuel variations in GIS-enabled DSSs since the 1970s (Canadian Forest Fire Weather Index—FWI) [3,4]; These systems, which include prediction models, risk mapping, fire behavior models, forest fire management, planning and coordination tools, and vegetation and fuel maps, have revolutionized the field of fire management [5]. Since the early 2000s, DSS has focused on multiple capabilities of integrating spatial data, satellite systems, and ground-based layers to address fire cores, plume tracking, and produce simulations of the extent of forest fire damage [6]. Other DSSs have focused on developing fire spread engines, which are computational models that predict the spread of a fire based on factors such as terrain, moisture content, wind direction, and fuel load. These engines incorporate the widely used Rothermal fire spread model [7].

Nevertheless, fire behavior, fuel load reduction (e.g., prescribed burns, mechanical treatments), forest fire severity, and land management are as important as fire suppression [8]. Community-based fire management is crucial because cultural knowledge and practices, such as controlled burns and firebreak maintenance, help reduce wildfire risks by managing fuel loads. Integrating these practices into fire management plans offers sustainable, low-tech solutions to wildfire threats. It can be an adaptation strategy to climate change and the increasing risk of mega-fires [9]. Apart from these measures, community forest fire management can be key when social capital, user involvement in crafting and enforcement, and the diversity of rules are substantial, as in the case of Community Forest User Groups (CFUGs) in Nepal, where the active participation of CFUGs has resulted in the control of forest fires, although this is negatively affected by their dependency on daily wages and a lack of transparency issues [10]. Community efforts to build fire lines or firebreaks are vital to prevent forest fires and remove dry litter, as applied in the case of Thailand's community forest fire management program [11]. These strategies need summarizing and comparisons from ecological and financial perspectives, which can be addressed by adding comparison tools to the DSS.

Enhanced fire management could benefit significantly from improved conflict resolution by tackling the root causes of human-induced forest fires, such as unfair land tenure systems. In a recent study, Picado and Chaves (2021) [12] identified a correlation between diverse land tenure structures and the occurrence of fires. Their findings indicate that areas adjacent to national parks, private lands, peasant settlements, and indigenous territories have a higher incidence of fire events. The historical enforcement of land use policies has shaped the cultural and ecological characteristics of fire regimes [13]. In Indonesia, for instance, more equitable government distribution of property rights over land and forests was crucial for preventing fires [14]. Hence, effective community fire management includes, although it is not limited to, equitable land tenure arrangement, traditional knowledge on fire use, eliminating resource conflicts, and incentivization along with sanctions [15].

In India, a Decision Support System (DSS) was proposed to facilitate multi-criteria analysis for socio-economic risk reduction and the logistical planning of fire management operations [16]. In the Indian state of Uttarakhand, a previous study has shown that the highest number of forest fire incidents occur sequentially in February, March, May, April, and June, which coincides with the dry season in this region [17]. In addition, it is

understood that fire incident data are imperative for analyzing seasonal and long-term fire frequency. Fire frequency studies estimate the time since a fire (survivorship) or fire interval (mortality). At the same time, spatio-temporal patterns are quantified using the fire rotation period, annual burned area percentage, and statistical measures of fire intervals. [18]. It is crucial to emphasize the importance of comprehending the characteristics of fire regimes. "Fire regimes" refer to the pattern, frequency, and intensity of fires over time. Consequently, modifications to these regimes increase the frequency of fires, which, in turn, gives rise to alterations in their ecosystem composition and structure [19]. This makes it important to understand fire regime intervals as different vegetation cover types have different fire intervals (return periods), e.g., grassland/shrublands/scrublands have shorter intervals than dense forests [20].

Fire size regimes help assess fire frequency, compare wildfire behaviors across regions, and predict ecosystem responses to climate change, aiding risk assessment, conservation, and hazard management. [21]. The data produced by this system would be of significant value in the strategic planning of resources allocated to combating forest fires [4].

Additionally, pyrogeography is important to map, as in the case of the European pyrogeography study, which was developed to classify fire regimes, showing that regional fire activity is related mainly to vegetation and human influences, with annual shifts responding to climate, thereby improving predictions of climate impacts on fire dynamics across the region [22]. Pyrobiocultural territories integrate local fire knowledge with ecological dynamics, recognizing the cultural, social, and environmental roles of fire in fire-dependent and fire-sensitive [23]. Some governments in the Americas have already adopted this approach and have revised their fire management programs based on the zoning of pyrobiocultural territories to reduce the risk of fires [24]. One of the objectives of this study is to enable users to gain an understanding based on three important components, i.e., frequency, intensity, and seasonality [25]. Fire (burn) frequency can be mapped with relatively higher-resolution satellite data. In contrast, intensity and seasonality require statistical visualization, which gives important information on the pyrography of the region for the last few decades, as shown in this study.

Moreover, remotely sensed forest fire datasets are one of the only types of uniform data covering larger regions that robustly observe temporal variability in the fire frequency and burned area [26]. Studies in India utilizing Indian satellite datasets, however, mostly lack imagery in frequency and coverage compared to Landsat satellite imagery. Although using forest classification maps assists in the general understanding of burnt areas and their relationship to forest type, they still lack the proper mapping of fire regimes and multi-temporal burnt area assessments, as in the case of a 2017 nationwide assessment study [27]. Hence, mapping and analyzing fire (burn) frequency and incidents can be crucial to the DSS.

Additionally, fuel load estimations based on remotely sensed data have been increasingly used in recent studies where it was found that SAR (Synthetic Aperture Radar)-based estimations correlated more highly with ground-measured fuel load compared to optical satellite data, i.e., VNIR-Visible and Infrared [28]. One study utilized the GEOCARBON (Operational Global Carbon Observing System) along with the BIOMASAR algorithm to map the forest aboveground biomass dataset as it provides biomass in Mg/ha standard units, and the spatial resolution of 1 km was relatively low for better estimations [29]. In a study on Europe, forest canopy fuel parameters were estimated using spaceborne LiDAR, such as GEDI on the ISS, which enables broader spatial coverage across Europe, and the results included the estimation of a mean forest canopy height of 9.65 m, which was similar but lower than other studies as this study also used calibrations to estimate the mean

canopy height of temperate and boreal European forests [30]. One of our objectives in this study was to utilize a similar approach to estimate fuel loads.

During-fire tools have previously been developed, which include route determination for rescue and relief vehicles in forest fire scenarios and dynamic obstacles using shortest path algorithms based on OpenStreetMap (OSM) road networks, but lacking any slope or terrain-based geoprocessing [31]. More recently, DEMs (Digital Elevation Models) have been used as the cost path function considers path length, slope (based on DEM), and obstacle (resistance) avoidance as the main factors that dictate path planning along with the raster-based forest fire path model, which allows detour effects or dynamic path planning [32]. With the increasing global availability of high-resolution terrain data and city models, terrain-based navigation is emerging as a viable solution for GPS-denied environments [33]. However, tools incorporating algorithms like the least-cost path and terrain-based hiking energy expenditure have not been widely integrated into forest fire management applications or commonly available for online navigation and field apps such as Google Maps, Google Maps, Qfield, Waze, Gaia, Apple Maps, Qfield; Field Maps ESRI, and others. Furthermore, apps like AllTrails, Komoot, and MapMyHike provide hiking navigations, but they do not process Digital Elevation Model (DEM)-based terrain data dynamically and, thus, lack real-time path optimizations [34,35]. Thus, the inclusion of during-fire tools is well justified in this context.

