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Geospatial Susceptibility Assessment of Landslide in Battagram, Khyber Pakhtunkhwa, Pakistan

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Abstract

A landslide is a natural disaster that can cause significant global damage and human casualties. As a flood-prone area, the Battagram district of Khyber Pakhtunkhwa, Pakistan, has seen an increase in urbanization, making it challenging to choose an appropriate location for seismic activity. This study seeks to assess the susceptibility to landslide risk through the application such as seismic activity and flooding. This analysis employs Geographic Information System (GIS) and Remote Sensing techniques. The research utilized several data sets, encompassing geological data processed with the ArcGIS 10.8 software, Shuttle Radar Topography Mission (SRTM) data, Landsat thermal images from missions 5 and 8, thematic data, meteorological data, and a seismic catalogue. SAR photos are used to map Sentinel-1A in Google Earth Engine (GEE) to determine the extent of floods. The landslide inventory was separated into training and validation sets for this investigation. Significant contributing factors, including slope aspect, elevation, land cover and use during earthquakes, normalized difference vegetation index (NDVI), road distance, fault distance, rainfall, and geology, are taken into consideration when assessing landslip susceptibility. To establish the spatial correlation between landslides and these parameters, the frequency ratio model and weighted sum analysis were utilized. The WSM analysis indicates that 1.74% of the region is classified as having very low susceptibility, with the remaining areas being classified as low (14.26%), moderate (36.01%), high (2.57%), and very high (5.41%). 44.67% of the region is classified as having very high susceptibility by the FR model, with high (40.94%), moderate (11.61%), low (1.96%), and very low (0.79%) following. The FR model demonstrated reliability in risk assessment, with an accuracy of 85.7% against known landslide events. These findings support the use of GIS-based statistical modeling in urban planning and hazard mitigation by demonstrating how well it can identify high-risk areas. For increased accuracy and scalability, future developments should concentrate on adding more localized data.

Keywords: Landslide susceptibility, weighted sum analysis, GIS, frequency ratio, remote sensing, Google earth engine

Introduction

One of the most common geological disasters, landslides are said to cause significant property loss and fatalities all over the world (Linkha, 2024). According to CRED, the landslides segment accounts for 17% of fatalities in all natural disasters worldwide (Alimonti & Mariani, 2024). Climate models project that the intensity of monsoon rainfall in southern Asia will rise in the future owed to climate change. This could feasibly enhance the winter rebound and cause more seismic events. Rainfall and flash floods can cause rockfalls and debris flow, and environmental factors like rock deterioration over time can also cause landslides. Similarly, natural disasters like earthquakes can cause a slope to become weak due to construction along its banks (Shabbir et al., 2023). Every year, during the monsoon season, landslides and floods in the Himalayan region reason fatalities and damage to property (Sana et al., 2024). The rough terrain, active seismicity, monsoon rains, and human activity on uneven slopes make northern Pakistan one of the most landslide-prone areas (Hussain et al., 2023). The deadliest and worst flood disaster in the past ten years occurred in Pakistan in 2022. Pakistan encountered a monsoon climate and extremely hot weather in mid-June 2022 (NASA, 2022), and as a result, at least two-thirds of the nation experienced the most precipitation in almost 30 years. Following the flood in 2022, some of the highland's volcanic mountains are still active. Additionally, fissures and cracks truncate the main rock types in this highland.

Many landslides have occurred in the area as a result of earthquakes destroying them (Sana et al., 2024). In order to forecast future landslides, it is vital to identify the zones that are vulnerable. By using scientific analysis to identify and forecast landslide-prone areas, appropriate preventative measures can reduce landslide damage (Jena et al., 2021). Therefore, the two main causes of landslides in the region are earthquakes and rainfall (Vasil Levski & Dolchinkov, 2024). Using the data that is currently available and geospatial techniques, this study attempts to create landslide susceptibility mapping over the Battagram district that is caused by earthquake and flood activity. As a result, the study evaluates the primary causes of landslides in the Battagram district as well as the effects of land cover change over the previous 16 years on landslides in the study area. The study area has a primarily monsoonal climate, and landslides are typically caused by heavy rainfall. The risk of landslides is influenced by human activity in addition to climate and geotectonic factors.

Disasters appear on the news headlines almost every day, according to (Dietrich et al., 2024). Most of them take place in distant areas and pass by swiftly. In light of (Lu et al., 2024), there have been eighteen fatal earthquakes worldwide between 1989 and 2015, which have caused extensive landslides across a wide area. Examples of large-magnitude earthquakes in the past ten years, according to (Saima Akbar, 2024), include the 2005 earthquake in Kashmir caused thousands of landslides in northern Pakistan, resulting in a thousand deaths. Some of the most notable landslide disasters that have occurred in northern Pakistan include the 2005 Kashmir earthquake, which caused thousands of landslides over an area of more than 7,500 km³ in Kashmir and its surroundings, killing 87,350 people. (Bali et al., 2025) stated that three major mountain ranges, the Himalayas, Karakoram, and the Hindu Kush, are the dominant feature of the northern regions of Pakistan. These mountain ranges comprise the world's steepest peaks with a 45° slope (Ahmed et al., 2019). Flash floods and landslides occurred on October 3-4 in Khyber Pakhtunkhwa Province (Northern Pakistan) due to heavy rain, leading to casualties. Across Charsadda and Lower Kohistan Districts, the Provincial Disaster Management Authority (PDMA) reports that two people have died and six have been injured. Rescue operations are taking place in Charsadda, as a few families have been relocated to relief camps. On October 6-7, there is a forecast of dry conditions over Khyber Pakhtunkhwa Province. Pakistan's history has shown numerous flood events starting from its creation, such as the floods of 1950, 1992, 1998, and 2010 (Saima Akbar, 2024)

Several revisions in this area focused on geospatial and GIS-based methods to analyze numerous spatial data types, the evolution of geostatistical models, and the predictable points of risk and vulnerability for a given area (Rehman et al., 2022) A susceptibility map that identifies areas that are likely to experience landslides in the future (Tyagi et al., 2023). An essential first step in hazard and risk assessment, landslide susceptibility assessment is a widespread practice worldwide, primarily utilized for landslide mitigation strategies. Landslide susceptibility assessment requires the use of remote sensing and Geospatial-derived outcomes, such as landslide inventory and contributing and triggering factors. Landslide susceptibility assessment methods can be divided into two categories: quantitative methods, such as statistical models, heuristics (multi-criteria analysis), and physical-based models, and qualitative methods, such as knowledge-based and geomorphological mapping (Batar & Watanabe, 2021). According to (Dou et al., 2019) usually, rainfall or earthquakes cause landslides, though sometimes an earthquake causes a rainfall event, or vice versa. A digital elevation model (DEM) is used in large-scale physically based landslide susceptibility processes to describe the terrain constraints that fundamentally define the local elevation, slope, hydrologic, and further geomorphic processes (Schlögel et al., 2018). Land use and land cover variation can modify the geological circumstances and distress the manifestation of the landslides (Chen et al., 2019). Remote sensing data, land-based data, and numerous other data sources are used to extract the spatial information related to the aforementioned factors. Landslide susceptibility maps demonstrate the comparative possibility of future landslides based exclusively on the vital assets of a background or site (Rahim et al., 2018). Landslide susceptibility mapping (LSM) is regarded as a prime phase in the execution of instant disaster management planning and risk mitigation events (Camilo et al., 2017).

The occurrence of landslides is primarily ascribed to the combined effect of various factors, and it is never easy for researchers to assess the extent of these factors' influence (Abdı et al., 2021). Unusually, in recent years, firm changes in global climatic conditions have controlled to extreme weather events that increase the propensity of landslides (Zou et al., 2021). Even though landslides have been studied extensively, little is known about how floods and seismic activity interact to cause landslides. This is especially true in Northern Pakistan's Battagramdistrict, which is particularly vulnerable because of its complicated topography, active tectonics, and unpredictable climate. Current models frequently ignore the compounding effects of multiple hazards and only take into account landslide triggers in isolation. Additionally, little research has been done to incorporate changes in land cover over the past few decades into susceptibility assessments. By using the Frequency Ratio (FR) model and Geospatial techniques to generate an extensive Landslide Susceptibility Map (LSM), this study seeks to close these gaps.

