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Article

Forest Fire Hazards Vulnerability and Risk Assessment in Sirmaur District Forest of Himachal Pradesh (India): A Geospatial Approach

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Abstract: The Himachal Pradesh district's biggest natural disaster is the forest fire. Forest fire threat evaluation, model construction, and forest management using geographic information system techniques will be important in this proposed report. A simulation was conducted to evaluate the driving forces of fires and their movement, and a hybrid strategy for wildfire control and geostatistics was developed to evaluate the impact on forests. The various methods we included herein are those based on information, such as knowledge-based AHP-crisp for figuring out forest-fire risk, using such variables as forest type, topography, land-use and land cover, geology, geomorphology, settlement, drainage, and road. The models for forest-fire ignition, progression, and action are built on various spatial scales, which are three-dimensional layers. To create a forest fire risk model using three different methods, a study was made to find out how much could be lost in a certain amount of time using three samples. Precedent fire mapping validation was used to produce the risk maps, and ground truths were used to verify them. The accuracy was highest in the form of using "knowledge base" methods, and the predictive value was lowest in the use of an analytic hierarchy process or AHP (crisp). Half of the area, about 53.92%, was in the low-risk to no-risk zones. Very-high- to high-risk zones cover about 24.66% of the area of the Sirmaur district. The middle to northwest regions are in very-high- to high-risk zones for forest fires. These effects have been studied for forest fire suppression and management. Management, planning, and abatement steps for the future were offered as suitable solutions.

Keywords: geospatial modeling; MCDA; AHP; risk zone; management

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1. Introduction

India is one of the world's mega-rich areas in biodiversity, both in terms of fauna and flora. The incredible richness of India's biodiversity includes 6 million square kilometers of forest cover. The forests of the country are both environmentally and economically valuable. In India, there are only around 1.7 million hectares of well-defined conifer forest, consisting of important species such as fir, teak, sal, and chir pine. The estimated timber growth in these forests is close to 2 billion cubic meters, which is worth around 60 million rupees (100 million USD) [1]. Large forest fires impact the climate, human health, and property, as well as resulting in danger to life. Global attention to forest fires has increased recently due to their major long-term threat to forest habitats and public safety, as well as shorter-term risks to property and human lives [2]. Fire plays an important role in ecological processes, including altering the composition of plant populations, conserving water, enhancing soil quality, and promoting biodiversity. Due to their role in natural plant succession, forest fires are an important mechanism for initiating new growth in the ecosystem. A region equivalent to 6 million km^2 of land in India has been destroyed over the past two centuries due to forest fires [3]. Throughout that time, the Forest Survey of India (FSI) has been carrying out fieldwork in the country's different forest plots since 1965 in order to record fires. For statistical significance, long-term observations of forest conditions were analyzed, and the results were released in [1]. A total of 95% of the country's forest fires are of human origin, according to FSI research. As per data from the Indian Forest Service, 50% of the forests are likely to be vulnerable to burning. A few national and foreign NGOs (non-governmental organizations), including the Survey of India and state agencies, are also conducting research on forest fires. "India has carried out several forest fire incident case studies in various locations and this booklet summarizes it all their findings" [4].

Despite all of these interventions, the forest-fire-danger data bank remains inadequate. New methods will be needed to circumvent this problem. Satellite data can be very valuable in terms of new fire management strategies. Some new innovations, such as the use of satellites, should be applied in conjunction with the country's extensive field-based fire data-collection programmed. According to analysts, the research data and facts that have been published show that the country is in a very serious crisis that requires immediate action to be resolved. In India, there are no details on the area and value of the forests burnt, as well as the amount of forest devastated by fire, which makes it impossible to determine the losses. They are incomplete because the number and extent of fires is not available. The explanation given for this is the fear of having to bear responsibility. There is thought to be about 1 million hectares of forest loss due to fire annually. According to an assessment conducted by the Indian Forest Service, each year, there are 3.73 million hectares of wildfires in India that have an effect on forests [5]. There are very few fire outbreaks in India that are caused by natural factors. There is widespread (99%) agreement among observers that the majority these fires are of the people's own doing, and there is a connection to their socioeconomic status. The chief sources of forest fires in India are grazing, shifting cultivation, and the collection of non-wood products.

Forest-fire risk modeling uses remote sensing, and GIS, in 1990 [6], used an advanced very high-resolution radiometer to detect the fire risk for Rajaji National Park in Uttar Pradesh in India, which is considered to have a more than 50% higher fire risk. This paper also presents one of the earliest papers on this topic for areas in India. The authors of [7] used remote sensing to map vegetation types and using slope, proximity to settlements, and distance from roads to predict fire risk in Madhya Pradesh in India. The authors of [8] used neural networks, knowledge-intensive systems, in order to predict forest fires based on temperature, humidity, rainfall, and fire history. Similar to [8], the author in [9] used fuzzy sets and semi-triangular membership function in order to perform long-term prediction of forest-fire risk based on fire history and drought cycles. The authors in [10,11] also considered different areas for fire risk prediction. For areas in India, multiple authors considered estimating forest-fire risks [12–15]. The mentioned authors provide an overview of forest fire risk for different areas in India. The authors of [16] used multicriteria decision analysis and an analytical hierarchy process to estimate Bhajji forest fire risk in Himachal Pradesh in India. This paper presents only one forest part of Himachal Pradesh, while our paper presents the whole area of the Sirmaur district.

2. Study Area

The Sirmaur district is in the outer Himalayas and is also commonly known as the Shivalik range. The district shown in Figure 1 and is located between the latitudes of 31°00′ North and 77°00′ South, and 77°00′77′ longitude, between the base latitudes of longitude and the Surveys of India sheet 'A' and 'L' (Figure 1). It is located at an altitude ranging from 300 to 3647 m, with four major rivers. The forested area is around 48,682 hectares [17].

It is connected to the capital Shimla to the west and to the east. In the south is the state of Haryana and in the east is the Indian state of Uttar Pradesh.

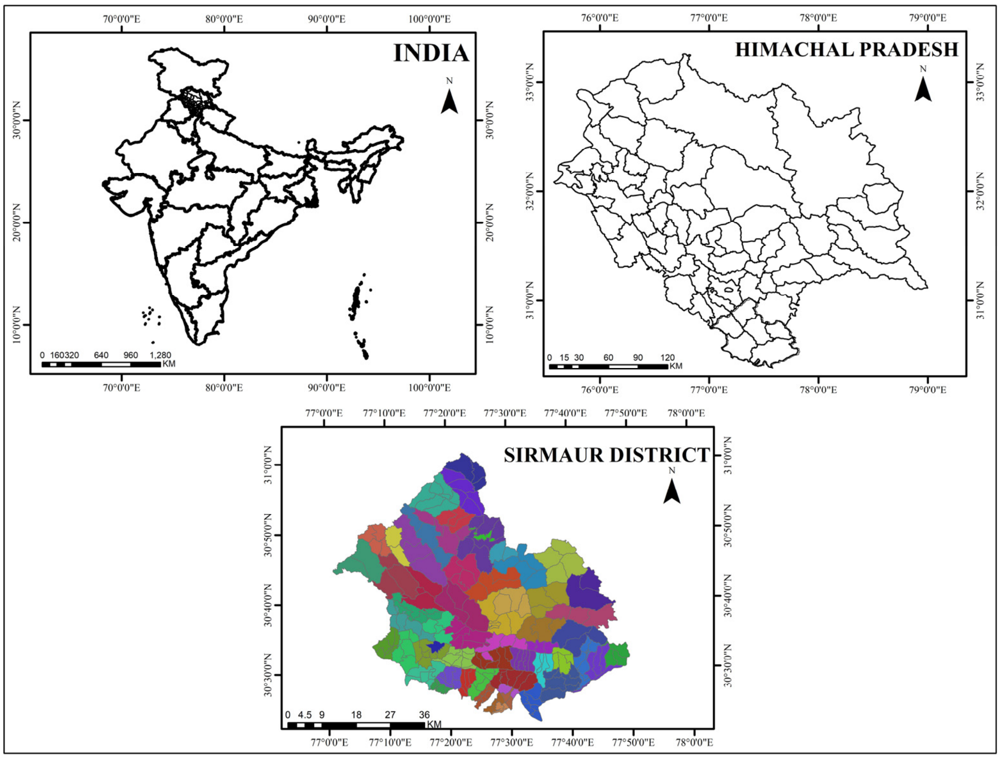

Figure 1. Study area.