The Rothermel surface fire spread model, enhanced by Albini in 1976, remains foundational in fire management systems, often paired with models for fire line intensity, flame length, and cross-slope wind effects. While widely used, particularly in the U.S. National Fire Danger Rating System (NFDRS), variations exist in equations and fuel models, providing essential reference points for custom model developers and users examining input variable impacts on spread rate calculations [36]. Moreover, recent studies also show that the Rothermel model for fire spread simulations shows higher accuracy than other fire behavior models as it incorporates key factors, including wind, slope, heat, and other factors in computing fire behavior [37]. Hence, incorporating a simplistic Rothermel-based fire spread model can become a useful during-fire spatial tool, which is also included in this DSS because such tools are often omitted in forest fire studies in India.

Long-term fire management and post-fire restoration integrate strategies such as grazing, active seeding, and plantations, with prescribed burns as a key fuel reduction technique, supplemented by mechanical treatments like thinning or chipping to enhance efficacy or serve as alternatives when burning is impractical [38]. However, where land abandonment in rural areas and forested landscapes is ongoing, nature-based solutions can include herbivory or grazing [39]. The communities can be enabled to carry out post-fire restoration as they can opt for Agroforestry and Silvicultural practices in degraded forests as it may provide them benefits like Timber, Firewood, Honey, and other non-timber forest products (NTFPs), and this can be achieved along with biodiversity conservation by planting catalyst or endangered species [40]. Thus, post-fire tools like tree selection for restoration and future fire prevention strategies are justifiably important components of this prototype DSS.

Furthermore, fire-resistant trees and shrub species, such as *Ginkgo biloba* L., *Quercus leucotrichophora* A. Camus, and *Populus ciliata* Wall. ex Royle, can be identified. They can be planted for long-term restoration and to prevent soil erosion, along with urgent restoration options [41]. Therefore, comparing all these fire prevention and management techniques in ecological, financial, and temporal terms can be integrated into a Decision Support System (DSS).

Hence, we aim to develop a Decision Support System with unique spatial tools and visualizations to enhance knowledge-based forest fire management decision-making,

addressing existing gaps in the system. The primary objectives of the DSS tools and associated datasets developed in this study are as follows:

1. Wildfire Risk and Fuel Management tools
    - Fuel load mapping to identify risk zones;
    - Fire burn frequency data for fire regime analysis;
    - Fire incident data with which to understand ignition trends seasonally and spatially.
2. Fire Management tools
    - KBDI viewer for quantifying forest fire risk;
    - Optimal path tool for aiding navigation and planning in rugged terrains;
    - Rothermel fire spread model for the simplistic visualization of fire spread;
    - Walk–hike time isoline tools for optimizing firefighter team deployment.
3. Post-Fire Restoration and Fire Prevention tools
    - The tree selection tool for restoration efforts with fire resilience;
    - The fire prevention strategies comparison tool enables science-based mitigation planning.

2. Materials and Methods

This study builds upon recent advancements in decision-support system research, integrating data-driven statistical analysis with the development of interactive web-based tools to enhance analytical capabilities and decision-making [42–44]. The prototype forest fire DSS web application is available online at https://shreyrakholia.shinyapps.io/UKFFDSS/ [accessed on 1 March 2025]. The major components included in the forest fire prototype DSS (FPDSS), including the summary of the conceptual framework and workflow (Figure 1) for Uttarakhand, are as follows:

1. Pre-fire (visualization) tools: fuel load, fire (burn) frequency, fire incidents, and optimal path and hiking time isoline tools (Area of interest: Uttarakhand, India).
2. During-fire spatial decision support tools: Rothermel-based fire spread tool, optimal path tool, and walk–hike time isoline tools (area of interest/sample terrain: Almora, Uttarakhand, India, although the user can use this analysis on any digital elevation model file).
3. Post-fire planning information tools: tree selection tool for the comparison of restoration and ecological fire prevention techniques (area of interest: Uttarakhand, India).

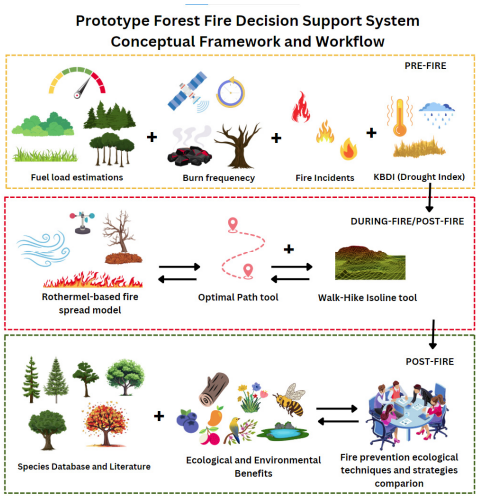


Figure 1. Conceptual framework and workflow schematic diagram for prototype forest fire Decision Support System for Uttarakhand, India.

The data sources utilized in this process are listed in Table 1.

Table 1. Major components of the FPDSS and the utilized raw datasets with reference citations.

Component	Data Source and References	Rationale	Existing Gaps
Fuel load	Global Ecosystem Dynamics Investigation (GEDI); Forest Survey of India (FSI); [45,46]	Since different forest types (e.g., Sal, Chir Pine, Mixed Conifers) have varied fuel load capacities, mapping them helps identify high-risk zones	Lack of existing Lidar-based fuel load estimates for Uttarakhand
Fire (burn) frequency	Global Annual Burned Area Maps—(GABAM); [47]	Historical fire occurrences help understand fire regimes (frequency, seasonality, and intensity). It helps in decision-making for fire suppression, resource allocation, and restoration efforts	Lack of readily available visualization and absence of detailed satellite-based fire regime maps
Fire incidents (2000–2024)	MODIS Collection 6 and 6.1; [48]	Fire incident datasets complement burn frequency data by providing ignition trends	Fire incidents were available on FSI and NASA FIRMS but lacked detailed statistical analysis.
KBDI (Keetch–Byram Drought Index)	Institute of Industrial Science, The University of Tokyo, Japan; [49]	KBDI helps forest managers assess wildfire risk by quantifying soil and duff dryness, enabling proactive fire prevention, resource allocation, and decision-making	Widely used in fire danger rating systems globally. However, no region-specific and online accessible fire management tool utilizing KBDI has been developed for Uttarakhand, India.
Optimal path tool	User-generated; *leastcostpath* R package [50]	Helps fire management teams find the quickest, least energy-intensive routes for fire suppression and escape planning	Tool/algorithm not available on commonly used navigation/field apps: Google Maps; Qfield; Waze; Gaia; Apple Maps; Field Maps ESRI, etc.
Rothermel-based spatial fire spread tool	User-generated; general R packages: *Leaflet*; *raster*	Simulates fire spread under various conditions to help proactive fire management and planning	Despite the widespread use of the Rothermel fire spread model globally, no dedicated web or GIS-based application has been developed specifically for Uttarakhand, India
Walk–hike time isoline tools	User-generated; *movecost* R package; [51]	Helps in optimizing deployment locations for fire response teams	Tool/algorithm not available on commonly used navigation/field apps: Google Maps; Qfield; Waze; Gaia; Safari; Field Maps ESRI, etc., or any known online web/mobile app yet
Tree selection tool for post-fire restoration	India Biodiversity Portal; bibliographic literature; [52–54]	Attributes like bark thickness, foliage type, and fire sensitivity ensure that restored forests are more resilient to future fires—THEY aid in ecosystem recovery, aligning species selection with fire prevention strategies	There is a lack of such a web application for Uttarakhand, India, that accounts for tree selection for restoration
Fire Prevention strategies comparison tab	Ecological Techniques for Forest Fire Prevention | *Fire* | MDPI [55]	Helps forest managers implement long-term, science-based fire mitigation plans	There is an absence of existing tools that discuss the comparison of these fire prevention techniques

Since Uttarakhand, like many states in India, is a data-deficient region regarding forest fire information, this study relied more on bibliographic resources and satellite data, along with tools that model and visualize user-generated data. In this prototype, we focus on the study area of Uttarakhand, India, as highlighted in Figure 2.