Study Area

The geographical location of District Battagram is latitude 34.79147 and longitude 73.121641, which covers an area of 350,172 acres. The district usually has dense forests and mountains with peaks higher than 4000 meters. It is bordered to the north by Kohistan District, to the east by Mansehra District, to the south by the Kala Dhaka Tribal Area, and to the west by Shangla District.

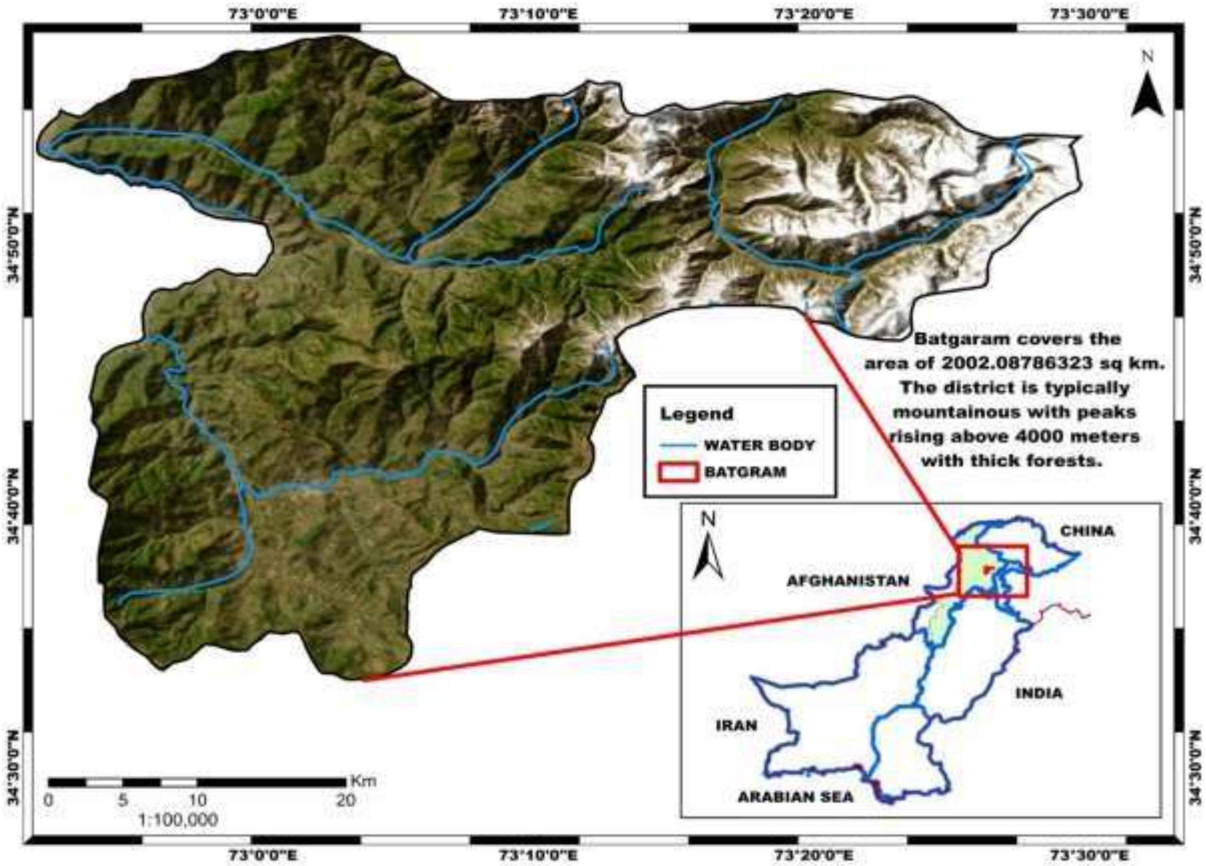


Figure 1: *Study Area Map*

The corporate headquarters is located in Battagram town, which is about 75 kilometers from Mansehra along the Silk Highway. Battagram and Allai are the two tehsils that make up the district. It features a number of stunning valleys. The Nindhyarkhawar and Allai Khawar are the two main streams, which are referred to as Khawar in the local dialect. Beginning in the "Hill" mountains, the Nindhyar Khawar flows over the main village before joining the Indus River at Thakot in the east. The Chaur Mountains are the source of the other large stream, Allai Khawar, which empties into the Indus River at Kund in the east. The maximum temperature on an average day for each month in Battagram is displayed by the "mean daily maximum" (solid red line). Similarly, the average minimum temperature is displayed by the "mean daily minimum" (solid blue line). The average of each month's hottest day and coldest night over the previous 30 years is displayed by hot days and cold nights (dashed red and blue lines).