The Monsoon that generally starts in the Sirmaur district is from the third week of June and lasts up to the second week of September. April and May are also the rainiest months of the spring season in the Sirmaur district. In July and August, rainfall is more active. The early rainy season provides 80% of the rainfall and the average rainfall of the Sirmaur district is about 1324.3 mm. Figure 2 shows the average rainfall of the district from temporal variation between 2001 and 2020.

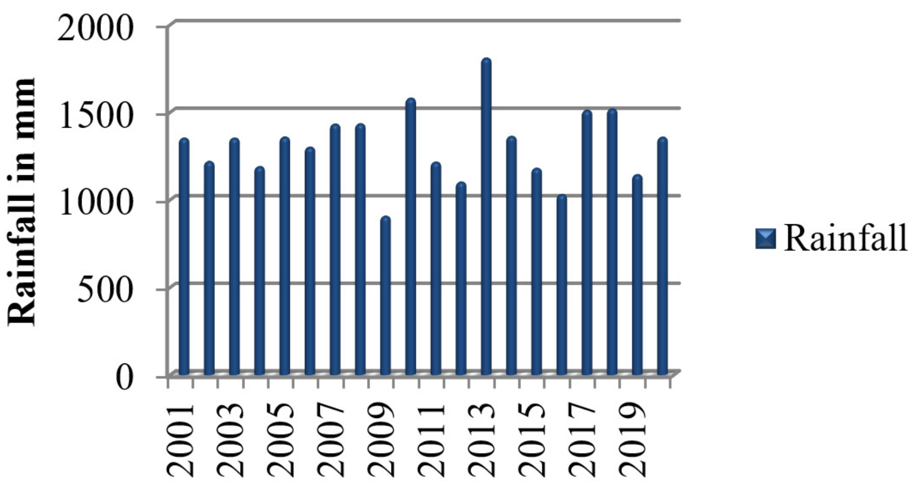

Figure 2. Rainfall (in mm) in the Sirmaur district.

3. Data and Methodology

The following resources and equipment are needed to complete the analysis. Below are the following various data used for the forest fire analysis and methodology with their flow chart for analysis. The land cover layer was created by combining digital image classification and visual interpretation techniques to view satellite images. As supplementary data, the region's current land use/cover map was used. The key remotely sensed data source in this study was Sentinel 2 imagery from 20 May 2019, resized to a spatial resolution of 10 m [18]. Forest and wild land fire risks, including elevation, slope and aspect, population density and precipitation, were incorporated into ArcGIS for further analysis. The reasons for fires range greatly. The full data used for forest fire risk incorporates slope, elevation, aspect, land use and land cover, geology, geomorphology, buffer zone of road, drainage buffer, built up area buffer, and forest type. Slope, elevation, and aspect data were calculated from the Cartosat-1 digital elevation model [19]. Based on [20], with the increase of elevation, the probability of fire decreases and aspect is only significant on the warmer sides. Land use and land cover is defined with Sentinel-2 imagery [21]. Geology and geomorphology data were downloaded from Geological survey of India [22]. Geology and geomorphology data do not directly affect the risks of forest fires but wildfires can cause problems such as landslides and erosions [23,24]. The roads were downloaded from Geological Survey of India and the road and built-up area proximity of the 200-m buffer zone can significantly increase forest fire risk [25,26]. Therefore, a 200 m buffer zone is included around roads and built-up areas.

The moderate resolution imaging spectroradiometer (MODIS) has been widely used for wildfire incidence and distribution detecting and fire risk assessments. To check the data distribution and accessibility under the Universal Transverse Mercator (UTM) projection, 1:50,000 topographic paper maps with the MODIS hotspot data were mapped to the 1:50,000 topographic paper maps of the WGS84 datum. The comparatively higher temperature on the day of the fire was due to the burned and ash-covered pixels nearby, releasing the latent heat more quickly than usual, resulting in a higher temperature for ID11.

The full workflow is presented in Figure 3.

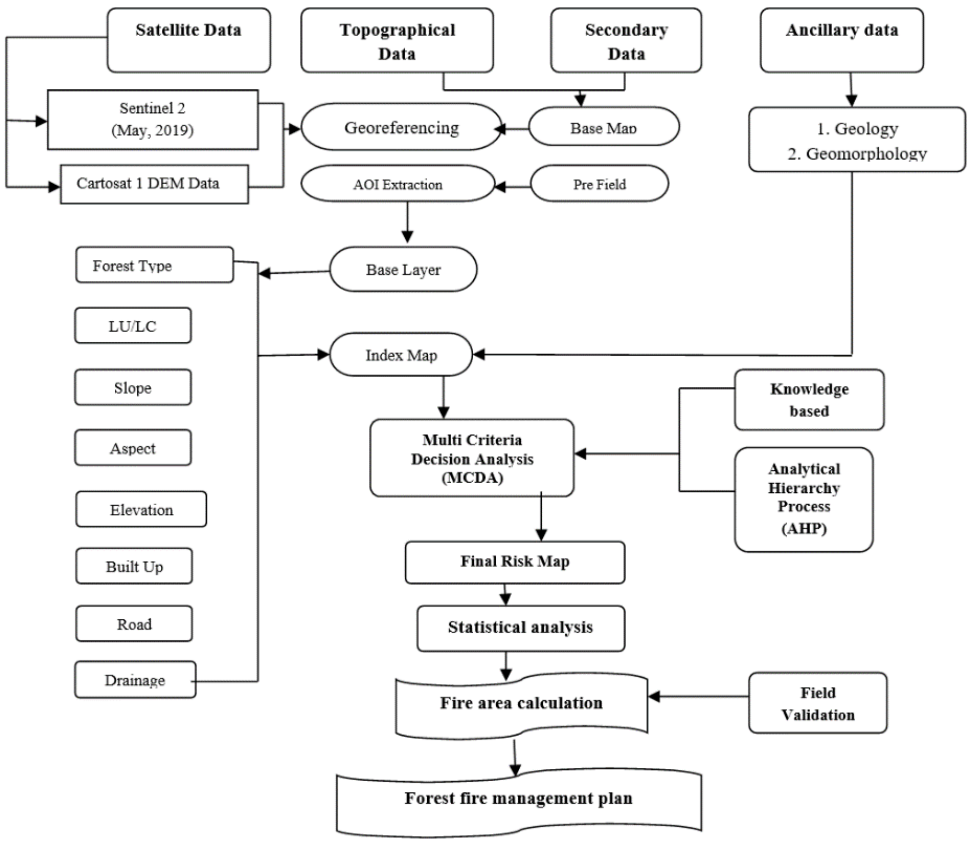

Figure 3. Flow chart of forest fire area calculation.

3.1. Analytical Hierarchy Process (AHP)

As a multi-criteria approach, the analytical hierarchy process (AHP) is one of the best for defining forest fire locations. Many studies have explored the proof of AHP's claimed forest fire effectiveness [27]. In AHP strategy, the enormous choices are made comprehensible by knowledge from math and experts. We have used the nine-point non-stop scale to review the two parameters. Both odd numbers (1, 3, 5, and 7) and even numbers (2, 4, and 6) refer to equal and humble characteristics, but the odd ones stand out (Table 1). The AHP is a methodology focused on objective objectives branching into multiple criteria (objective branches) that is used for multiple-criteria problems. Table 2 shows the random consistency index (RI).

Table 1. The ratio scale and definition of AHP [28].

Importance	Definition	Explanation
1	Equally Important	Equally vital to the target
3	Moderately Important	Compared to the overall profit or damage
5	Strong Importance	A strong preference for one factor over another
7	Very Strong Importance	The one thing that has gained preeminence, considered to be above all the others and vastly superior in the real world, is the theory world of practice.
9	Extreme Importance	If it is strongly proven with evidence and facts, then one element is favored in comparison to the other
2, 4, 6, 8	Inter values	

Table 2. Random Consistency Index (RI) [28].