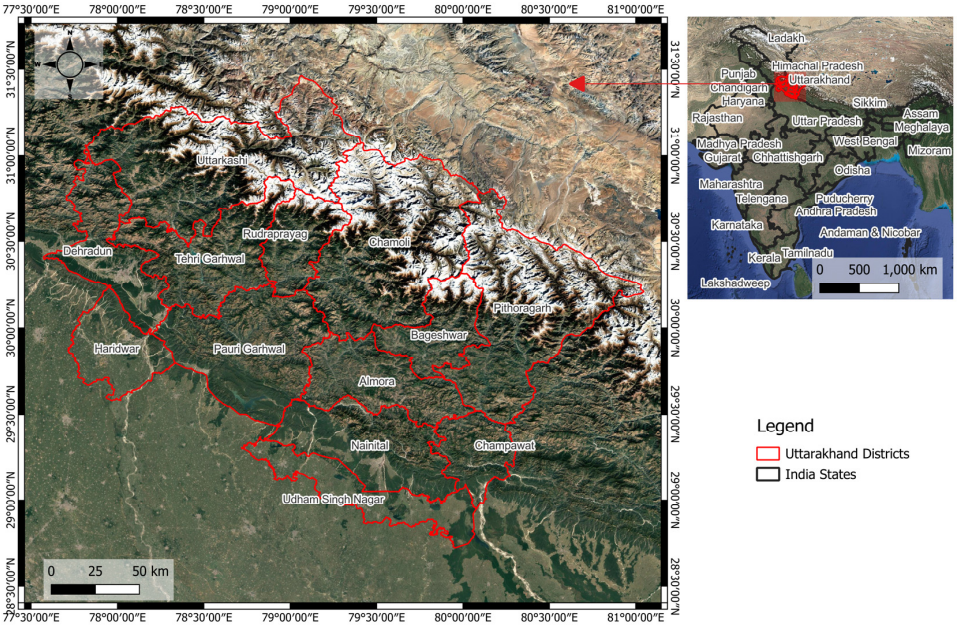


Figure 2. Study area map showing districts of Uttarakhand and its geographic location in India.

2.1. Fuel Load Estimations

The fuel load estimation process is a critical step in fire management. It involves various studies to calculate fuel load estimations; based on this, we developed an equation based on the available literature for indicative fuel load. For instance, an allometric equation for calculating fuel load found that the diameter (broadly DBH) and height (canopy height) are key structural variables in computing fuel loads [56].

In a study to estimate canopy fine fuel, DBH was used in the equation $\ln(\text{FFcnp}) = -3.69 + 1.76 \times \ln(\text{DBH})$, reflecting how DBH significantly influences biomass and fuel load in large trees. This study also showcased the sensitivity of fuel load estimation to tree dimensions, particularly for tall trees with a large DBH, emphasizing that both DBH and canopy height are effective predictors of biomass [57].

Based on this, we developed an equation that internalizes both the essential variables, i.e., DBH and canopy:

$$\text{Fuel load} = a \times (\text{dbh})^b \times (\text{canopy height})^c \quad (1)$$

Here, DBH is the diameter at the base height (obtained from literature), and canopy height refers to the tree height (obtained from GEDI, also known as the Global Ecosystem Dynamics Investigation, for lidar-based forest structure measurements). The fuel load computation was performed using the '*raster edit*' tool and the SCP Plugin in the QGIS 3.34 Open-Source Environment. The equation was used, respectively, for various forest types using vector shapefiles of different forest cover types upon the tree height raster file.

The coefficient "*a*" represents a species-specific scaling factor accounting for wood density variations and tree species' biomass allocation patterns. Denser woods (e.g., Banj Oak and Mixed Conifers) typically have a higher biomass per unit volume, warranting a slightly larger *a* value. Lighter woods or sparse vegetation types (e.g., Scrub and Shisham)

have lower biomass, reducing *a*. The coefficients "*b*" and "*c*" are exponents that determine the sensitivity of biomass to changes in DBH and height, respectively.

Theexponent *b* governs the sensitivity of biomass to changes in diameter at breast height (DBH). A higher *b* value (e.g., 2.55 for Mixed Conifers, Shisham, and Rest) implies that slight variations in DBH significantly affect biomass, which aligns with species that allocate more biomass to trunk growth. A lower *b* value (e.g., 1.9 for Scrub) is justified as scrubs and small trees have less pronounced DBH-related biomass scaling. Exponent *c* controls the contribution of canopy height to biomass estimation. Larger trees (Deodar, Sal, Chir, Banj Oak, Mixed Conifers) have a higher *c* (i.e., 0.9), reinforcing the idea that biomass strongly correlates with height in these species. Scrub vegetation has a lower *c* (i.e., 0.7), indicating the reduced influence of height, as these plants tend to have denser but shorter structures (Table 2). These parameters were adapted from similar studies that developed biomass equations in the past [58–60].

Table 2. Description and values of parameters utilized for computation of fuel load for various forest types.

Forest Type	*a*	*b*	*c*	Description
Deodar	0.005	2.4	0.9	Large trees with high biomass per unit DBH increase.
Sal	0.005	2.4	0.9	Similar to Deodar but with slightly lower DBH.
Scrub	0.002	1.9	0.7	Sparse vegetation with lower wood density.
Banj Oak	0.006	2.45	0.9	Denser wood, moderate DBH, and high height dependency.
Chir	0.004	2.4	0.9	Moderate wood density, similar to Sal, but slightly lower biomass.
Mixed Conifers	0.006	2.55	0.9	Dense conifer species with high DBH sensitivity.
Shisham	0.004	2.55	0.9	Moderately dense species with high DBH dependency.

We used the equation to compute fuel loads for various fuel types based on DBH for dominant tree species/vegetation types, including Sal (5.5), Deodar (6), Banj Oak (2.5), Chir Pine (5), Shisham (2), Mixed Conifers (2.5), and Scrub (1.5). The equation was obtained from the Forest Survey of India forest type map 2011 [46,61].

2.2. Rothermel-Based Spatial Fire Spread

The Rothermel model, a widely used mathematical model in fire simulation, is instrumental in predicting forest ecosystems' spread, fire rate, and intensity. It is based on fuel type, moisture, temperature, wind speed, and terrain topography. This model is a cornerstone in simulation systems such as FARSITE or BehavePlus, playing a crucial role in fire management planning and decision-making.

The tool's prerequisites include multiple parameters for accurate spread prediction, namely wind speed (m/s), wind direction (degrees), moisture content (%), and fuel load (tons/ha). The slope values would be computed directly from the DEM itself. Given the season and weather conditions, these estimates can be acquired easily.