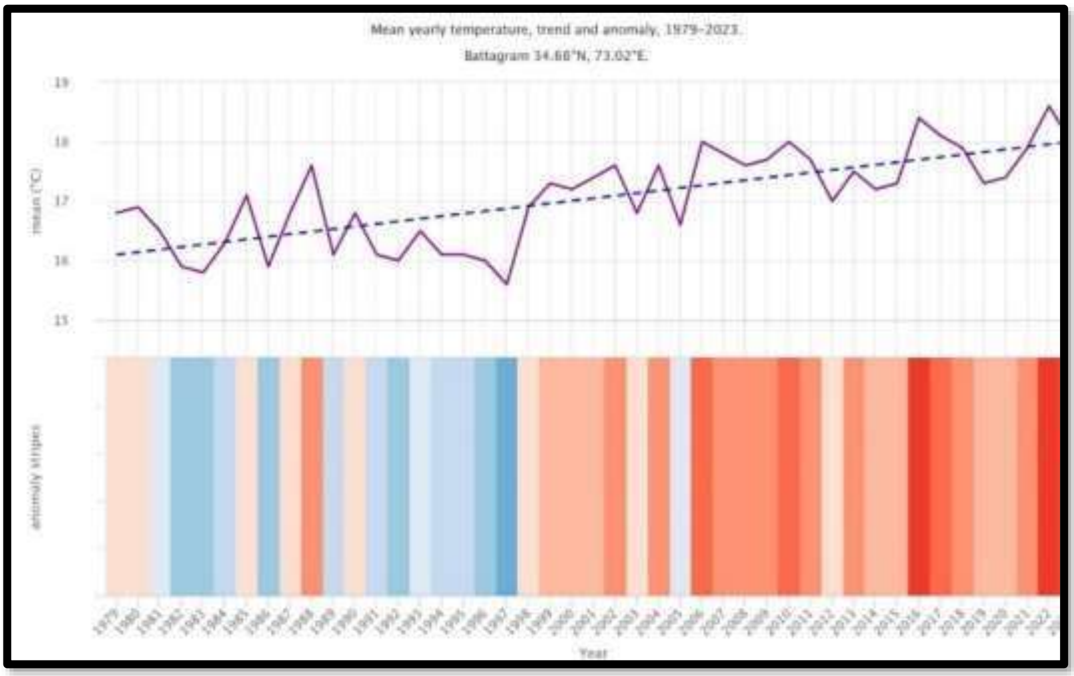


Figure 2: *Graphical representation of temperature (1979_2023)*

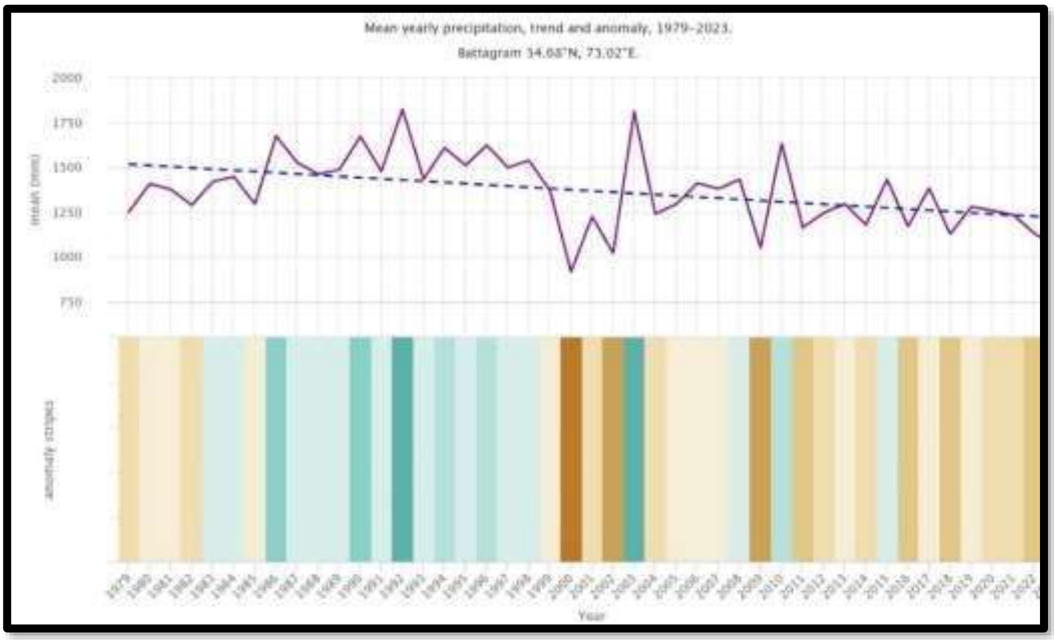


Figure 3: *Graphical representation of precipitation (1979-2023)*

The graph displays an approximation of the mean total precipitation for the greater area of Battagram. The dashed blue line is the linear climate change inclination. In the lower part, the graph demonstrates the so-called precipitation stripes. Respectively colored stripe represents the total precipitation of a year - green for wetter and brown for drier years. There is an entire 369 km road network in the valleys. The Karakoram Highway or the Silk Highway, arrives in the district at Sharkool, Mansehra, and leaves it at Thakot. The major roads in the district are Battagram-shamlai, Batagram-Oghi, Battagram-paimal Sharif and Chattar-Kuzabanda road.

It's interesting to note that geologists have long recognized a connection between seismic activity and rainfall rates. For instance, the yearly rainfall cycle of the summer monsoon season in the Himalayas affects the frequency of earthquakes (Mir et al., 2024). According to investigation, only 16% of Himalayan earthquakes happen throughout the monsoon season, with 48% occurring during the drier pre-monsoon months of March, April, and May. (Munir et al., 2021) stated that Pakistan continues to experience flooding and landslides due to the country's heavy rainfall, which also causes an increasing amount of damage and fatalities. In Khyber Pakhtunkhwa Province, flash floods and landslides caused at least 13 fatalities and 27 injuries between August 31 and September 1. According to the NDMA report, there have been 2,245 damaged homes, 189 fatalities, and 128 injuries since the start of the monsoon season. According to (Bahram & R. Paradise, 2020), nearly every element of the people's socioeconomic lives as well as the district's physical infrastructure was impacted by the earthquake. In the last ten years, 1389 earthquakes of magnitude four or higher have occurred within 300 kilometers (186 miles) of Battagram, Khyber Pakhtunkhwa. This translates to an average of 11 earthquakes per month, or 138 earthquakes annually. Near Battagram, an earthquake occurs approximately every two days on average. Battagram has experienced 19 earthquakes with magnitudes greater than 2 and up to 5.0 since 2022.

Materials and Methods

Data acquisition

Multi-source data has been used for landslide susceptibility monitoring in Battagram. This study's landslide susceptibility map was created using ten factors. The factors were entirely chosen based on their availability and efficacy. For LULC variation analysis, multi-temporal cloud-free Landsat 5 and 8 Thematic Mapper (TM) data of August 2010, 2015, and 2022 (Table 1) were obtained from USGS Earth Explorer (EarthExplorer (usgs.gov). The extraction of topographic information, including elevation, slope, aspect, hill shade hydrology, was obtained from the Shuttle Radar Topography Mission-Digital Elevation Model (SRTM-DEM) with 30 m resolution. The geological data were obtained from toposheets from the Geological Survey of Pakistan (GSP) and satellite data from the U.S. Army KMZ. The monthly rainfall data from 2010 to 2022 were collected from the Data Access Viewer-NASA POWER (https://power.larc.nasa.gov/data-access-viewer/). The historical landslide data have been collected from the NASA Landslide Viewer.

Table 1: Evidence about satellite data

Satellite	Dates of Images	Resolution	Reference system/Path/Row
Landsat 5	18/06/2010	30m	WRS/150/36
Landsat 8	15/06/2015	30m	WRS/150/36
Landsat 9	20/06/2022	30m	WRS/151/40

Data processing

The data was then imported, processed, and analysed in ArcGIS software to create various maps of the factors impacting the incidence and spreading of groundwater in the watershed. Multiple factors have been considered to regulate landslide-susceptible zones.

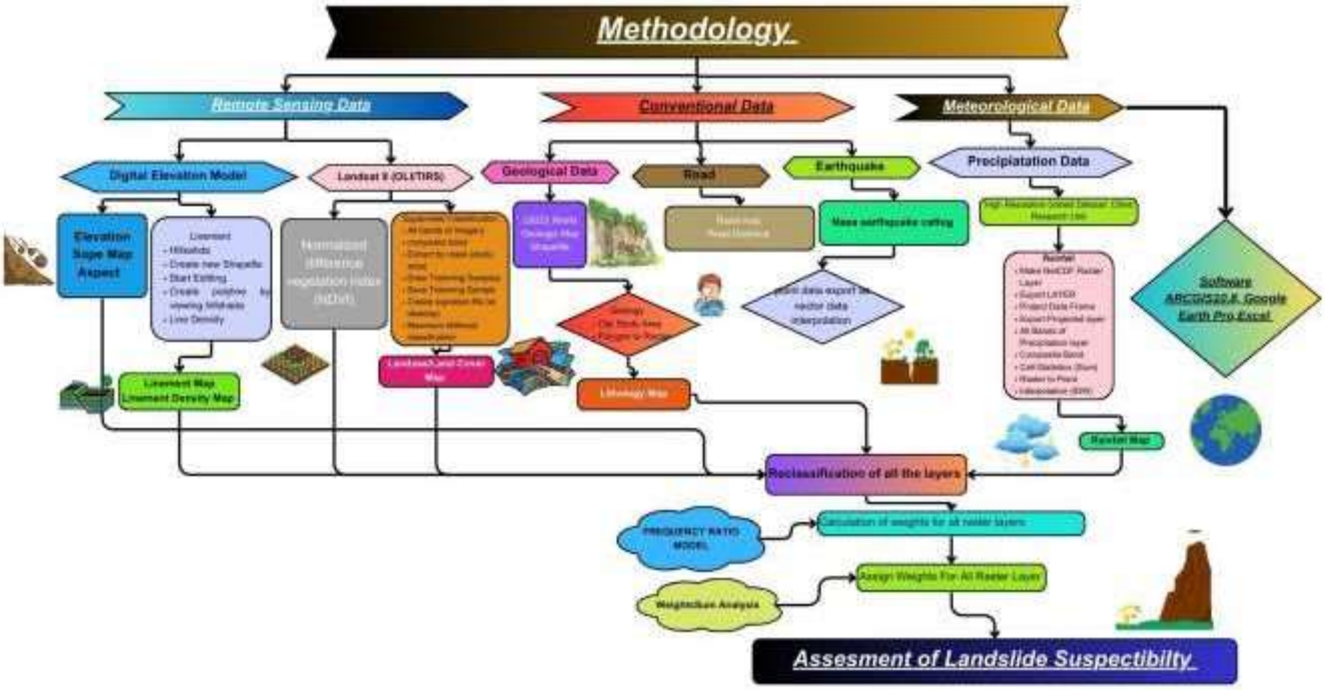


Figure 4: *The methodological framework*

Data analysis

Flood extent

Sentinel-1 SAR data were principally utilised in this study to map the flood inundation in the Battgaram District in 2022. A population dataset and land use/cover (LULC) have been used in the evaluation of flood damage. The Global Human Settlement Layers (GHSLs) and Gridded Population of the World (GPW v4) datasets were analyzed for population and density, respectively, in order to assess the effects of flooding. Using the monthly precipitation data from Terra Climate, the rainfall pattern and anomaly during the 2022 flood event have been recognized. The crop land and population density had been calculated using ArcGIS software.