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53	1.56	1.57	1.59

3.2. Deriving the Weights Using AHP/ANP

Analytic network processing (ANP) is a way of evaluating different parameters by prioritizing and compiling them [29]. Each layer is multilayered, indicating that the relationships between these interdependent groups are too complicated to understand without some effort. This results in their relationship to the different classes being calculated by ANP, so the relationship among these nine has been figured out thusly. The thematic layer weights using ANP and AHP can be derived by following these steps:

1. Construction of a model: many models have been found for the forest reserve map ability, based on a literature review. It is imperative that the problem is identified at both an abstract and thematic level before putting it into model layers.
2. Generation of pairwise comparison matrices: with this handy table—aside from arbitrary designations of importance as found in arbitrary scales—the relative values are assigned as follows: 1 means the same importance of the two themes, while a score of 9 represents an extreme priority of one of the themes [30]. In Table 3, the order of the classes indicates the way we want to implement the priority. Saaty's nine-scale levels for the delineation of groundwater capacity were used in a grid. It aims to capture what is unknown in opinions with AHP views [29]. Referring to the previous entry, the consistency index (CI) is a measure of the consistency by using Equation (1):

$$\mathrm{CI} = \lambda max - \mathrm{n}/\mathrm{n} - 1 \quad (1)$$

As a result, n, Lambda *max* or λmax is the most frequently occurring Eigenvalue of the pairwise comparison matrix. The measure of consistency of pairwise consistency (MC) is expressed as Equation (2):

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI} \quad (2)$$

In addition to the Empirical Tables, we have a Ranking Tables section that allows RIs to be obtained by reference to different measures and countries that apply the indexes. We have Ranking Tables that include the Empirical Table, ratios, and countries that use those indexes as measures. Table 2 gives the value of RI for various values of n [31]. As long as the variability does not exceed 0.1, it is permissible. In cases where CR is higher than 10%, our judgments must be refined. The 10 pairwise consistencies are presented in Table 3. CR: 0.089; count value: 10.00; λmax: 11.179; CI: 0.131; CR: 0.09; constant: 1.49.

Table 3. Pairwise comparisons.

	Item Number	1	2	3	4	5	6	7	8	9	10
Item Number	Item Description	Forest Type	Aspect	Slope	Road Buffer	Elevation	Built up Land	Land Use/Land Cover	Drainage Buffer	Geomorphology	Geology
1	Forest Type	1.00	5.00	3.00	5.00	4.00	3.00	4.00	5.00	3.00	1.00
2	Aspect	0.20	1.00	2.00	1.00	0.50	4.00	1.00	5.00	1.00	2.00
3	Slope	0.33	0.50	1.00	1.00	1.00	3.00	1.00	6.00	3.00	1.00
4	Road Buffer	0.20	1.00	1.00	1.00	1.00	2.00	1.00	2.00	4.00	2.00
5	Elevation	0.25	2.00	1.00	1.00	1.00	1.00	1.00	2.00	2.00	2.00
6	Built up land	0.33	0.25	0.33	0.55	1.00	1.00	0.50	4.00	0.33	2.00
7	Land use/land cover	0.25	1.00	1.00	1.00	1.00	2.00	1.00	2.00	1.00	1.00
8	Drainage Buffer	0.20	0.20	0.17	0.50	0.50	0.25	0.50	1.00	3.00	0.33
9	Geomorphology	0.33	1.00	0.33	0.25	0.50	3.00	1.00	3.00	1.00	1.00
10	Geology	1.00	0.50	1.00	0.50	0.50	0.50	1.00	3.00	1.00	1.00
	Sum	4.10	12.45	10.83	11.75	11.00	19.75	12.00	30.33	19.33	13.33

The physical multi-criteria model includes the following variables: slope, elevation, aspect, land use and land cover, geology, geomorphology, buffer zone of road, drainage buffer, built up area buffer, and forest type. Electronic clinometers were used to measure the slope of the lines on the map. After that, it was cross-checked with the digital elevation model of Cartosat 1. The data source for the topography maps is the Cartosat 1 digital elevation model with a spectral resolution of the panchromatic band of 2.5 m [19]. Table 4 shows the weighted value assigned to each class according to the fire hazards.

Table 4. Weighted values assigned to each class.

Item Number	Variable	Forest Type	Aspect	Slope	Road Buffer	Elevation	Built up Land	Land Use/Land Cover	Drainage Buffer	Geomorphology	Geology	Weight
1	Forest Type	0.24	0.40	0.28	0.43	0.36	0.15	0.33	0.16	0.16	0.08	25.9%
2	Aspect	0.05	0.08	0.18	0.09	0.05	0.20	0.08	0.16	0.05	0.15	11.0%
3	Slope	0.08	0.04	0.09	0.09	0.09	0.15	0.08	0.20	0.16	0.08	10.5%
4	Road Buffer	0.05	0.08	0.09	0.09	0.09	0.10	0.08	0.07	0.21	0.15	10.0%
5	Elevation	0.06	0.16	0.09	0.09	0.09	0.05	0.08	0.07	0.10	0.15	9.4%
6	Built up land	0.08	0.02	0.03	0.04	0.09	0.05	0.04	0.13	0.02	0.15	6.6%
7	Land use/land cover	0.06	0.08	0.09	0.09	0.09	0.10	0.08	0.07	0.05	0.08	7.9%
8	Drainage Buffer	0.05	0.02	0.02	0.04	0.05	0.01	0.04	0.03	0.16	0.03	4.4%
9	Geomorphology	0.08	0.08	0.03	0.02	0.05	0.15	0.08	0.01	0.05	0.08	6.3%
10	Geology	0.24	0.04	0.09	0.04	0.05	0.03	0.08	0.10	0.05	0.08	8.0%

According to the AHP, participation is encouraged for a community decision to be ensured. The theory of AHP is one of hierarchical structure. The hierarchy makes it possible to evaluate the quality of an individual's contribution at lower levels of the hierarchy. The role of the AHP is to help the decision-makers to choose the alternative with the greatest overall impact on the different priorities when they have to choose among many alternatives. Nonetheless, multi-criteria spatial issues such as land suitability are not mentioned in the land analysis. Currently, GIS-based multi-criteria analysis can be used to pick sustainable sites for new development. Many alternate decisions may be present, so the AHP helps to focus on the best of them. A literature survey demonstrates that the use of GIS for spatial problems has increased steadily over the last three decades. It provides validation for researchers for the realization of the value of a GIS-based multiple-criteria decision analysis or MCDA. Nowadays, computer technology is being increasingly applied to various decision-making tasks. As a result, it is important for geographic information systems (GIS) to be incorporated into sustainable development decisions.

3.2.1. Forest Type

Spatial data is the most important since it must be understood using a map. The radiometric maps are of the highest resolution for points far away from major landmasses due to reduced ground checking. The knowledge derived from remote sensing techniques has already been employed in India and abroad. The photo interpretation and georeferencing was performed. The forest types were as depicted in Figure 4, according to the visualization and translation of the data presented. Later on in the process, the layout was adjusted using topology.

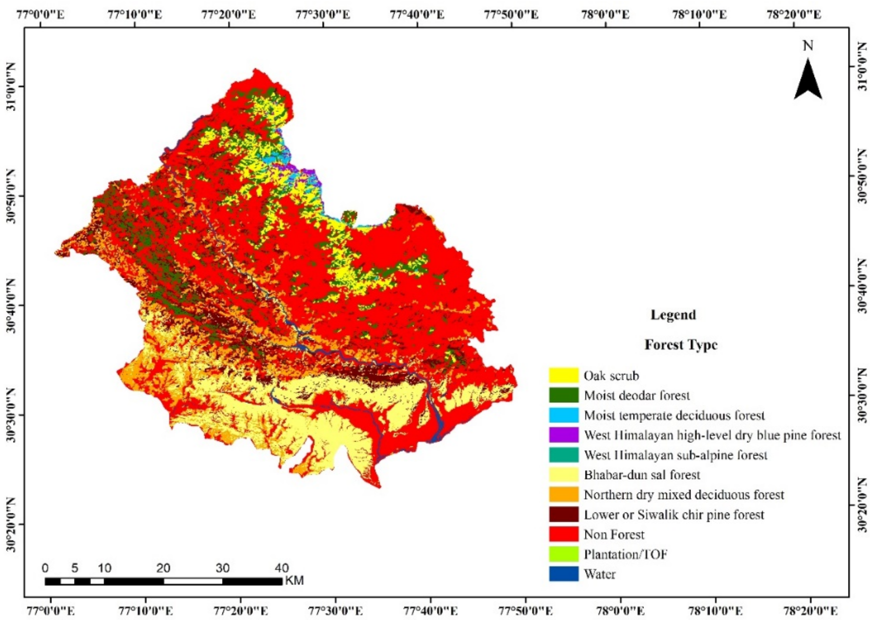

Figure 4. Forest type map.

3.2.2. Aspect Index Map

Due to the greater sunshine in the states to the southwest and southeast being particularly fire-prone, as well as direct sunlight in the south and southeast (Figure 5), those regions were given higher indices. The south is played up to full (Appendix A Table A1). Fires erupt and move faster in the southern regions where sunshine is prevalent.