The rate of fire spread is usually 1/10th of the standard meteorological wind speed, as this is observed in a large number of high-intensity wildfire observations across various types of forests (e.g., conifers, dry forests), including shrublands but excluding grasslands, as this rule provides highly accurate results for dry fuels and high wind conditions [62]. In a study on the forest fire spread in Karst ecosystems of southern China, modifications to the Rothermel model—either by re-estimating parameters or reforming the model—reduced errors significantly, making it more suitable for regional conditions [63]. While we have applied similar simplifications for Himalayan conifer forests, given the data deficit in this region regarding forest fire parameters, our model also integrates a wind speed rule where the rate of spread (ROS) is calculated as 10% of the prevailing wind speed [62] Hence, more straightforward approaches to the complex Rothermel equation can be used as predicting

the forest fire spread rate is often limited by its complex formula and numerous required input parameters; in a previous study, fuel moisture content, wind speed, fuel load, and fuel thickness were included and validated in an indoor fire model [64]. The fuel load and slope are important parameters in influencing the ROS, as a higher fuel load and higher slope (during upslope fires) causes the ROS to increase in general but variably under different conditions because this inclusion was based on Albini's modifications of the original Rothermel equation which excluded wind and slope conditions [65].

In our study, the Rothermel-based fire spread simulation tool helps identify probable fire spread based on four parameters: fuel load, slope, moisture content, wind speed, and wind direction.

2.3. Fire (Burn) Frequency

As discussed before, fire (Burn) frequency is used to study previously burned areas; the GABAM (Global Annual Burned Area Map) dataset has been used for the past 30 years as it is based on Landsat Imagery (30 m resolution). This dataset details the extent of past burned areas due to fire, which is derived from the burned probability for each pixel computed calculated using all available Landsat images and various spectral indices, with a globally trained random decision forest model and a seed-growing method, refined by the NDVI (Normalized Difference Vegetation Index), NBR (Normalized Burn Ratio), and temporal filters [47]. These annual burned area rasters were accessed using Google Earth Engine (GEE) and then processed in the QGIS Open-Source Environment using a raster calculator to generate a fire frequency map showing the past 30 years in Uttarakhand, which provided the spatial extent of fires and the number of times any given area was burnt in the entire period.

2.4. Optimal Path Tool

The prerequisites of this tool are that any DEM/DTM file in Geotiff has to be uploaded (either open access or privately acquired). The optimal path tool can assist in planning and executing fire management strategies by providing the most efficient paths for fire management activities. The tool is user-generated and utilizes the 'leastcostpath' R package. It is used to generate cost surfaces based on DEM-derived slopes to model pathways and movement potential within a landscape [50]. Using R 'Shiny' capabilities, a user can choose an origin and destination point on the screen, and the least cost path is computed rapidly depending on the distances and slope complexities. Here, two functions are utilized: *create_slope_cs* to compute a slope-based cost surface and *create_lcp* to compute the least-cost path from origin to destination. Therefore, the least cost path considers increasing the slope with increasing costs, i.e., the effort required.

The least-cost path utilizes Dijkstra's algorithm. It represents the study area as a graph, where raster cells or network nodes are vertices, and edges are weighted by movement costs from a cost surface [50]. The algorithm initializes the origin node's cost to zero, assigns all others to infinity, and iteratively updates the lowest-cost paths until the destination is reached. The final path is extracted as a sequence of nodes and converted back into the GIS format for spatial analysis.

2.5. Walk–Hike Time Isoline Tool

We used the *movecost* R package because it computes non-isotropic cost surfaces and enables the creation of least-cost paths, corridors, and networks based on various human movement-related cost functions requiring a Digital Terrain Model (Digital Elevation Model), a start location, and optionally, destination points [51]. Here, we provide multiple origin points for users to select to compute multiple isolines or walking cost boundaries for a 30 min default period using an R 'Shiny'-based interface. This allows several forest

department firefighters to visualize multiple teams' walking–hiking time boundaries for a 30 min fire suppression effort from numerous road access points. The *movebound* R function was used to calculate the walking cost boundaries in walking time to create these isolines.

2.6. Visualization Layers and Statistical Analysis

For the visualization of functional layers, QGIS's open-source environment was used for all geoprocessing offline, whereas Google Earth Engine was used for all data access and geoprocessing online. The spatial layers include fire incident geolocations, burn frequency, and fuel load estimations. An R statistical environment was used for statistical analysis, including many packages for developing the DSS tools and statistical analysis. The packages used for statistical analysis included fuel *dplyr*, *ggplot2*, *tidyverse*, *ggridges*, *patchwork*, and *lubridate.* As understanding fire regimes was crucial in this study, spatial and statistical visualizations were performed to cover the three major components of fire regimes, i.e., intensity, frequency, and seasonality.

The KBDI (Keetch–Byram Drought Index) was used as it is the well-known index used for long-term fire risk assessment, effectively capturing seasonal drought conditions that influence wildfire potential. Its slow buildup provides a reliable indicator of prolonged dry periods, helping to identify regions prone to fire outbreaks. This makes it a valuable tool for strategic fire management and preparedness planning [66]. The KBDI was integrated into the DSS using Google Earth Engine Python API in the R Shiny framework. The dataset provider was the Institute of Industrial Science, The University of Tokyo, Japan [49].

In addition, a decadal (2013–2023) statistical analysis of the KBDI regarding fire incidents was conducted to emphasize the use of the KBDI for the timely planning of fire prevention strategies. This statistical analysis was also performed in the R environment using the *ggplot2* package visualization.

2.7. Post-Fire Restoration Tree Selection Tool and Comparison of Fire Prevention Strategies

The tree selection tool was developed using *Shiny* and *DT* R packages. The tree species attributes were collected from the India Biodiversity Portal and other bibliographic literature [53,54], including attributes like foliage type, flowering season months, bark thickness, tree height, and fire sensitivity. In addition, this tool also included a comparison of various fire prevention strategies based on the recent literature, including 'Ecological Techniques for Forest Fire Prevention' as the techniques are also performed post-fire and subsequently pre-fire planning [55] to make it accessible for the decision maker to compare between these strategies holistically.

3. Results

The results of this study are presented in subsections includes the working and visualization of various tools. Firstly, spatial map visualization is performed (Section 3.1) to represent fire behavior and its effects. The Rothermel-based fire spread tool helps to model fire dynamics (Section 3.2) the optimal path tool (Section 3.3) is used to determine the most efficient routes for fire response; and the walk–hike time isoline tool (Section 3.4) helps to assess accessibility under different fire scenarios. In addition, statistical analysis (Section 3.5) is used to interpret the data. Finally, the tree selection for the restoration tool (Section 3.6) guides the selection of appropriate species for post-fire restoration. Together, these tools contribute to a comprehensive understanding of fire dynamics and restoration strategies.

3.1. Spatial Maps Visualization

Fuel load estimates, although indicative, are high in Sal, Mixed Oak forests, and Deodar forests. However, in the districts of Almora, Pauri Garhwal, and Nainital, the Chir Pine forests also have higher fuel loads and show higher fire incidences (Figure 3).

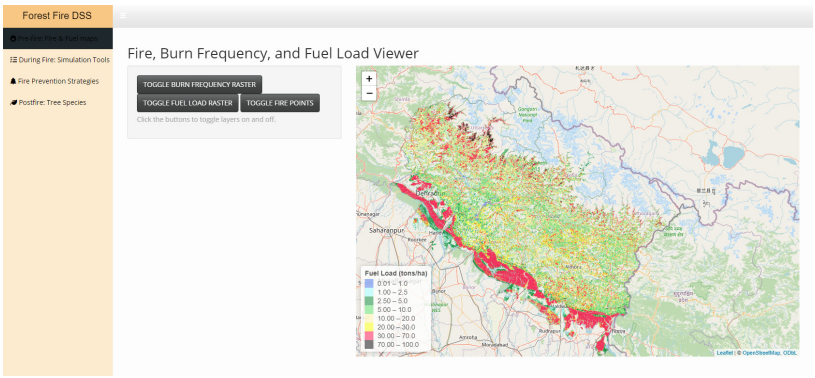


Figure 3. Estimated indicative fuel load (tons/ha) for vegetation in Uttarakhand, India.