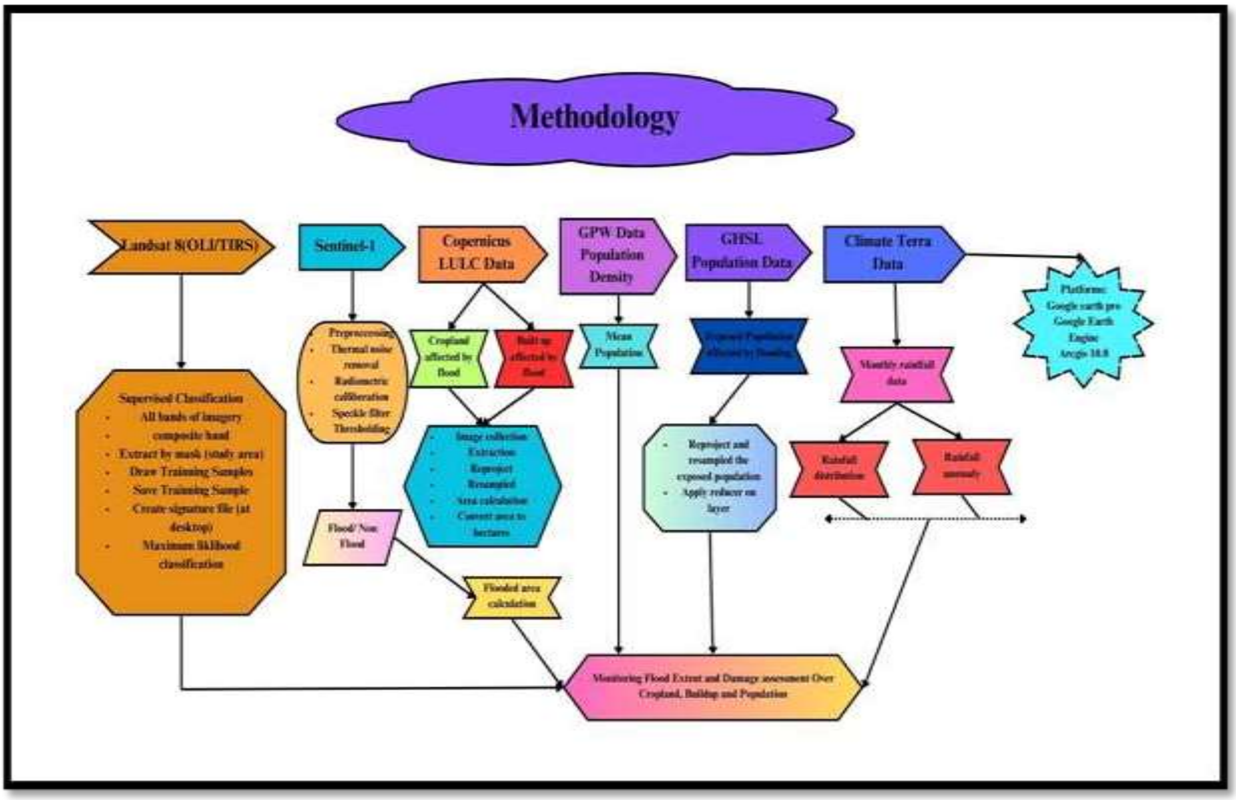


Figure 5: *The methodological framework for assessment of flood extent*

Landslide inventory map

A landslide inventory map, which illustrates the positions and contours of landslides, expresses the knowledge of landslides in a specific area. A data set that may include one or more incidents is called a landslide inventory. Forecasting the likelihood of landslides in a study area primarily relies on historical and present landslide inventory data. Sentinel-1 and Google Earth pictures were used to generate the landslide inventory map for this study.

Common factors controlling landslides

The primary determinants of seismic landslides include geological, seismic, and topographic factors. Ten common landslide-causative characteristics that are used to analyze landslides triggered by earthquakes and rainfall were examined in this study. The topography, geology, tectonic features, weather, land cover, and human activity all have a significant influence on the intensity and spatial distribution of landslides. It is crucial to assess how these causal elements affect the landslide's spatial distribution for the purpose to comprehend how they work and create a map of landslide vulnerability. The primary factor influencing the location and severity of landslides is the slope of the terrain (Jin et al., 2024).

Slope is an important causal component in landslide inquiry, according to (Mir et al., 2024), since it causes loose sediment material to migrate downslope. The current research area's slope was calculated using a DEM with a spatial resolution of 12.5 m. Next, using ArcGIS 10.8, the computed slope was divided into five classes, as Figure 8 illustrates. The research area's terrain aspect was calculated using a 3*3 moving window in ArcGIS 10.8 based on the DEM. It is usually recognized that lithological structures have a substantial influence on the physical potentials of both surface and subsurface material, counting their strength and permeability, which in turn influences the probability of landslides (Khan et al., 2019). The distribution of landslides is greatly affected by land cover; generally, landslides are less common in forested areas than in barren ones. Strong root systems of the vegetation give the mechanical and hydrological forces that frequently stabilize the slopes. The area's land cover was categorized as consisting of permanent snow, glaciers, irrigated agricultural land, barren ground, woodland and shrub land, and water bodies. The prevalence and intensity of co-seismic landslides are primarily determined by the spatial spreading and character of fault lines (Duan et al., 2023). The region's fault lines were taken from the geological map of the region. Using ArcGIS 10.8 software, the distance to the fault was split into five regions spaced 50 meters apart (Fig. 6e). Building roads and railroads as part of a communication network in hilly areas frequently causes instability in slopes and ultimately landslides (Dahiya et al., 2025). The road network was derived from the obtained Sentinel 1 pictures and then verified in the field to evaluate the influence of the road network on the landslides in the research area. Then, using ArcGIS software, distance from the road was measured at 50-meter intervals. Streams can cause undercutting from toe erosion and saturation of the slide toe from increased water penetration, both of which can negatively impact a slope's steadiness (Hussen et al., 2024). Using Arc Hydro tools, the stream network for the study area was computed using the ASTER

DEM to evaluate the influence of the streams on the distribution of landslides. The streams that accumulated more than 20 square kilometers were extracted.

Weighted Sum Analysis

There are ten elements - Roads, Streams, Vegetation, and Slope - and three criteria established for each element to regulate habitat correctness for the black bears. Feature to Raster, Euclidean Distance, Slope, Reclassify and Weighted sum are cast-off for the analysis. First, layers are converted and analysed to formulate for reclassification. Next, converted and evaluated layers are reclassified giving to the criteria provided in the study. Reclassification for additional specifics concerning reclassification. Finally, all the reclassified layers are draped. A map representing appropriate areas for the black bears, representing three levels of habitat suitability, is fashioned.

Frequency Ratio model

According to (Khan et al., 2019) to assess the likelihood of landslides, it is crucial to comprehend the physical features unique to the place and the mechanisms that cause them. A quantitative method for assessing landslide susceptibility that makes use of geographic data and GIS technology is the frequency ratio. For mapping landslide susceptibility, the frequency ratio (FR) technique is widely and successfully employed. It depends on the measured correlation between the causal variables for landslides and the landslide inventory. We compute the FR for each factor using Eq. 5.

$$\mathbf{FR = (Ni\ P\ x/N)/N\ i\ l\ Q/Nl}$$

Where N is the total number of pixels in the study area, N i lP is the number of landslide pixels in each landslide conditioning factor, Nl is the total number of landslide pixels in the study area, FR is the frequency ratio, and Ni Px is the number of pixels in each landslide conditioning factor class.

Landslide susceptibility mapping

It is crucial to make the assumptions that future landslides will occur within the same conditions as prior landslides and that the geographical distribution of landslides is inclined by the elements that trigger landslides while doing landslide susceptibility mapping. Frequency Ratio (FR) has been utilized throughout this research to map the vulnerability to landslides.

Results and Discussion

Although landslide growth is influenced by a variety of natural and man-made elements, it is a complex process. (Khan et al., 2019). The most significant criteria for precipitation and the detachment to the fault lines were determined to be those created by consulting experts in the landslide susceptibility study (Konurhan et al., 2023). In order to lessen the effects of present and future hazards, LSM was created in this work using geospatial approaches that consider landslide events and risk influences (elevation, slope, aspect, curvature, precipitation, LULC, distance to fault, lithology, distance to road, and distance to streams).

Landslide inventory map

First, we used data from satellites and ground stations to create an inventory map. The determining characteristics for landslides can be observed in the topographic aspects of aspect, curvature, slope, and altitude. As seen in Figure 1, 324 past and present landslide occurrences in the research area were found using ground-based data and satellite imagery.