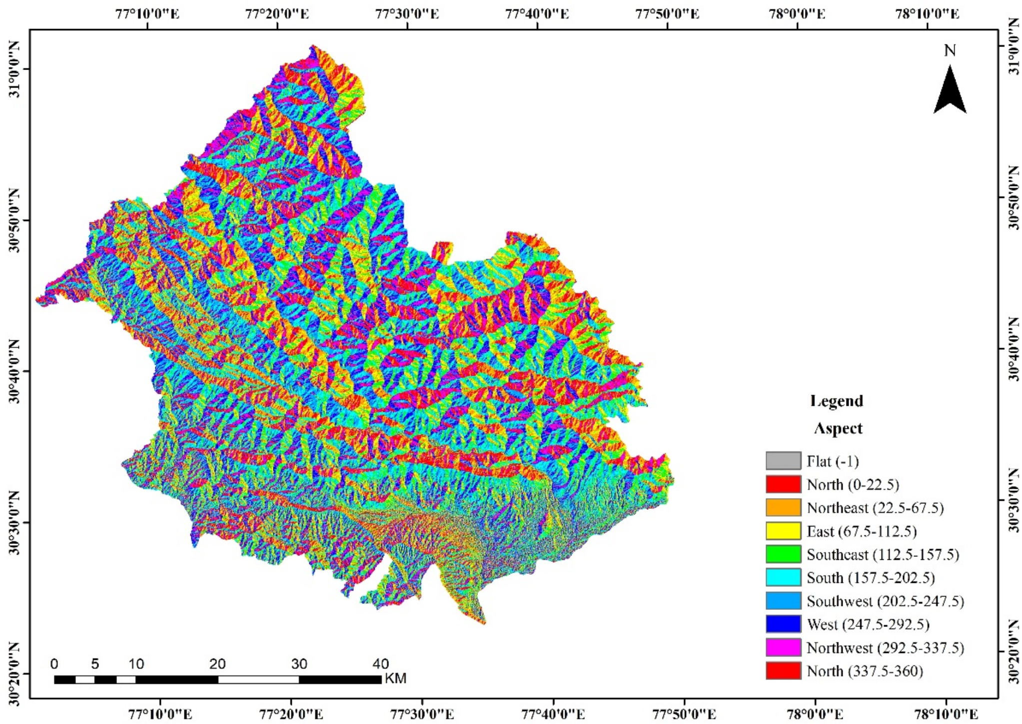

Figure 5. Aspect buffer map.

3.2.3. Slope Index Map

As slopes grow steeper, the rate of fire spread increases due to convective pre-ignition and ignition. Larger slopes had more importance given to them in the mathematical model. Slopes ranging from 50 to 60 degrees and above have a weight of 5 as the upper limit. The gradient of this hose goes up, so there is less water to lose and it is more effective at convective pre-heating (Figure 6).

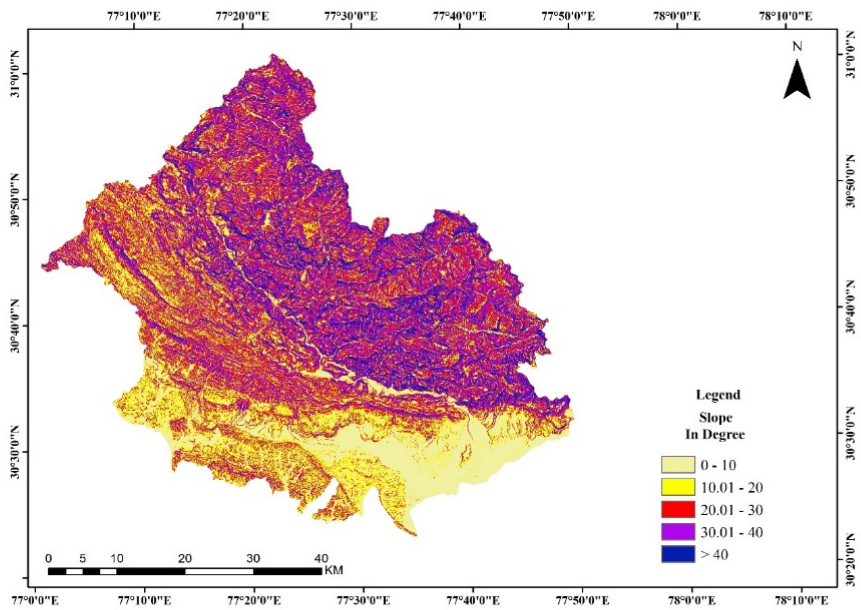

Figure 6. Slope map.

3.2.4. Road Buffer Index Map

Due to the road density, area index values were assigned to the closer areas. It is possible to come close to these hotspots, which can be a fire hazard. The traffic intersections were set up at a distance of 500 m intervals (Figure 7). Approximately 200 miles of white markers were required to delineate the study area in order to cover the full extent of road lines at 1000 m (Appendix A).

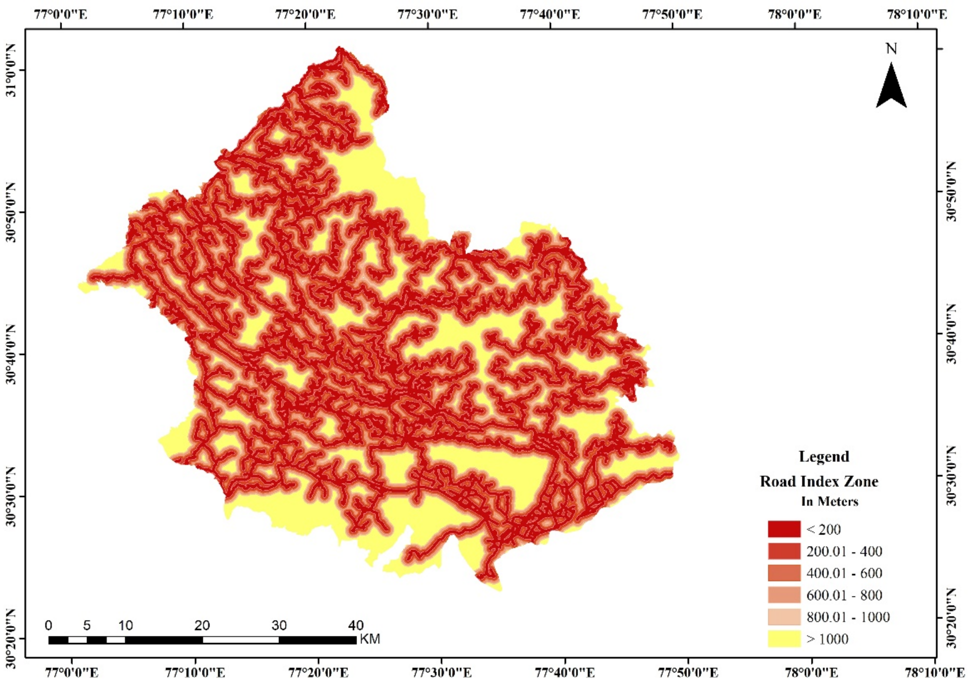

Figure 7. Road buffer map.

3.2.5. Elevation Index Map

There is less risk of fire at higher altitudes due to the effects of climate. When this research was carried out, the possibility of fire was calculated. It was then discovered that in this region, with a maximum elevation of 4700 m and lower elevations averaging 750 m, the chances of fire were greater (Figure 8). Hence, the maximum weight was used as the base for the findings. The last weight for elevations lesser than 1000 m is set to five pounds (Appendix A).

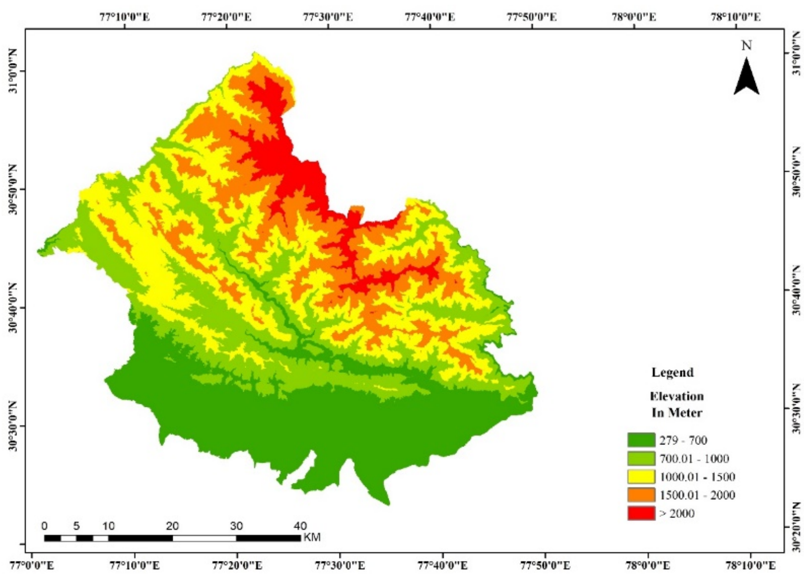

Figure 8. Elevation map.