The mean total fine fuel load was 17.8 tons/ha, and the maximum value of the estimation was 110.2 tons/ha. These results are similar to rigorous acceptable fuel load assessments in the past, including in Hunan, China, where the mean total fine fuel load was 13.5 tons/ha, and the maximum value was 106 tons/ha [67]. Similarly, a study in the Eucalyptus forests in Victoria, Australia, estimated the mean total fuel load as 18.4 tons/ha [68].

Sal forests in the Southern parts of Uttarakhand have relatively higher fire incidences (Figure 3), as it is reported that Sal trees dominate in high fire zones where the fuel load is very high [69]. Furthermore, even in past susceptibility mapping studies that utilize moisture conditions and slope data, high fire susceptibility has been observed in these forests [70]. In terms of fire proneness, these Sal forests have high and extreme fire proneness compared to other forests. These Sal forests constitute the majority of the high fire-prone areas, i.e., around 10% of the total forest in the state [71]. However, these forests' burn frequency values and actual burnt areas are not necessarily high. Instead, the fire incidents, burn frequencies and burnt areas are higher in the Chir Pine- and Oak-dominated forests in Pauri Garhwal, Tehri Garhwal, and Almora (Figures 4 and 5).

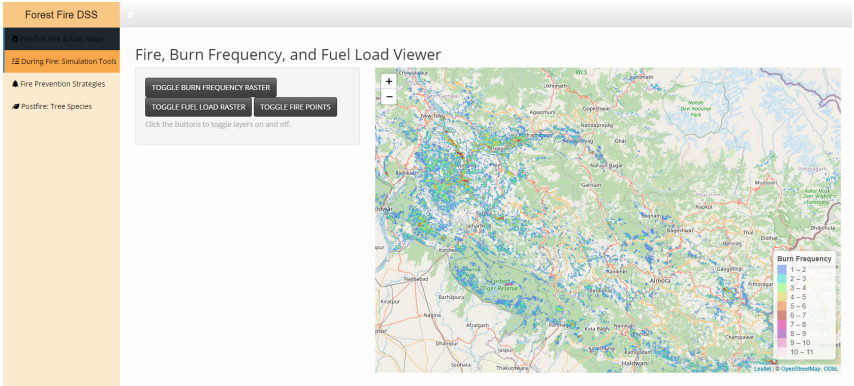


Figure 4. Burn frequency map of Uttarakhand showing the frequency of forest fires and burnt areas (in years) based on 30 years of satellite observations.

The KBDI viewer (Figure 6) offers multi-temporal access to the index data for the latest and historical periods. It also provides other functionalities, such as selecting layer opacity and coordinates to select focus areas.

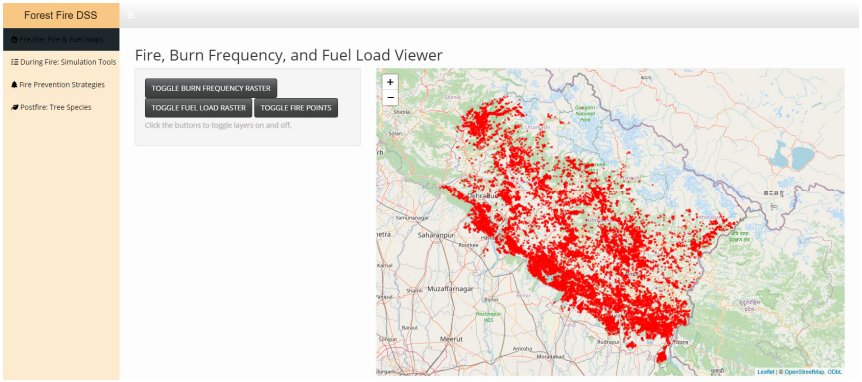


Figure 5. Fire incidents map of Uttarakhand showing geolocations of fire incidents from 2000 to 2024 using MODIS datasets.

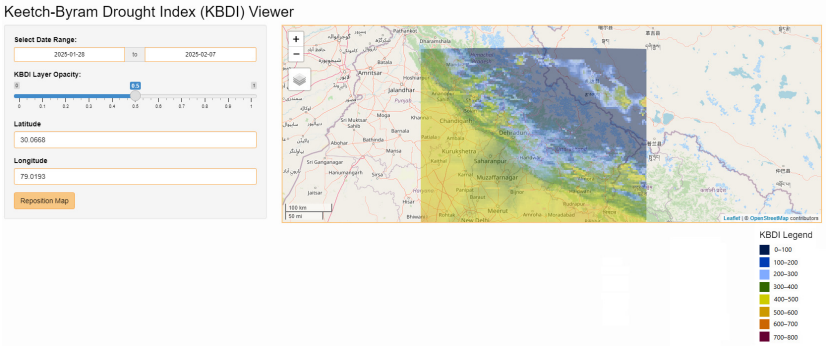


Figure 6. The KBDI (Keetch–Byram Drought Index) viewer visualizes the index by selecting a date range. The default date range is 10 days preceding the system date.

3.2. Rothermel-Based Fire Spread Simulation Tool

Upon entering the parameter values, this tool provided instant visualization (<1 s). The visualization includes representative buffers of fire spread in hourly buffers respective to the prevailing wind direction (Figure 7). Since testing these tools requires extensive fieldwork and complex access to these areas, the tool can only be considered a prototype. However, this tool can still be a preliminary source of estimation of fire spread for a data-deficit region like Uttarakhand, where Rothermel-based fire simulations have never been implemented.

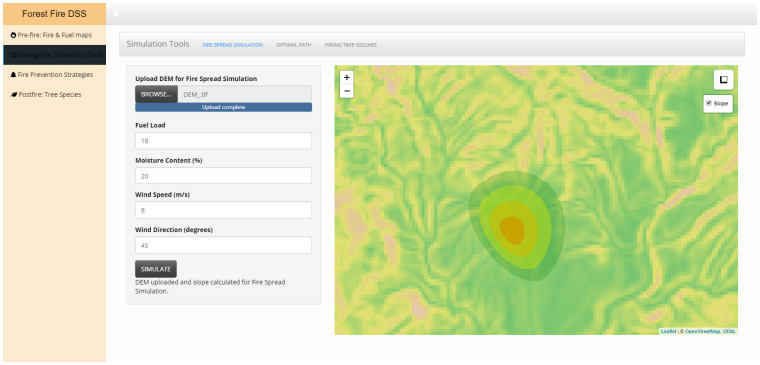


Figure 7. Rothermel-based spatial fire spread simulation tool tab visualizes the spatial spread of a sample site based on the Rothermel parameters.

3.3. Optimal Path Tool Utility

The average computation time required to process was 10–15 s for an area of 100 sq km (performed in diagonal length) of an open-access Digital Terrain Model with moderate

satellite resolution (Figure 8). The optimal path tool is essential for fire response because it can compute the best route that minimizes distance while avoiding steep slopes or ridges. By allowing users to input the origin and destination points from a motor vehicle-accessible feature, this tool aids in planning access and containment routes, thereby optimizing the response of firefighting teams.