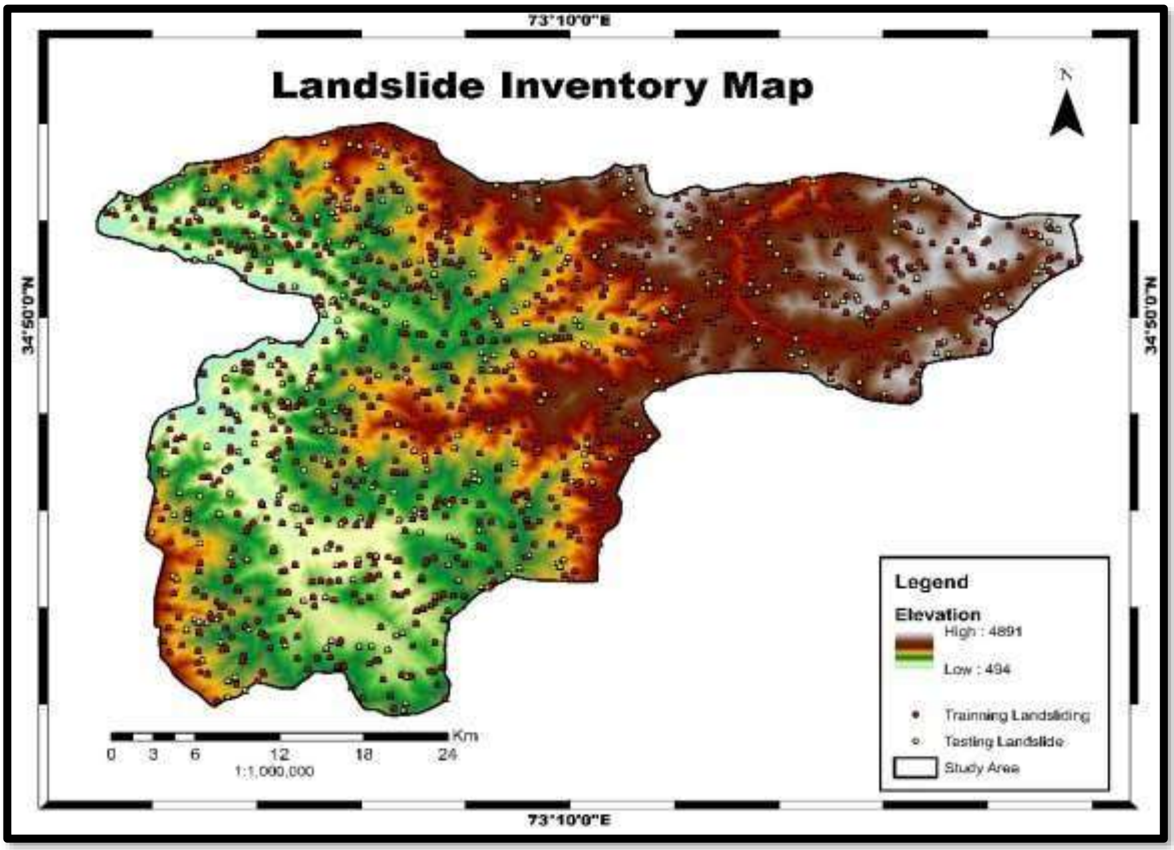


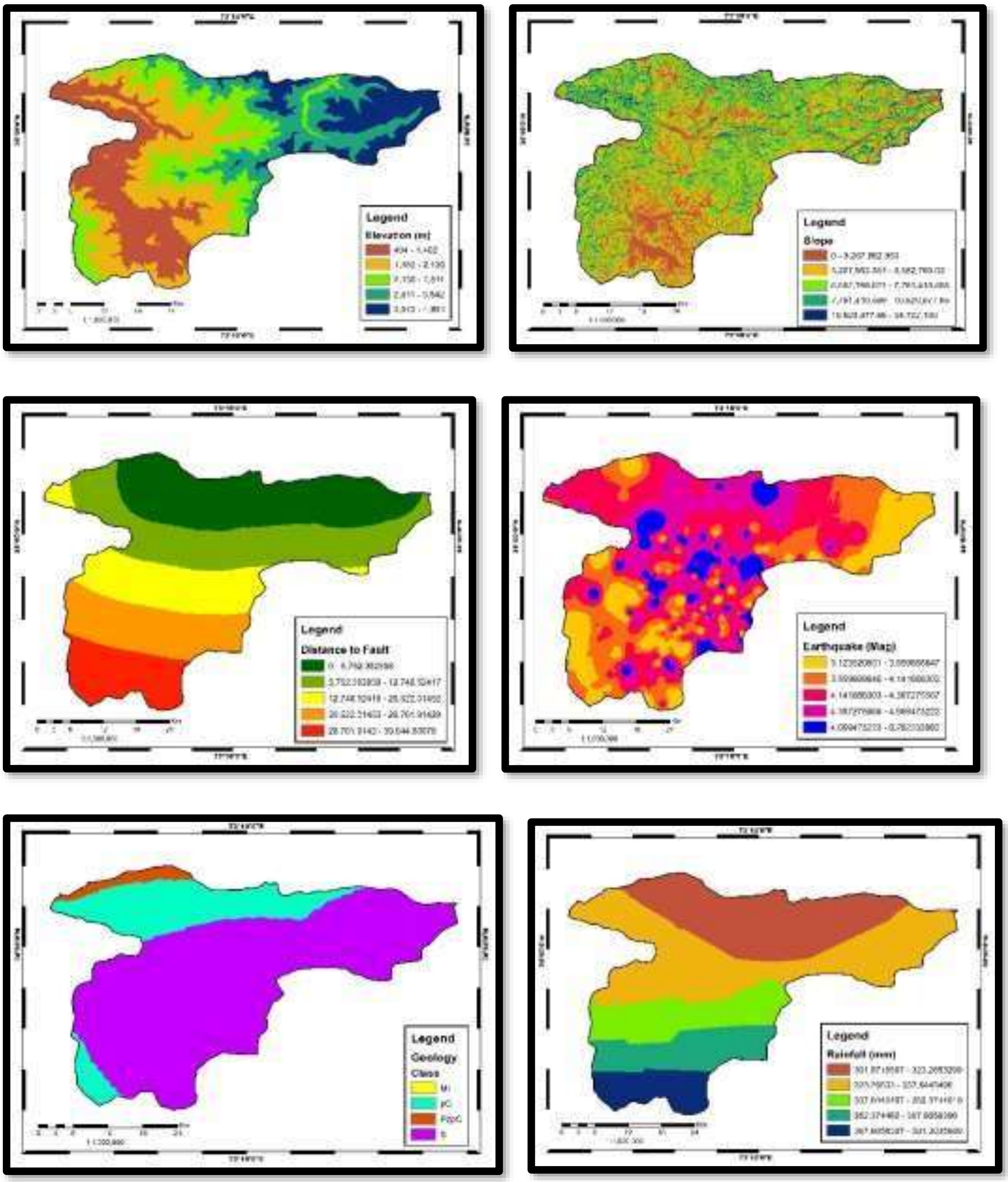
Figure 6: *The landslide inventory map of Battgaram*

To generate a non-landslide area, we first abstract the landslide polygon after the research area polygon. Next, we created random spots in the study zone which has been designated as a non-landslide area using ArcGIS tools(Jin et al., 2024). The various forms of landslides that occur during these occurrences include mudflows, debris flows, rockfalls, and rockslides, topples, and creeps. Three bivariate models are used in this study to generate the study area's LSM. Table 2 displays particular details of each model's outcomes.

Causative Factors of Land sliding

According to (Khan et al., 2019), elevation is a significant requirement for landslide incidence. The current study's elevation characteristics show a substantial correlation with landslide occurrences. >4,500 m is the most significant elevation class, followed by 494 – 4,891 m. The slope, which is the independent variable in this study, is seen to be the most important component. According to Table 2, the slope component has an impact up to 30° because landslides occur more frequently at higher slopes. Above that point, however, landslide activity declines as the slope increases. The results showed that the most prone class of slope is 15-30 °, while the most resistant class to landslides is >30 °, followed by the 10°–15 ° class. According to Table 2, the most important class of aspects is SE, which E, S, and SW. As shown in Table 2, the tabulated findings clarified that the critical class of landslides is concave structure. As Table 2 illustrates, the current study's findings suggest that faults have no direct bearing on the likelihood of landslides. The findings show that a relatively limited number of landslide pixel values of 0−39,644 for WOE and FR, respectively, occurred in a zone <50 m equidistance from the fault. To measure the relationship between rainfall parameters and landslide incidents, a rainfall map derived from CHIRPS data was created in the current study, verified using data collected from the ground, and classed into five classes. The precipitation data in Table 2 indicate that rainfall plays a substantial part in the occurrence of landslides.