3.2.6. Built Up Buffer Index Map

Accidental and intentional forest fires were the origin of the wild land fires. A value assignment buffer of 200 m with five rings (Figure 9) has been developed with the index value mention in Appendix A according to their risk of forest fire. The buffer rings surrounding the homes were the most critical in containing a fire; thus, they were given greater weights near the citizens and lesser on the periphery.

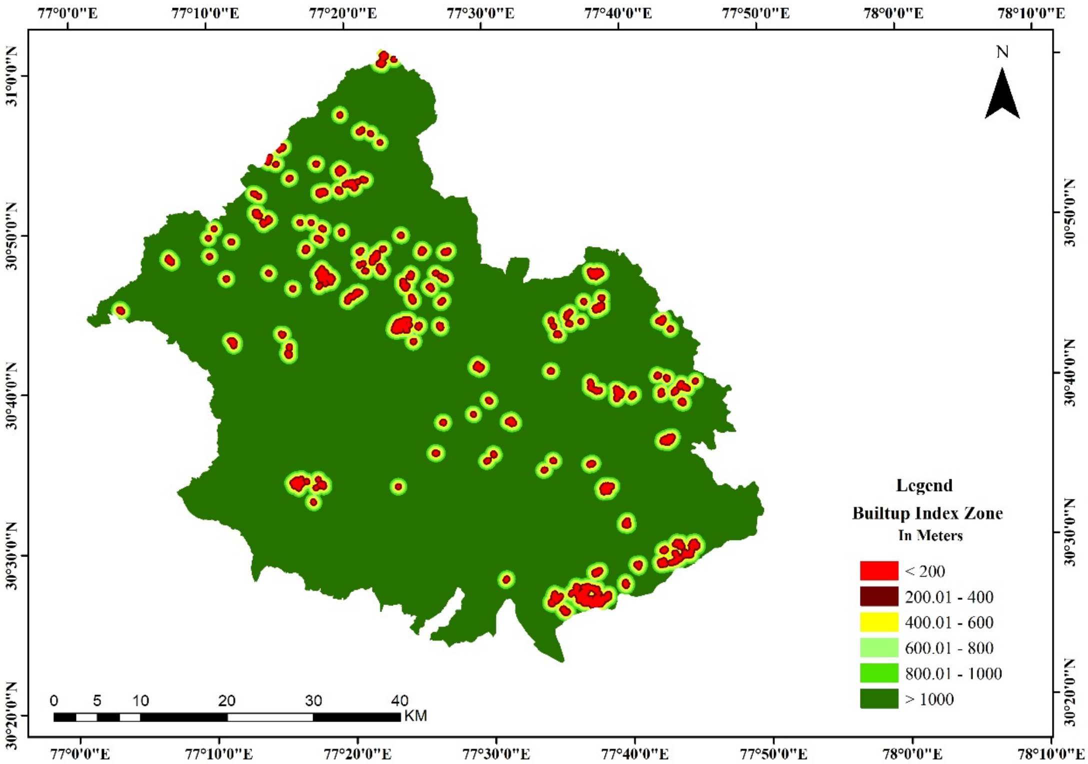

Figure 9. Built up buffer risk index.

3.2.7. Land Use and Land Cover

Initially, the image on Sentinel 2 [32] was resembled at a 10-m spatial resolution. It was attempted to correct the findings, and it was visually compared to the forest management chart on several occasions. The imagery is made up of six spectral bands from the approximate spectrum of different central wavelengths: band 2 (blue (0.490 µm)), band 3 (green (0.560 µm)), band 4 (red (0.665 µm)), band 8 (NIR (0.842 µm)), band 11 and 12 (SWIR (1.610 µm and 2.190 µm)) and land feature are made accordingly as shown in Figure 10. The risk analysis is shown in Table A1 (Appendix A).

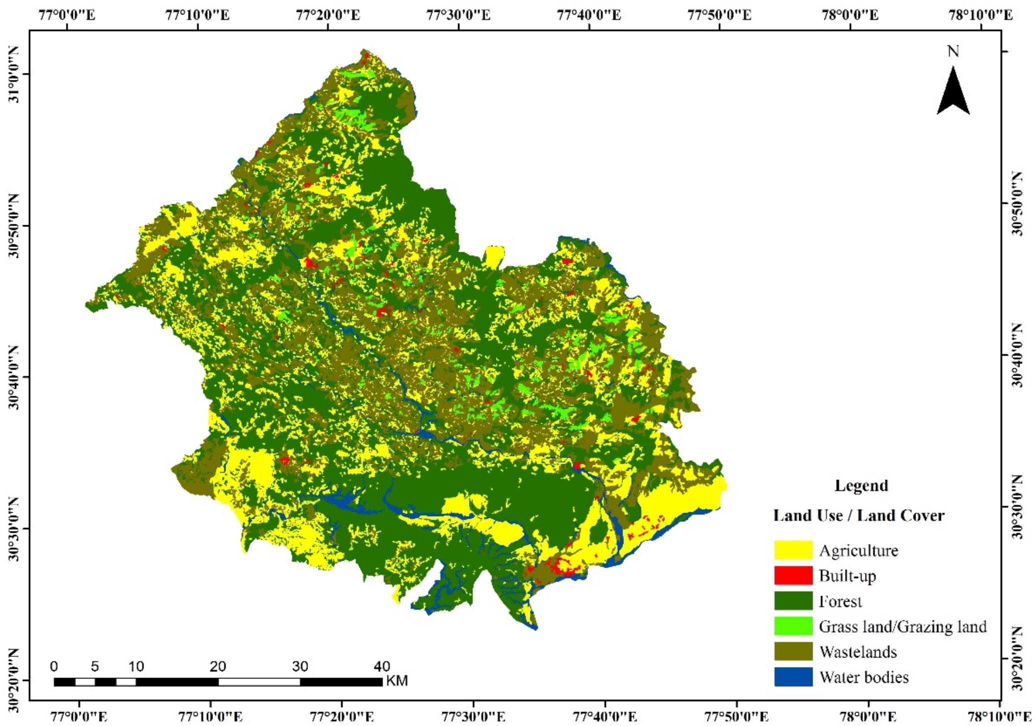

Figure 10. Land use/land cover map.

3.2.8. Drainage Buffer Index Map

The drainage, slope, aspect and elevation are calculated from the Cartosat 1 data of 30-m resolution downloaded from the Bhuvan ISRO [33]. When assigning index values to the buffer class, areas that were further away from the drainage points had higher indexes. It is possible to come close to these hotspots that can be a fire hazard. Drainage was invented at a unit distance of 200 m (Figure 11). Drainage and grout pipes of various sizes have been employed, from 100 m up to 1000 m in order to cover the area (Appendix A).

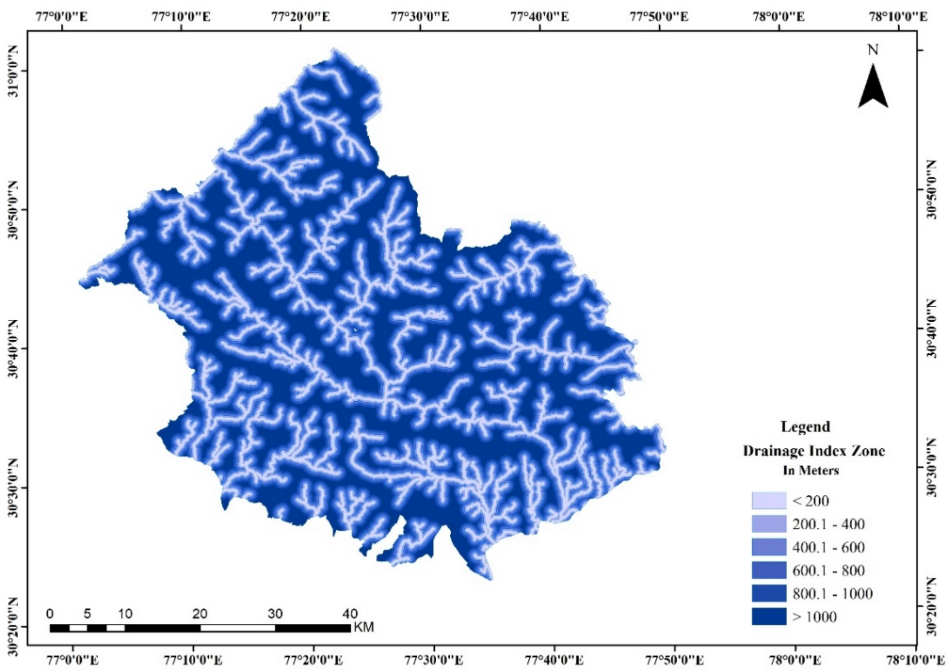

Figure 11. Drainage buffer risk index.