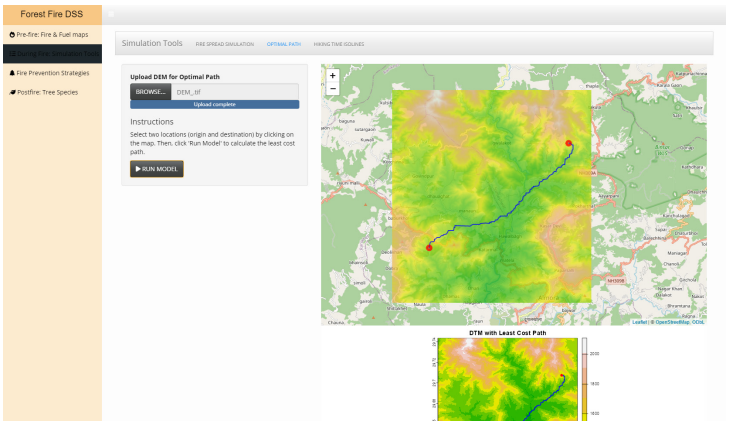


Figure 8. The optimal path tool tab visualizes the slope/terrain-based computation of the optimal path based on the least-cost path algorithm.

3.4. The Benefits of the Walk–Hike Time Isoline Tool

This tool can be key for tactical planning and resource allocation for firefighters navigating steep, forested landscapes; this tool provides a more realistic understanding of travel times compared to standard Euclidean models. The average computation time for five-point-based isoline buffers was 12–14 s with a similar DTM as the previous tool (Figure 9). In Euclidean environments, it draws perfectly round buffers; however, this model accounts for slope and terrain effects, which are critical for ensuring firefighter safety and efficient movement in rugged environments. There is also an option for utilizing functions expressing cost as metabolic energy expenditure using the '*p*' and '*pcf*' cost functions in the '*movecost*' package, which internalizes the metabolic costs of standing and walking with added weights (*here* backpacks), thus providing a wide range of predictions based on different conditions [72]. This tool can be used for both prescribed burn planning and firefighting. It helps identify escape routes that avoid dangerous terrain for prescribed burns. During a fire, it facilitates the planning of access and containment routes, optimizing the response of firefighting teams, and improving the safety and effectiveness of fire management.

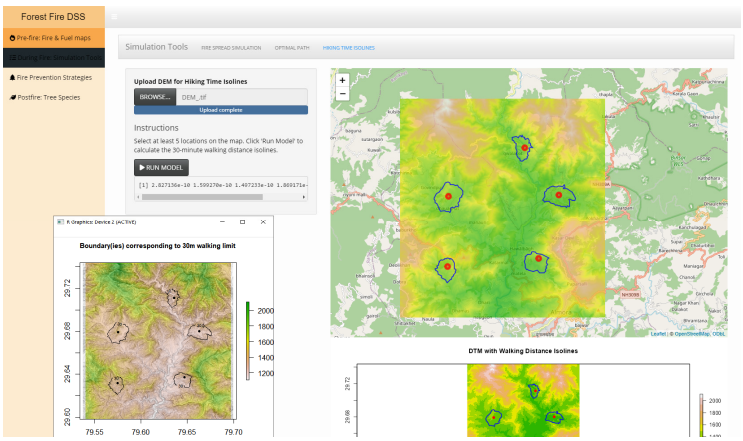


Figure 9. Hiking time isolines tool tab for visualizing the slope/terrain-based computation of multiple isolines at a 30 min distance for firefighting/fire response teams.

3.5. Statistical Analysis

Based on the month-wise ridge plots, there are two important observations, i.e., the months of March, April, May, and July have higher fuel load distributions than the mean, and fire incidents in October, November, and December have relatively lower fuel loads. This could indicate that the latter part of the year has stubble-burning or surface-fire incidents with low fuel loads and grasslands (Figure 10). Furthermore, brightness and temperatures are lower for Oct, Nov, and Dec compared to the major fire season (March, April, May, and June), which can suggest that the presence of low-intensity surface fires is predominant in the later fire season of the year compared to the major fire season which has high-intensity crown fires as well [73]; Figure 10.

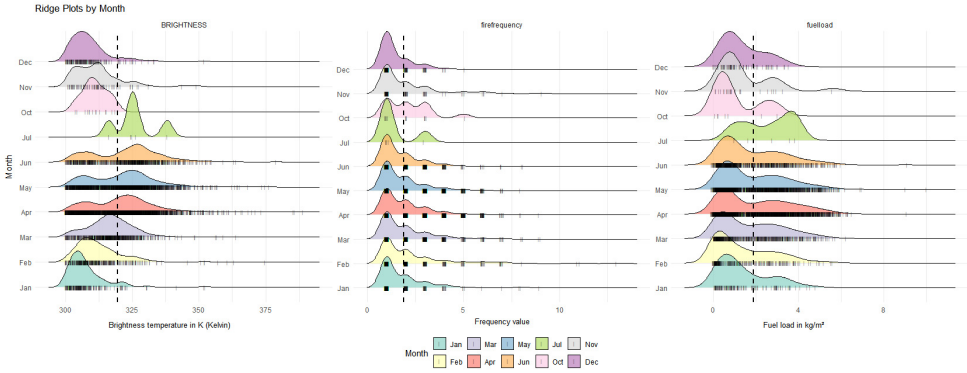


Figure 10. Month-wise ridge plots showing the fire counts below the density plots with the "|" with respect to brightness and temperature (in Kelvin), fire frequency (for the last 30 years of available data), and fuel load (kg/m^2).

The fire incidences were measured based on kernel densities to quantitatively compare fire incidences based on fuel load type and Burn frequency. It was notable that the *p*-values for burn frequency between 0 and 4 had significant differences ($p < 0.001$), whereas there was no significant difference for classes 5–7 in terms of the kernel density of fire incidences (Figure 11). Fuel-load type has little to do with fuel load for landscapes with higher burn frequencies as they would have a distinct fire regime. Also, the results show that relatively higher fire incidents are associated with higher burn frequencies and higher fuel loads in the comparison of all burn frequency classes and fuel load types (Figure 11).

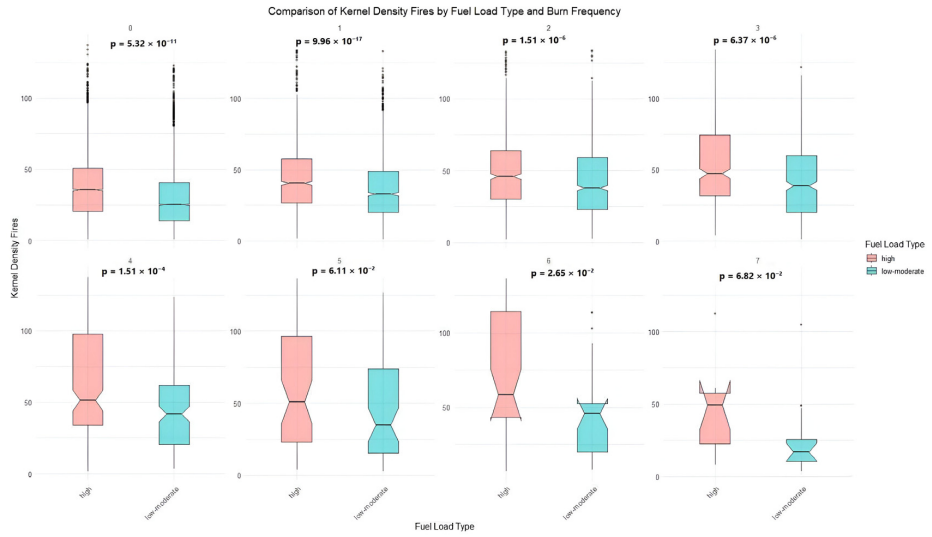


Figure 11. Boxplots showing a comparison of the kernel density of fire incidents by fuel load type (high and low/moderate) and burn frequency.