The precipitation period is the censorious class for landslides, according to the results, followed by 301.87–391.30 mm/year. The vegetation cover is crucial for stabilizing slopes because roots anchor and strengthen soil layers. The NDVI values of plant formations are mainly positive and fall between 0.571 to 0.086. The results demonstrate that lithology plays a major causal role in the analysis of landslides. The furthermost prone geological creation for landslides is pC, tracked by Mi, PzpC, and S, as Figure 9 illustrates. It is believed that road construction is a direct effect of human activity, which leads to slope instability. The road network map is a polyline vector generated from the data, as seen in Figure 9. As a result, varying land use plays a vital role in determining landslide susceptibility in numerous studies (Abdı et al., 2021). Different land uses have varying effects on landslides. Table 1 results indicate that the current study area's flooded vegetation and forest land make it particularly vulnerable to landslides.



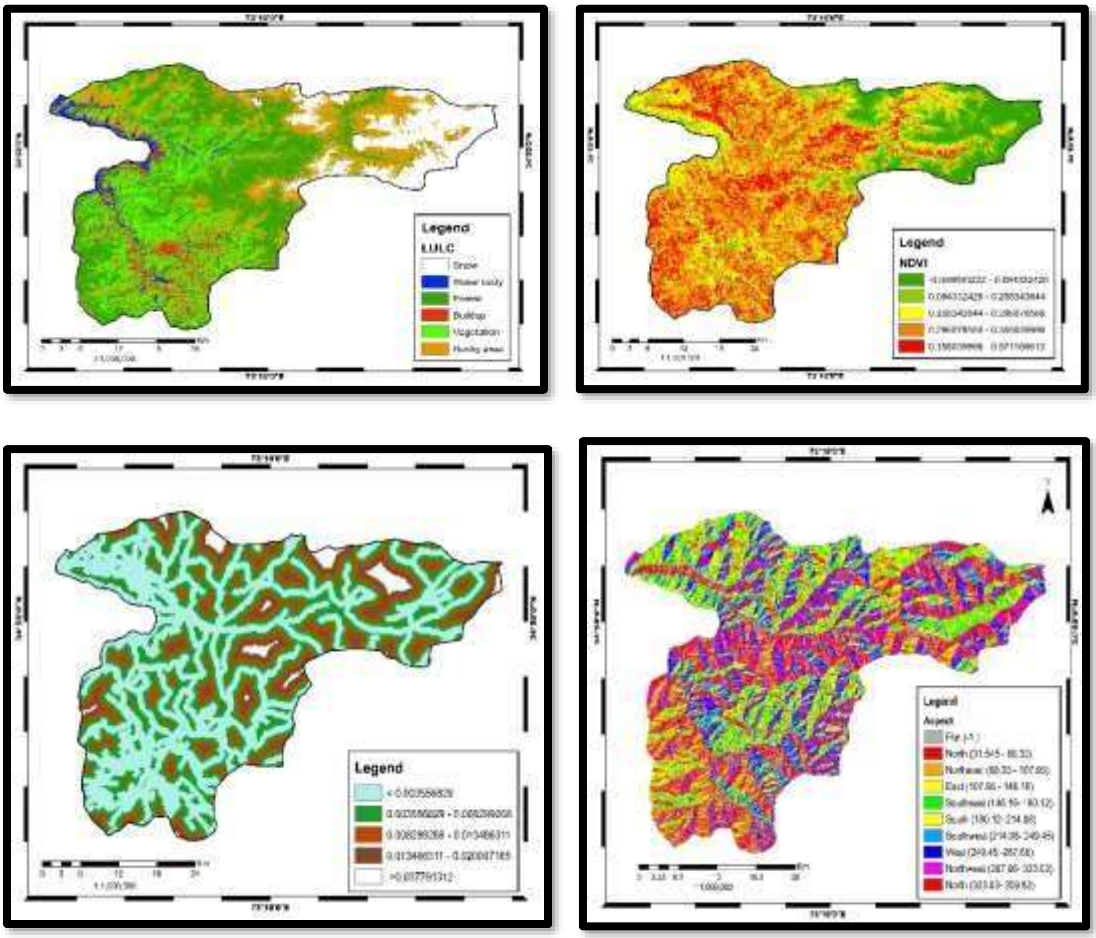


Figure 7: *The resultant maps included land use and cover, geology, rainfall, lineament density, slope, and soil.*

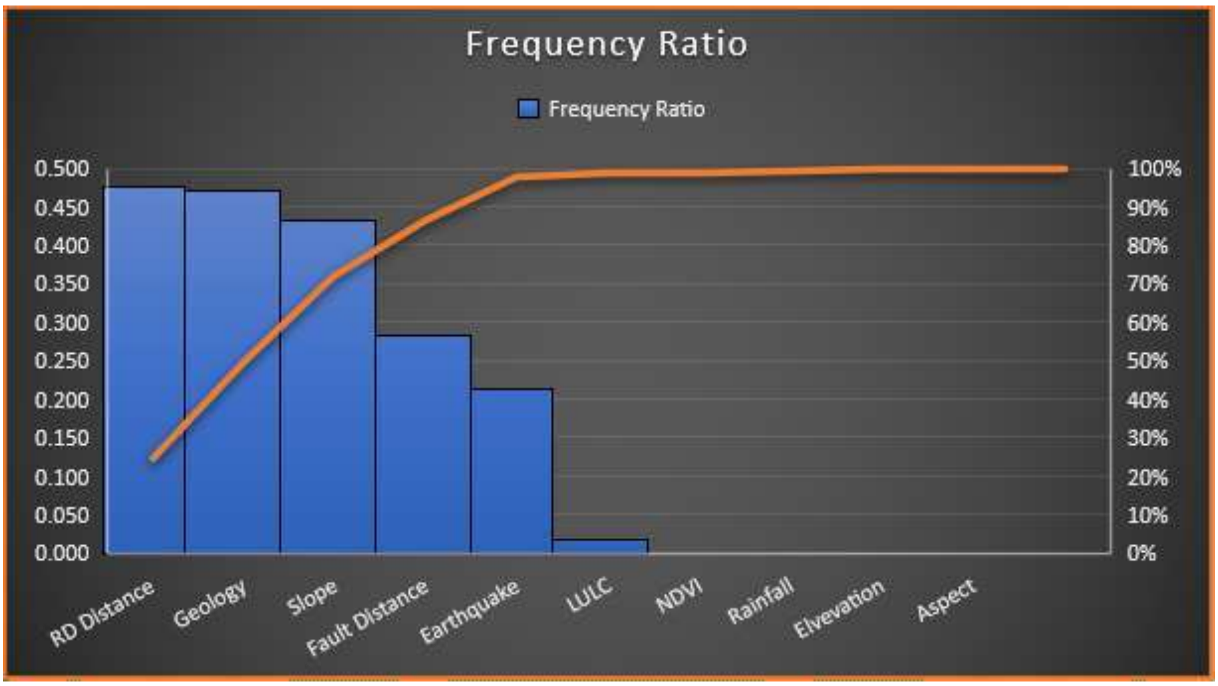


Figure 8: *The frequency ratios of different landslide-related factors*

Flood Extent in 2022 as Derived from SAR

A continuous rise in flooding was pragmatic in the inundation area from the Sentinel-1A data within 3 months since 13 March 2022 to 31 August 2022. In March, a significant percentage of the region was flooded under water owing to a particularly impacted exposure in Figure 10. Nevertheless, in later months, such as August of 2022, the extent of the flood inundation increased. The comparison between these months has been shown in the display figure that has been generated in the software ArcGIS 10.5 after applying the analysis of the normalized difference water index (NDWI). The difference in water bodies has been shown very clearly through magnificent results. The Indus River touches the borderline of Battagram, and some stream coverage in which the flood extends seems to be through image processing.