3.2.9. Geomorphology

The area in the Sirmaur district presents a dazzling geographic mosaic of high mountain ranges, hills, and valleys with elevations ranging from 300 m to 3000 m and the source of data from the Bhukosh site of Survey India in 1:50,000 scale (Geological Survey of India [22]). The mountain peaks of denudational hill remain snow-covered all year round. For the Siwalik range of hills, which takes up the southwestern part of the district, the words "low denuded" would be appropriate. Table 5 shows the index value according to the risk of forest fire of the geomorphological features. The Piedmont zone of the area covered with 0.13% is very high and with 88.31% is high (Figure 12).

Table 5. Forest fire risk area distribution with validation points.

Forest Fire Risk	Area (in km^2)	Area (in %)	Index Value	Validation Points	Brightness Range Value
Very high	339.152	12.13	5	5	343.8–327.5
High	350.442	12.53	4	7	327.4–323.9
Moderately high	599.352	21.43	3	11	323.4–306.1
Low risk	924.910	33.07	2	3	303.1–303.6
No risk	583.095	20.85	1	1	301–303

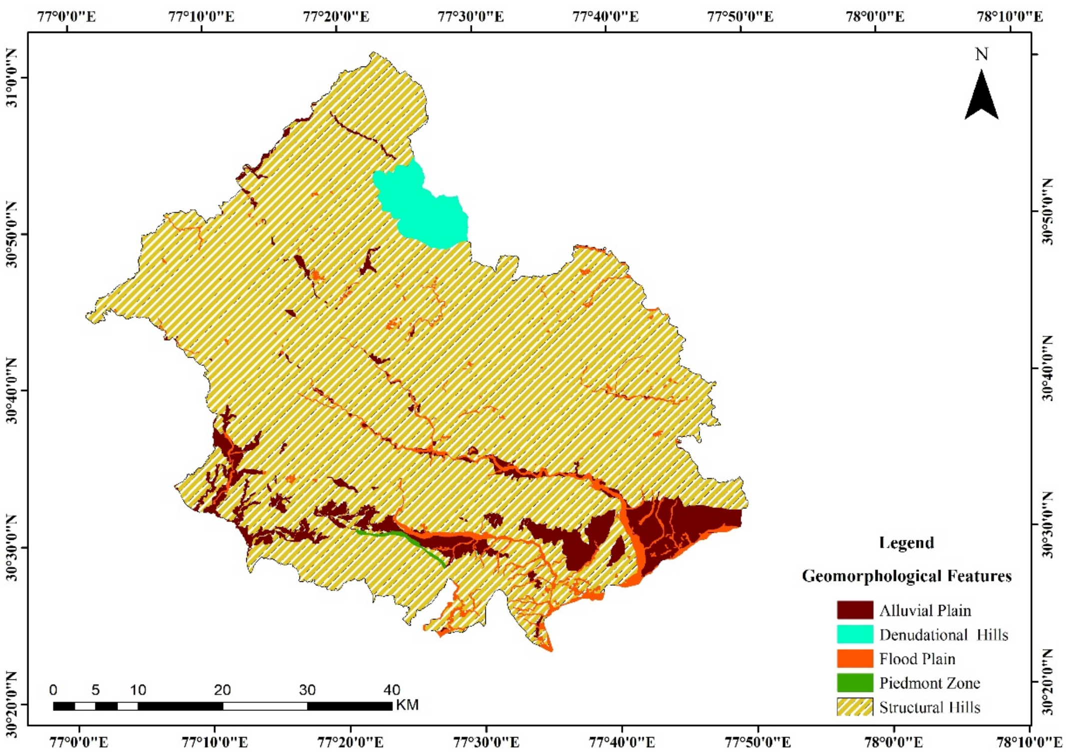

Figure 12. Geomorphology map.

3.2.10. Geology

The Sirmaur district is located in the Shiwalik and lesser Himalayan ranges and the source of data from the Bhukosh site of Survey India is presented on a 1:50,000 scale. The rocks in the region are all over 600 million years old and were deposited in a succession of sandstone, shale, limestone, and schist, with both limestone and schist forming at the same time during that time period. These geological formations are noted for their limestone deposits from the Krol epoch. The southern region is occupied largely by the Oligocene Sea deposit. Himalayan districts span into the southern area of the rivers' main flow to the Indus Brahmaputra. A total of 26.42% of the area is considered to be in the low-risk zone and 0.62% of the area is in the very high-risk zone mentioned in Appendix A and Figure 13.

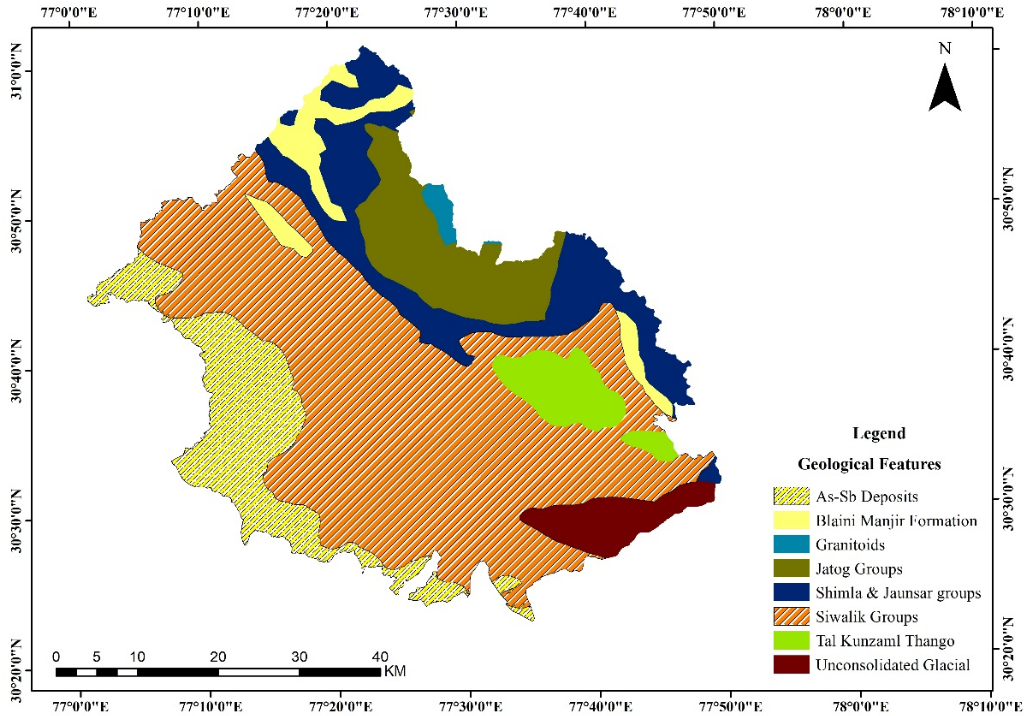

Figure 13. Geology map.