Higher mean KBDI values correlate with increased fire counts, with the peak fire months (April and May) preceded by moderate rises in the KBDI, suggesting a lagged relationship. January, April, and May show high fire risks, while wetter months (July and August) correspond to a lower KBDI and fewer fires. Notably, increases in the KBDI often precede fire incidents, as seen by January's high KBDI (~161.6), followed by rising fires in February and March. Over multiple years, this trend suggests that a high KBDI in one month signals that there will be elevated fire risks in subsequent months, particularly at the start of the dry season (Figure 12).

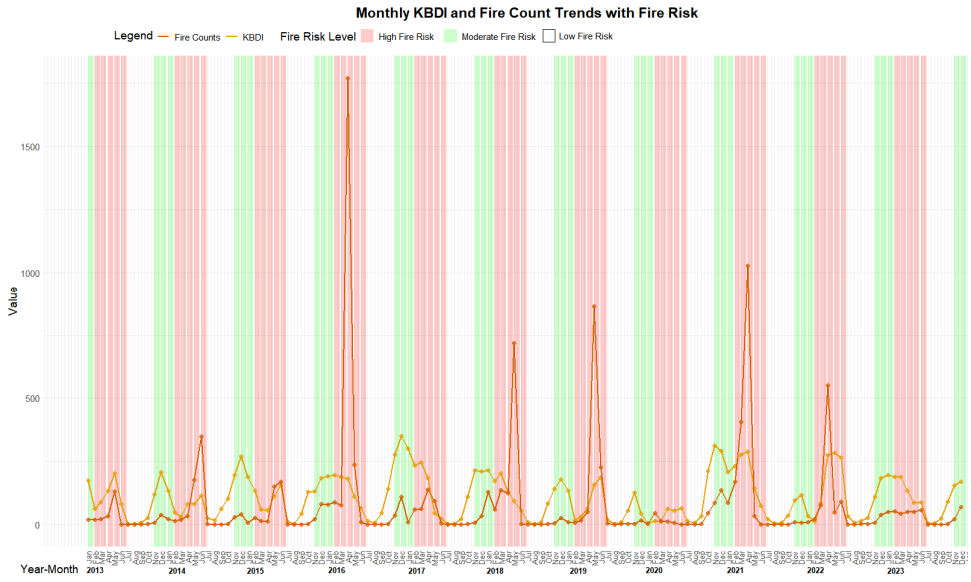


Figure 12. Time-series analysis of the KBDI and number of fire incidences for the decade 2013–2023.

3.6. Tree Selection Tool for Restoration (Post-Fire) and Fire Prevention Strategies Comparison Tabs

These data filter-based tools provide tree species results based on selected attributes (Figure 13). However, more data-driven functionalities can be added using ample bibliographic resources on tree species in different geographical subregions of Uttarakhand. The fire prevention strategies tool also provides research-based information by utilizing filters such as financial costs, sustainability, time priority, and seasons (Figure 14).

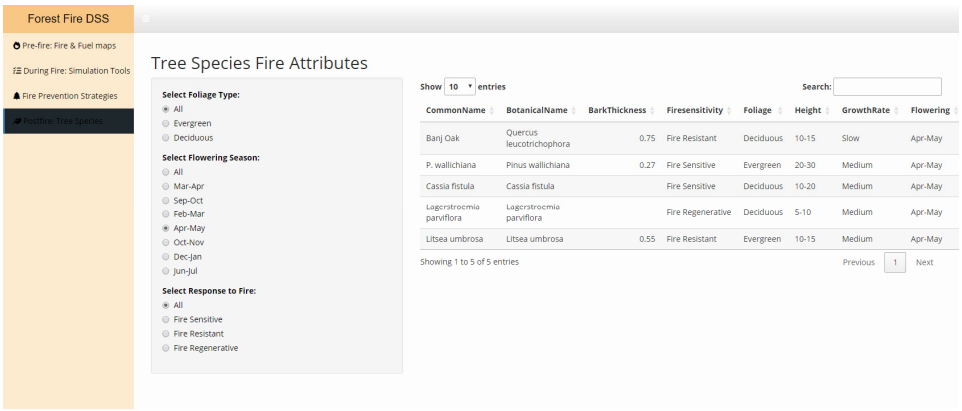


Figure 13. Tree selection tool, which filters tree species based on selected attributes in form fields.

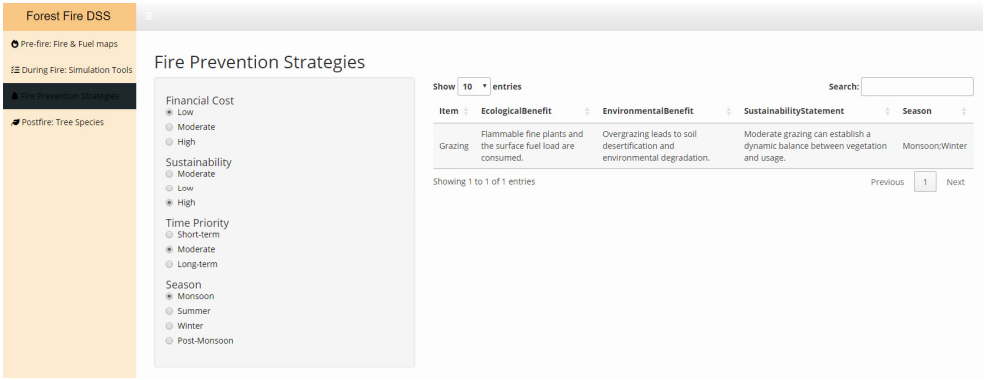


Figure 14. The comparison tab of fire prevention ecological strategies shows these strategies' ecological and environmental benefits and cost comparisons.

4. Discussion

Similar forest fire prevention and management tools have been developed with mobile and web applications. The Indonesian Forest and Land Fire Prevention Patrol System incorporates spatial datasets and analyses, including fire incidents, patrol locations, distance operations, water sources, and vegetation types [74]. Another DSS provides web- and mobile-based applications with route-generation capabilities, allowing users to find the shortest paths between multiple locations and identify the nearest water supply relative to their current position [75]. These spatial decision support tools, including the Rothermel-based fire spread model tool, can be used in particular during a fire or to assess the prescribed burning responses of surface fires to develop prevention plans in the future because they can assist in determining the spreading behavior of fires based on weather conditions and help predict the probability of extreme fire behaviors [76].

Furthermore, the predictive utility of tools like the KBDI viewer is higher, as it is a robust drought index, and it has been known that during fire days, especially those with escaped fires, consistently higher KBDI values have been exhibited, with the most pronounced differences in wetter regions. Hence, tools like KBDI viewer are invaluable for assessing dryness conditions and predicting fire potential, particularly in high-rainfall areas, as their ability to provide critical insights enhances fire management strategies and preparedness [77].