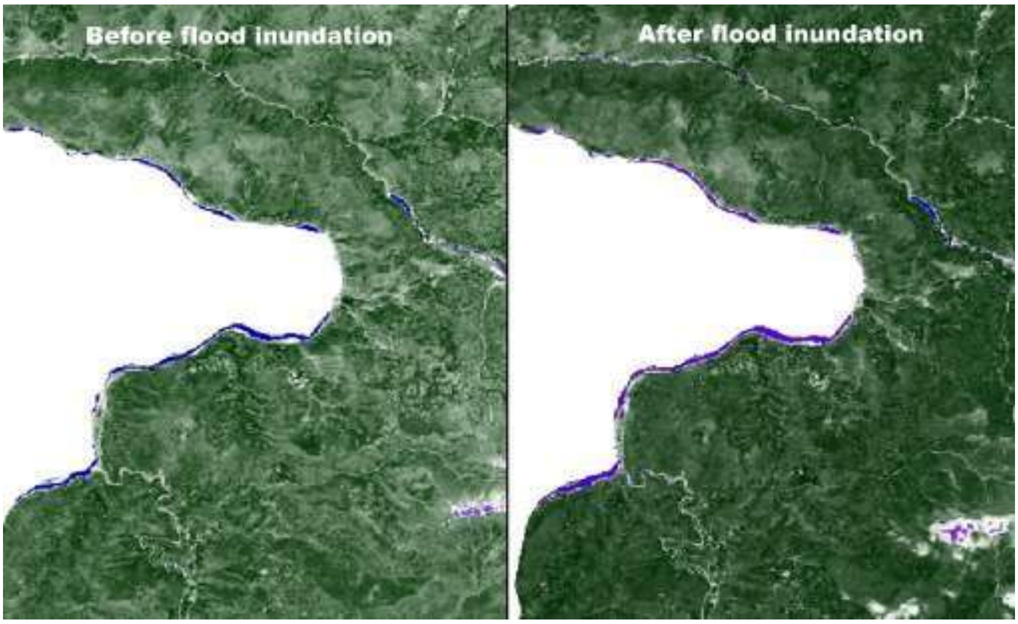


Figure 9: *Comparison between before and after flood simulation*

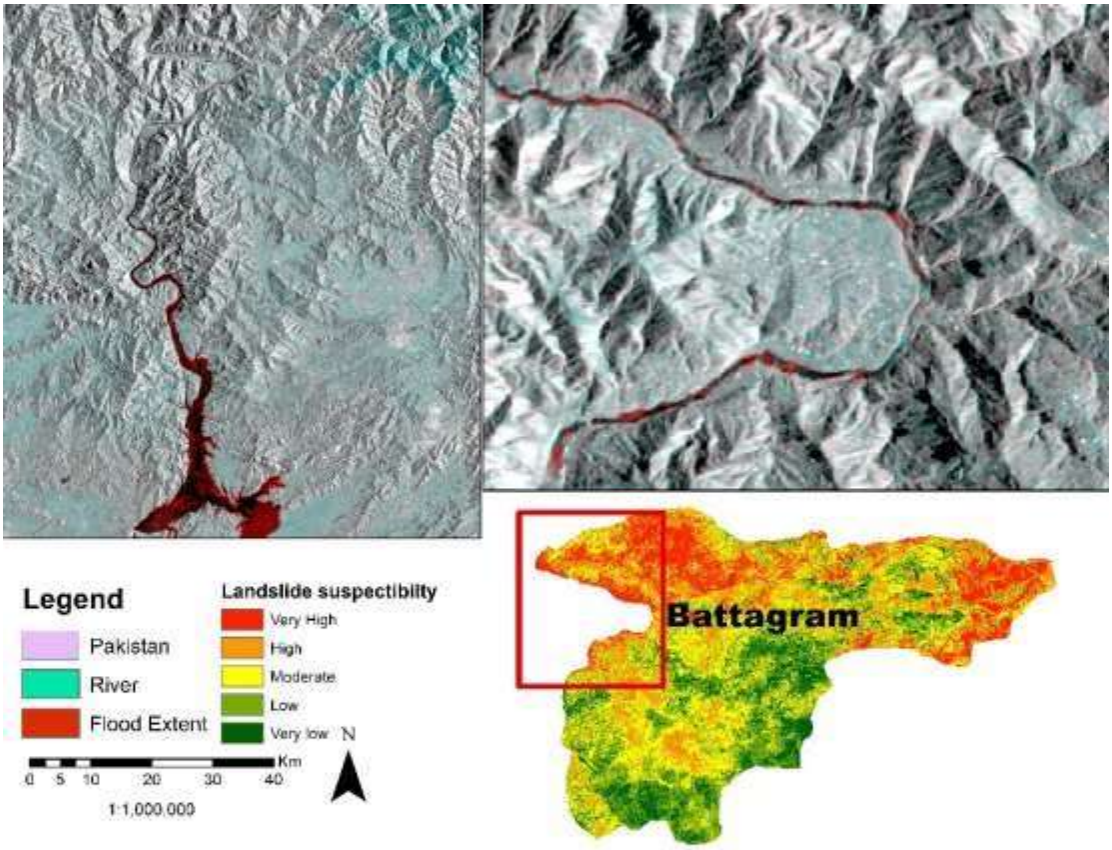


Figure 10: *The flood extend map*

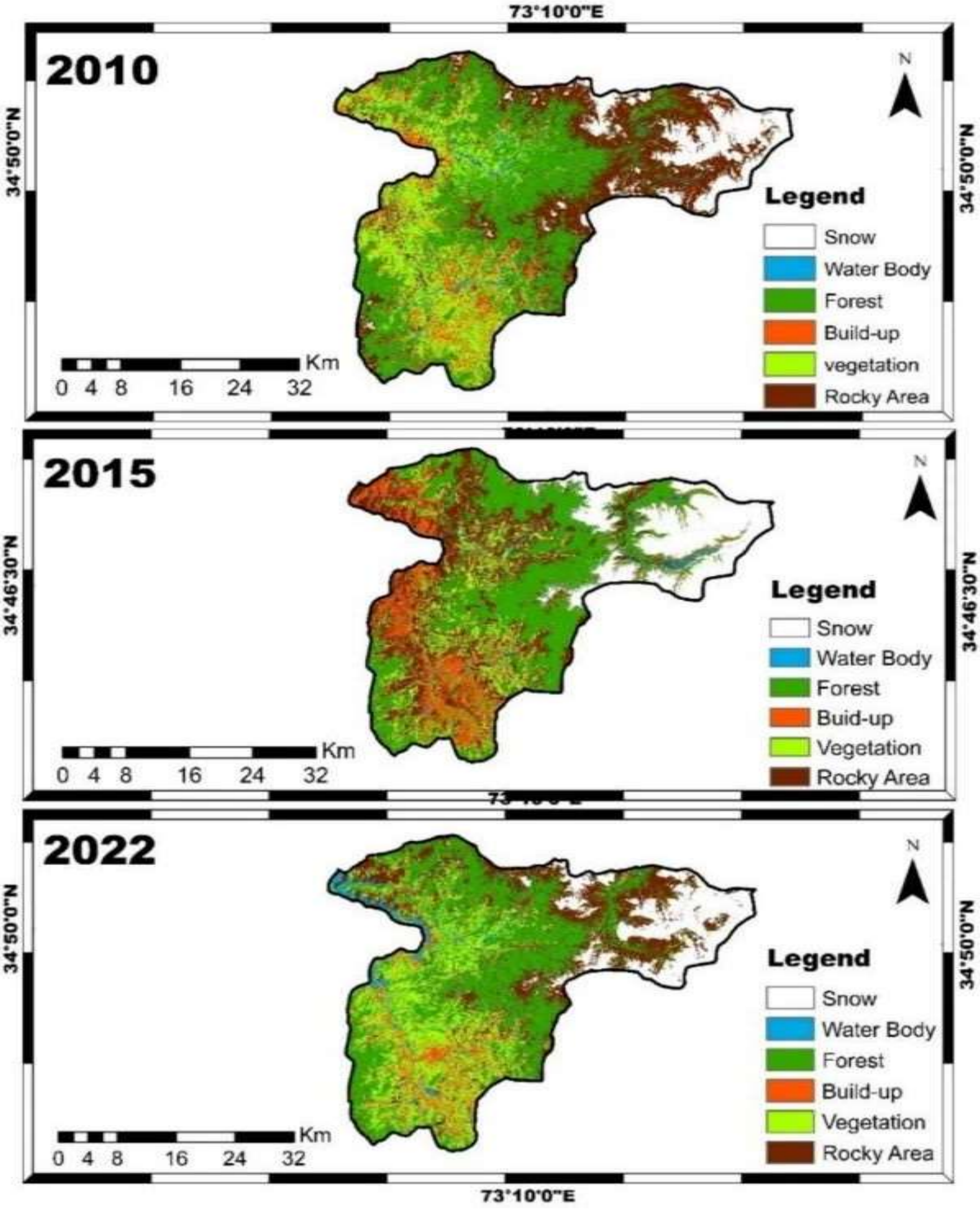


Figure 11: *Temporal map of land use and land cover (2010-2022)*

Figure 11. Presents the LULC changes by comparing categorized Landsat photos from 2010 and 2022. Significant increases were observed in the case of the water body, while major losses were observed in the forest. Although there was a minor increase in snow, the overall

amount of built-up contributing increased in 2015 to 11.85 then decreased due to flood, so the migration may be the reason of the declining rate of built-up. By using randomly selected samples that were spatially well-distributed, the total accuracy of the classification process was found to be 82.37%. Since our goal was to investigate agricultural land, the results were ultimately compared with LULC to mask out the permanent characteristics like forests and glaciers.