4. Results and Discussion

Appendix A shows the index value according to the risk of forest fire of the geomorphological features (Figure 12). The geomorphology shows that the Piedmont zone of area covering 0.13% is very high and 88.31% is high. Geology features of the Sirmaur district show 26.42% of the area in the low-risk As–sb deposits zone and 0.62% in the very high-risk granites area zone. The most important variable is the forest type, in which pine has the greatest risk of fires as it has an abundance of flammable materials as 18.38% of the forested land in this area is made up of grass and litter. It is highly vulnerable to wildfires. Pine forests, because of the high oil content of turbine resins, are more liable to be damaged by fires than other types of forests. After examination of the nature of the forest, the density of the wood, the physical characteristics of the forest, the animals, and the duration of fires to develop a forest fire risk, the findings are found in Figure 12 and Appendix A, with Table 4 showing the area in percent under the no- to low-risk zone and the total is classified as very high-risk, 14.28% as moderate, and 10.44% as low-risk. The elevation index map shows that 28.40% of the area comes under an elevation ranging from 0 to 700 m and 13.39% of the area is under 700 to 1000 m. Figure 9 and Appendix A show a comparison of the risks and return areas in various elevations, respectively. The slope variables show that 17.02% and 23.60% of all falls are from 0 to 10° and 10 to 20° angles, rather than just 10 to 30° (moderate risk), 30 to 40° (strong risk) and >40° (very high risk). There is a steepness to the gradient that is crucial to the fire's spread, visible in the table and Figures 5 and 10. The aspect index shows the direction of elevation in which the area exhibits about 14.00% in the south, 14.16% in the south-west, 11.97% facing the south-east, 11.53% towards the east, 23.88% under the north-west and west, and 24.47% under the north and the north-east. The risk index area chart data is shown in Figure 9. The closest-to-the-road buffers were given a 200 m limit. Figure 8 depicts the road network and buffer location for the purpose of analysis. Table 4 shows data according to their risk of a forest fire. The buffer rings surrounding the streams had no risk for containing a fire; thus, they were given lower weights near the drainage and higher on the periphery. Figure 7 depicts the results of the drainage and buffer planning calculations for forest fire risk. A value assignment buffer of 200 m with five rings has been developed with the index value shown in Table 4 according to their risk of a forest fire. The buffer rings surrounding the homes were the most critical in containing a fire; thus, they were given greater weights near the citizens and lesser on the periphery. Figure 6 depicts the results of the built-up land and buffer planning calculations. Figure 4 shows the land use and land cover classification risk zone; Figure 12 shows the area covered in the risk zone. A total of 51.86% of the area comes under forest cover, which is under the risk zone, 2.81% of the area is covered under no-risk zone, and 22.52% of the area comes under the low-risk zone.

The final result, according to the flow chart (Figure 3) methodology, shows that 12.13% of the area has a very high-risk of forest fire and 12.53% of the area has a high risk. A total of 53.92% of the area is covered under the low- to no-risk zone (Table 5). Red zones present in the map (Figure 14) are very high-risk-prone areas for forest fires. Hence, the Sirmaur district should be considered accordingly under this forest fire risk management plan by the government, local bodies, and NGOs, respectively. These classes shown in Table 5 could be validated using the data on wildfires for each category of forest fire risk index. Validation points are shown on Figure 15. A false alarm was detected in the north; it was one of 43 (or 2.33%) of the locations in the group, with an accuracy of 97.67%. MODIS data is downloaded from the Earthdata Firms site, from their archival data. By downloading MODIS data of 2019, the brightness value was converted into a shaped file. About 96% of the data shows accurate findings in the calculation of the forest fire risk zone. Table 5 shows that most of the points are shown in the moderately high- to very high-risk zone. Figure 15 shows the validation points on the forest fire risk zone and Figure 16 shows the brightness value range of the MODIS data. The three MODIS test site validation exercises completed in 2007 all had a final accuracy of 93.06% in the identification of forest fires. Additionally, the 2007–2008–2009 final organizational assessment in Thailand revealed a 95.64% level of confidence. In the India study of the Uttarakhand state through MODIS, the brightness value gives a 97% accuracy of wildfire zone assessment.

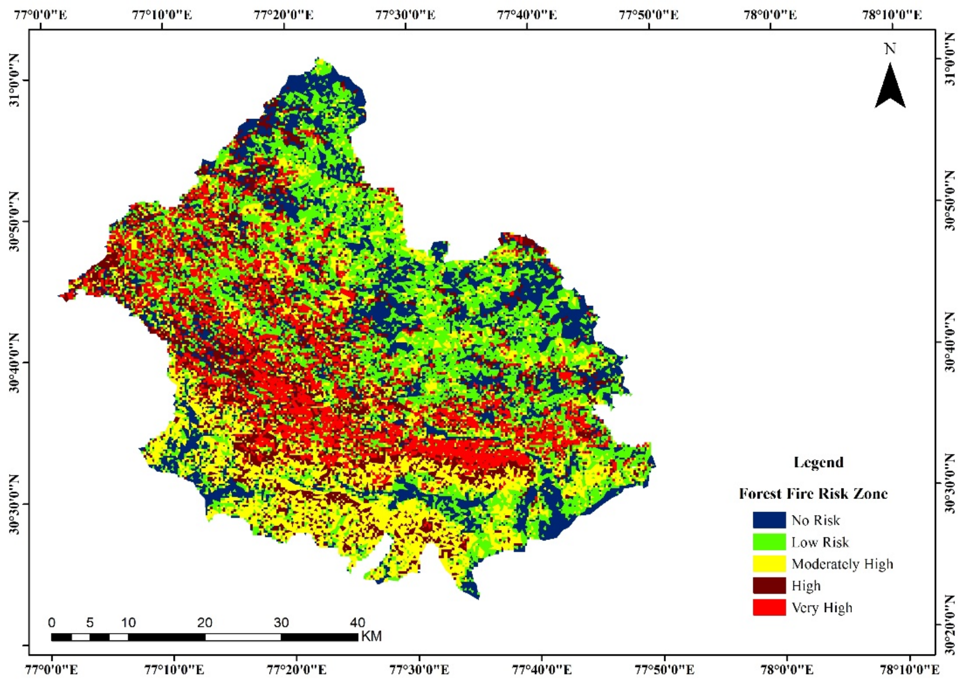

Figure 14. Forest fire risk map.

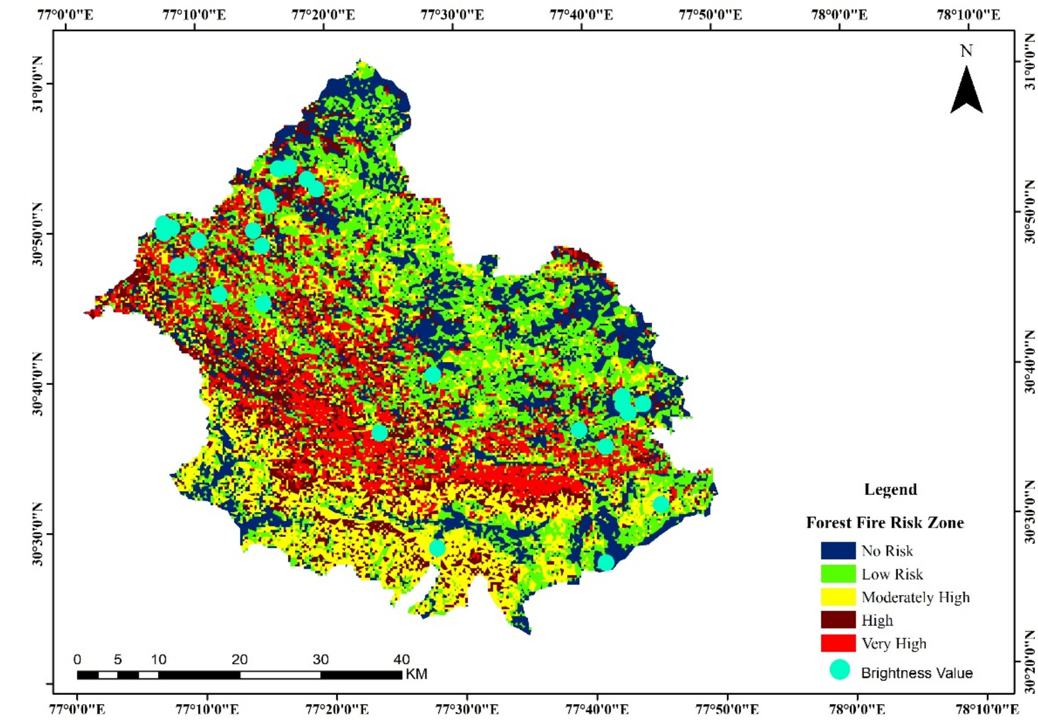

Figure 15. Forest fire validation hotspots in forest fire risk zone map.