The statistical analysis of this study shows that, in Uttarakhand, most fire incidents occur during the early part of the year, specifically in March, April, May, and June—with another peak in October, November, and December. This pattern contrasts with the monsoon season in the year's middle months when conditions remain relatively moist, and the DSS remains practical and applicable. The vegetation during the peak fire months tends to be dry and clear (Figure 9). Additionally, brightness and temperatures are lower in October, November, and December compared to the major fire season (March, Apr, May, and June), suggesting the presence and prevalence of low-intensity surface fires during the latter part of the year in contrast to the high-intensity crown fires common in the major fire season [73]. Similarly, State Forest Department forest fire incidents data have also shown that high-frequency surface fires are dictated by moisture conditions of the pre-monsoon dry season (March–June) and are closely associated with the traditional practices of biomass collection by local people [78]. Hence, the detailed statistical analysis of extensive fire incident data was justified so that decision-making could incorporate seasonal variations and various fire types.

Spatial decision support tools, such as optimal path tools based on LCP algorithms, offer a deterministic and mathematical approach to solving spatial problems; incorporating indigenous knowledge and accounting for seasonal variations can yield more realistic

results [79]. The hiking time isoline tool is particularly useful in forested and rugged terrains like Uttarakhand. This tool can be accessed remotely, making it a valuable resource not typically available in popular GIS software, such as ArcMap [52]. The hiking time isoline tool, created with the *movecost* R package, can enhance fire response and planning, especially in challenging terrain. By visualizing 30 min walking time boundaries from various access points, this tool helps fire management teams effectively plan and allocate resources, positioning firefighting teams where they can respond most efficiently. The isolines consider terrain impacts on travel speed, providing a realistic overview of accessible areas within critical response times. Moreover, this tool facilitates scenario-based pre-fire planning and can be accessed remotely via an R Shiny interface, unlike traditional GIS software. This remote accessibility allows the adjustment of real-time fire dynamics, improving response speeds and safety in challenging mountainous landscapes.

Furthermore, issues like out-migration from hill villages, land abandonment, and reduced livelihood security are important reasons that the traditional practices of fire management are non-existent in many places in Uttarakhand [80]. Therefore, DSS tools like fuel load and burn frequency maps can play a pivotal role in empowering specific rural and urban communities by identifying REDD+ project implementation areas (and associated result-based payments), which has a high potential in Uttarakhand [81]. This can strengthen the economy in areas with persistent forest fires, such as Almora, Pauri Garhwal, and Nainital, that are facing various ecological, social, and economic challenges. By addressing these issues and respecting and integrating local management strategies and practices (using DSS's fire prevention strategy comparison tool), the DSS ensures that community members are actively involved in the fire management process, fostering a sense of engagement and shared responsibility.

Rural communities that depend on forest resources, such as in Almora, including firewood, forage, and water collection, can use post-fire tree selection tools to help select tree species that increase ecosystem services and non-timber forest products. Also, The DSS could prove invaluable for these community leaders, providing up-to-date information on fire risk by observing the Keetch–Byram Drought Index (KBDI) early on in the fire season and enabling the planning of preventive measures, such as constructing and maintaining firebreaks, managing fuel loads, and harvesting firewood in high-risk areas. Furthermore, it could facilitate collaboration between government authorities and residents. Numerous studies have highlighted the detrimental effects of fire when fuel loads are elevated or when the fire regime has [9,82,83]. This system could monitor fuel dryness and predict potential risks related to specific local activities.

In the urban zones of the Almora and Nainital districts, tourism is a significant economic activity but also places considerable pressure on surrounding forests. Therefore, involving the urban population in fire prevention campaigns may be beneficial as the comparison of fire strategies and post-fire restoration tools can increase awareness and the decision-making capabilities of citizen groups, non-governmental organizations, REDD+ implementation partners, and government bodies as well. Hence, the DSS can be a powerful tool for monitoring and managing fire risks in these areas when all the pre-fire, during-fire, and post-fire management and strategy comparison tools are used for holistic forest fire management.

Additionally, the DSS can be crucial in addressing rural–urban migration's ecological and social consequences. While this trend may reduce pressure on forest resources, it can also increase fire risk due to the accumulation of combustible materials on abandoned lands. Conversely, migration may occur in fire-prone areas in high-risk zones [84]. The DSS can help local authorities and communities anticipate and manage these changes, thereby contributing to more effective and sustainable fire management in Uttarakhand.

Whether developing new hand tools or a DSS, it is crucial to revisit core considerations in fire management. These questions ensure that tools benefit users by assessing accessibility, usability, and decision-making values. Key aspects include whether the DSS is understandable, informs planning, and adapts to evolving data inputs. Users must easily access and comprehend the system to support effective decision-making.

Users must have relevant knowledge of fire management, including experience with ignition, fuel, weather, and fire behavior. The DSS should support decision-making by providing tools, SOPs, and communication support for operational efforts. Continuous field feedback is essential for system improvement, ensuring a dynamic link between the DSS and field operations. High-tech innovations must address real issues and be practical for users. Tools like optimal path and hiking time isolines are only effective if users have the necessary skills, training, and organizational support. Consulting potential users is crucial to assessing usability, determining training needs, and evaluating functionality.

In addition to the core considerations outlined above, this manuscript seeks to provide a more precise explanation of the Decision Support System (DSS) to enhance its comprehensibility for users at the Forest Division level. This document will serve as the primary reference for the DSS, ensuring that users have a comprehensive guide for effectively engaging with the system. While this manuscript presents an overview and essential details, a dedicated workshop will be organized following its publication to facilitate in-depth training and hands-on experience. It is important to emphasize that this represents the initial stage of the prototype, and the development process remains ongoing.

5. Conclusions

This study addressed existing challenges by developing a prototype Spatial Decision Support System (DSS) for forest fire management in Uttarakhand, India. The DSS integrates pre-fire visualization, during-fire response, and post-fire restoration tools, utilizing satellite LiDAR-based fuel load estimations, the Keetch–Byram Drought Index (KBDI), Rothermel fire spread simulations, and movement isoline analysis. Implemented in an R Shiny framework, it incorporates ecological, community-based, and financial considerations to enhance fire prevention and restoration efforts. By bridging key gaps in forest fire planning with comprehensive datasets and user-friendly spatial tools, the DSS strengthens decision-making for fire mitigation and recovery.

In contrast to hypothesis-driven studies that primarily identify and discuss forest fire management challenges, our study takes a development-focused approach, directly addressing these issues by designing and integrating practical spatial decision support tools.

Author Contributions: Conceptualization, N.Y. and S.R.; methodology, S.R. and P.M.; software, S.R. and M.K.S.R.; validation, S.R., N.Y. and P.M.; formal analysis, N.Y., S.R., R.Y. and P.M.; investigation, N.Y. and S.R.; data curation, S.R.; writing—original draft preparation, S.R., R.Y., P.M., L.P.P.-C. and M.K.S.R.; writing—review and editing, N.Y., S.R., R.Y., P.M., L.P.P.-C. and M.K.S.R.; visualization, S.R.; supervision, N.Y., S.R., R.Y. and L.P.P.-C.; project administration, N.Y. and S.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All tools and related data are readily available at the DSS web application online at https://shreyrakholia.shinyapps.io/UKFFDSS/ [accessed on 1 March 2025].

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

DSS, Decision Support System; LCP, Least-Cost Path; DEM, Digital Elevation Model; DTM, Digital Terrain Model; GIS, Geographic Information System; MODIS, Moderate Resolution Imaging Spectroradiometer; GEDI, Global Ecosystem Dynamics Investigation; FSI, Forest Survey of India; GABAM, Global Annual Burned Area Map; ha, hectares; Sec(s), Second(s); KBDI, Keetch–Byram Drought Index; REDD+, Reducing emissions from deforestation and forest degradation in developing countries.

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