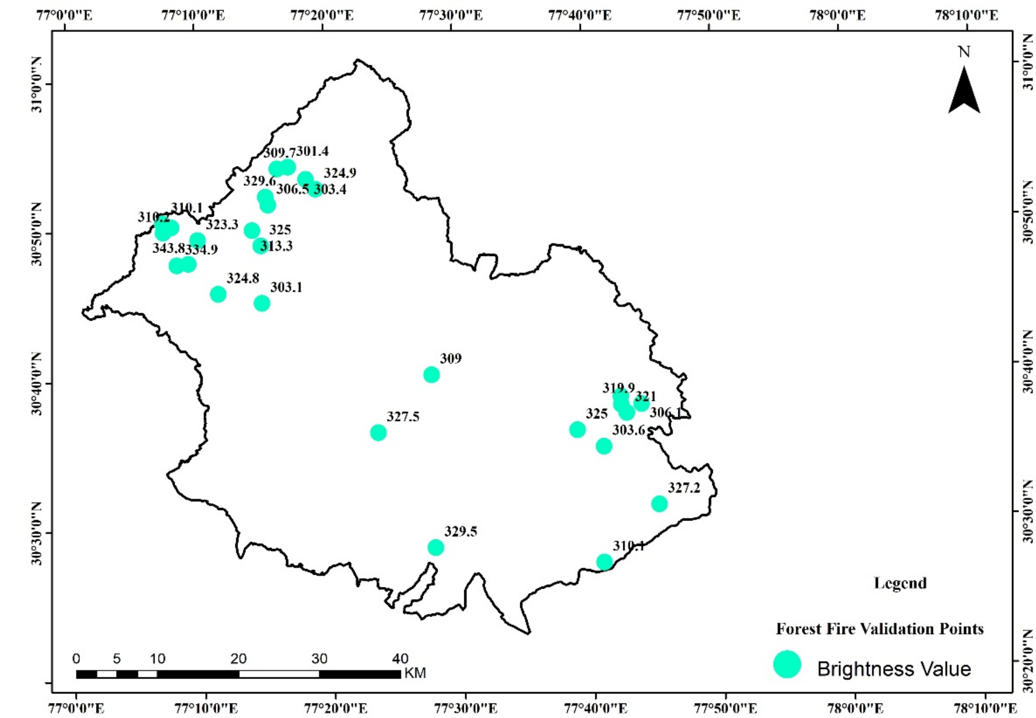

Figure 16. Modis point with its brightness values.

5. Conclusions

From the aforementioned result and discussion, we can conclude that geospatial technology can be used to quantify biomass, loss of forest, and loss of biodiversity due to forest fires in the future. Using high-resolution ground-satellite data, the forest fire risk-assessment will assist fire fighters serving in the location of administrative bodies such as local municipalities. We will measure the carrying capacity of herby habitat and use geospatial modeling to measure where the migratory animals reside in order to see whether there are any issues with these corridors being adequate. Such a model will work in the initial stages and will subsequently have to be devised to apply, for example, biomass density or degradation ratios, to the total human activity and biophysical parameters. Another kind of model could be created, allowing for both the total biomass loss and forest area change to be calculated including human-caused fire danger that exists in the region. Due to this, we have carried out research on the effect of climate changes on the current population, and socioeconomic location on people's vulnerability. Census data will be used to produce a socio-economic analysis of the area, as well as an analysis of fire hazards through the computation of population density, agricultural laborers' age demographics, and the number of children in the zero- to six-year-old age group. Every year in India, global warming has caused a rise in forest fires. There is an expected correlation between increased carbon emissions and boosts in burnt area and the number of fires. It can be shown that 12.13% of the area is under a very high risk of forest fires and 12.53% of the area is under a high risk. A total of 53.92% of the area is considered to be in the low- to no-risk zone. Validation of the final result by the MODIS brightness value shows the calculation of the forest fire risk zone and a 96% accuracy rate, which can be further utilized in these zones by not being affected from forest fire.

It has been shown that policies and activities aimed at empowering community participation are safer and produce significantly reduced risk than those previous wildfire preparations and executions. Research increasingly suggests that scientific research and planning also help communities in the West to deal with the danger of wildfires. In addition to the wildfire problems increasing, as more citizens migrate to riskier locations, it is important to address these inadequacies between the best practice and the importance of integrating wildfires in community decision-making. Thus, this research supports the notion that community development and advanced preparation strategies will help to deal with wildfire incidents. An adapted geospatial model was employed in the development of the forest fire hazard in the Sirmaur district of the Himalayan provinces of India. The greatest risk is seen in areas where the fire threat is moderate to high, and we need to be expeditious to prevent it from spiraling of control.

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Appendix A

Table A1. Fire hazard classes.

Variable	Classes	Intensity of Importance	Fire Hazards Classes	Area in km^2	Area in %
Land Use/Land cover	Agriculture	5	High	605.85	21.42
	Built-up Land	2	Low Risk	12.11	0.43
	Forest	7	Very High	1466.94	51.86
	Grass Land/Grazing Land	4	Moderately High	39.33	1.39
	Waste Land	3	Low Risk	624.68	22.09
	Water Bodies	1	No Risk	79.49	2.81
Geology	As–Sb Deposits	2	Low Risk	372.961	13.17
	BlainiManjir formation	1	No Risk	123.61	4.37
	Granitoids	7	Very High	17.6021	0.62
	Jatog Groups	4	Moderately High	257.035	9.08
	Shimla and Jaunsar groups	3	Moderately High	375.189	13.25
	Siwalik Groups	6	High	1461	51.60
	Tal Kunzaml Thango	5	High	120.419	4.25
	Unconsolidated Glacial	1	No Risk	103.671	3.66
Geomorphology	Alluvial Plain	2	Low Risk	187.052	6.63
	Denudational Hills	3	Low Risk	67.0437	2.38
	Flood Plain	1	No Risk	72.0214	2.55
	Piedment Zone	7	Very High	3.73777	0.13
	Structural Hills	5	Moderately High	2492.39	88.31
Forest Type	Plantation/TOF	4	Moderately High	2.71	0.10
	Lower or Siwalik chir pine forest	9	Very High	518.39	18.38
	Non-Forest	1	No Risk	1386.66	49.16
	Moist deodar forest	2	Low Risk	178.89	6.34
	Oak scrub	3	Low Risk	103.48	3.67
	Northern dry mixed deciduous forest	5	High	203.46	7.21
	Water	1	No Risk	11.06	0.39
	Moist temperate deciduous forest	2	Low Risk	11.89	0.42
	West Himalayan sub-alpine forest	3	Low Risk	0.39	0.01
	West Himalayan high-level dry blue pine forest	7	Very High	6.73	0.24
	Bhabar-dun sal forest	4	Moderately High	397.12	14.08
Drainage Buffer	<200 m	1	No Risk	483.243	17.09
	400 m	2	Low Risk	444.229	15.71
	600 m	3	Moderately High	400.589	14.16
	800 m	4	Moderately High	354.951	12.55
	1000 m	5	High	311.513	11.01
	>1000 m	7	Very High	833.783	29.48
Road Buffer	<200 m	7	Very High	907.499	32.09
	400 m	5	High	582.693	20.60
	600 m	3	Moderate	405.018	147.61
	800 m	3	Moderately High	274.392	9.70
	1000 m	1	Low Risk	185.152	6.55
	>1000 m	1	No Risk	473.344	16.74
Built-Up Buffer	<200 m	7	Very High	70.3744	2.49
	400 m	5	High	78.2607	2.77
	600 m	4	Moderately High	96.1169	3.40
	800 m	3	Moderately High	107.646	3.81
	1000 m	2	Low Risk	113.995	4.03
	>1000 m	1	No Risk	2362.05	83.51
Slope	<10	2	Low Risk	506.46	17.02
	10.1–20	3	Moderately High	702.186	23.60
	20.1–30	4	Moderately High	960.044	32.27
	30.1–40	5	High	646.021	21.71
	40>	7	Very High	160.628	5.40

Table A1. *Cont.*

Variable	Classes	Intensity of Importance	Fire Hazards Classes	Area in km^2	Area in %
Aspects	North (0–22.5); North (337.5–360); Northeast (22.5–67.5)	1	No Risk	727.494	24.47
	East (67.5–112.5)	3	Moderately High	342.679	11.53
	Southeast (112.5–157.5)	4	Moderately High	355.775	11.97
	South (157.5–202.5)	7	Very High	416.389	14.00
	Southwest (202.5–247.5)	5	High	420.902	14.16
	West (247.5–292.5); Northwest (292.5–337.5)	2	Low Risk	710.092	23.88
Elevation	0–700	6	Very High	844.955	28.40
	700.1–1000	4	High	398.448	13.39
	1000.1–1500	3	Moderately High	927.634	31.18
	1500.1–2000	2	Low Risk	570.535	19.18
	2000.1–3536	1	No Risk	233.768	7.86

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