Table 2: The area calculation of LU/LC throughout 2010-2022

LULC results of the study area and comparison of both the years (2010–2022).						
Years	2010		2015		2022	
Classes	Area(sq km)	Percentage (%)	Area(sq km)	Percentage (%)	Area(sq km)	Percentage (%)
Snow	1687.06	11.27	2542.01	16.98	2051.09	13.7
Water Body	254.97	1.7	431.74	2.88	544.24	3.63
Forest	4784.61	31.96	4731.33	31.61	4818.3	31.19
Build-up	847.91	5.66	1774.36	11.85	809.89	5.41
Vegetation	3062.92	20.46	1731.58	11.56	3324	22.2
Rocky area	4328.97	28.92	3755.42	25.09	3418.92	22.84

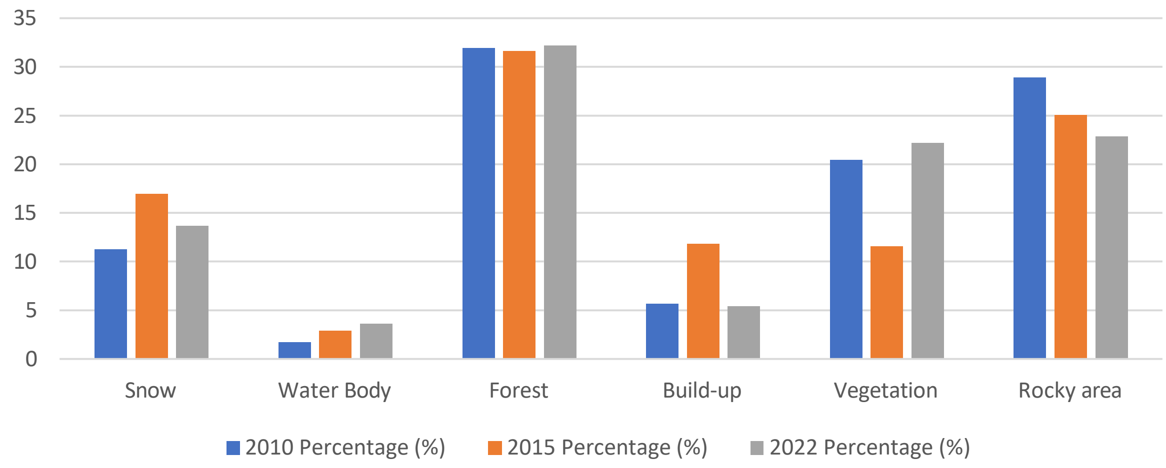


Figure 12: *Graphical representation of landcover*

Weighted Sum Analysis

These final weights are integrated into the GIS environment and used in ArcGIS software to generate the resulting map using the Weighted Sum method. Five classes have been generated from the results as shown in the map Very high (5.41%), high (42.5714%), moderate (36.0127%), low (14.2585%), and very low (1.74178%).

Table 3: The weights assigned to all factors

Data layer	Weight
Aspect	3
Slope (degree)	30
Elevation(m)	11
Rainfall	10
Rd distance	5
Fault distance	8
Land use/land cover	8
Geology	10
Earthquake	10
NDVI	5

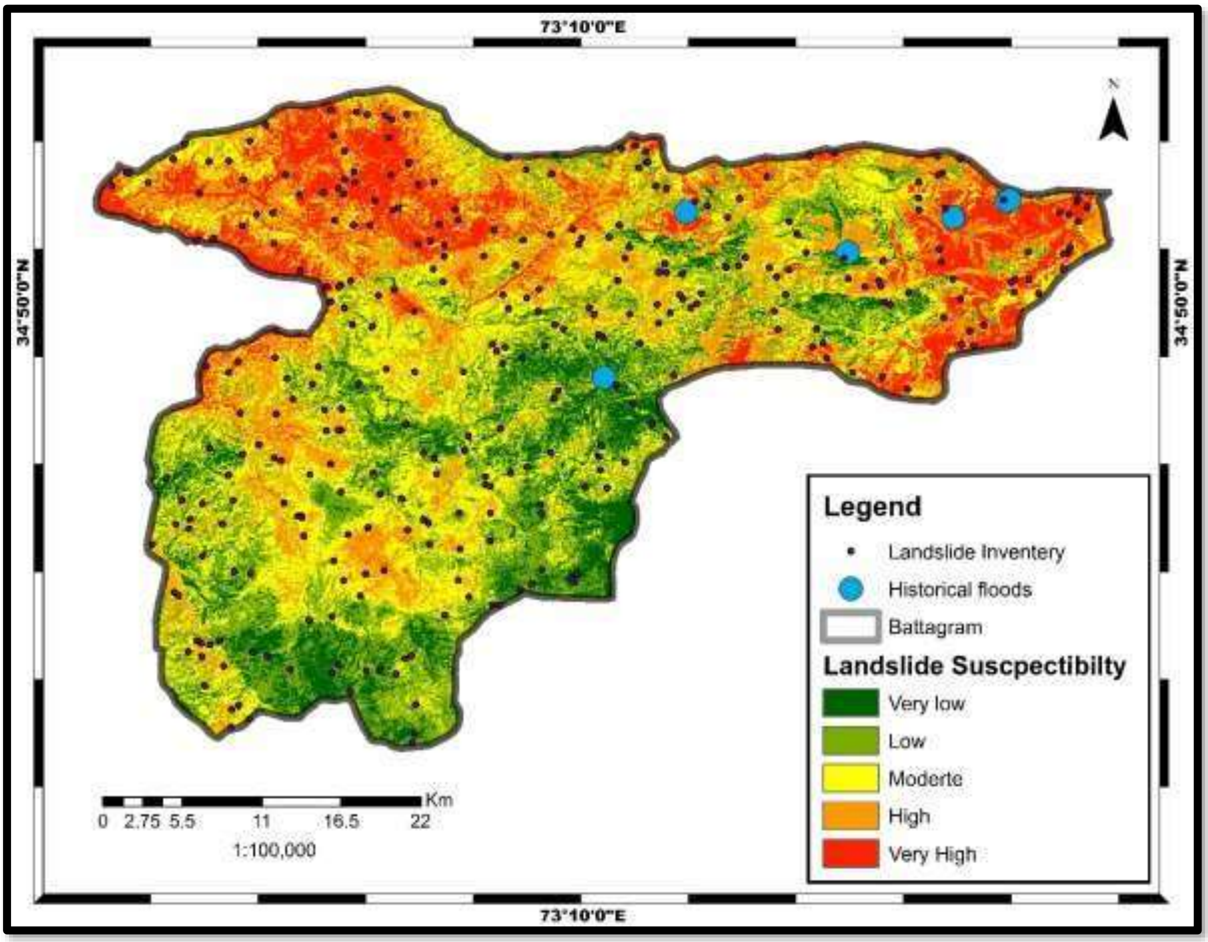


Figure 13: *The landslide susceptibility map by using weighted sum analysis*

Frequency ratio model

From the association between the landslide-causing factors and the places where landslides had not happened, one might infer the relationship between the landslide occurrence area and the landslide causal factors. A straightforward statistical method known as the frequency ratio approach has been used to determine the landslide susceptibility. To advance an LSM map, the frequency ratio for the designated contributing influence classes was mutual in geospatial (Figure 13).

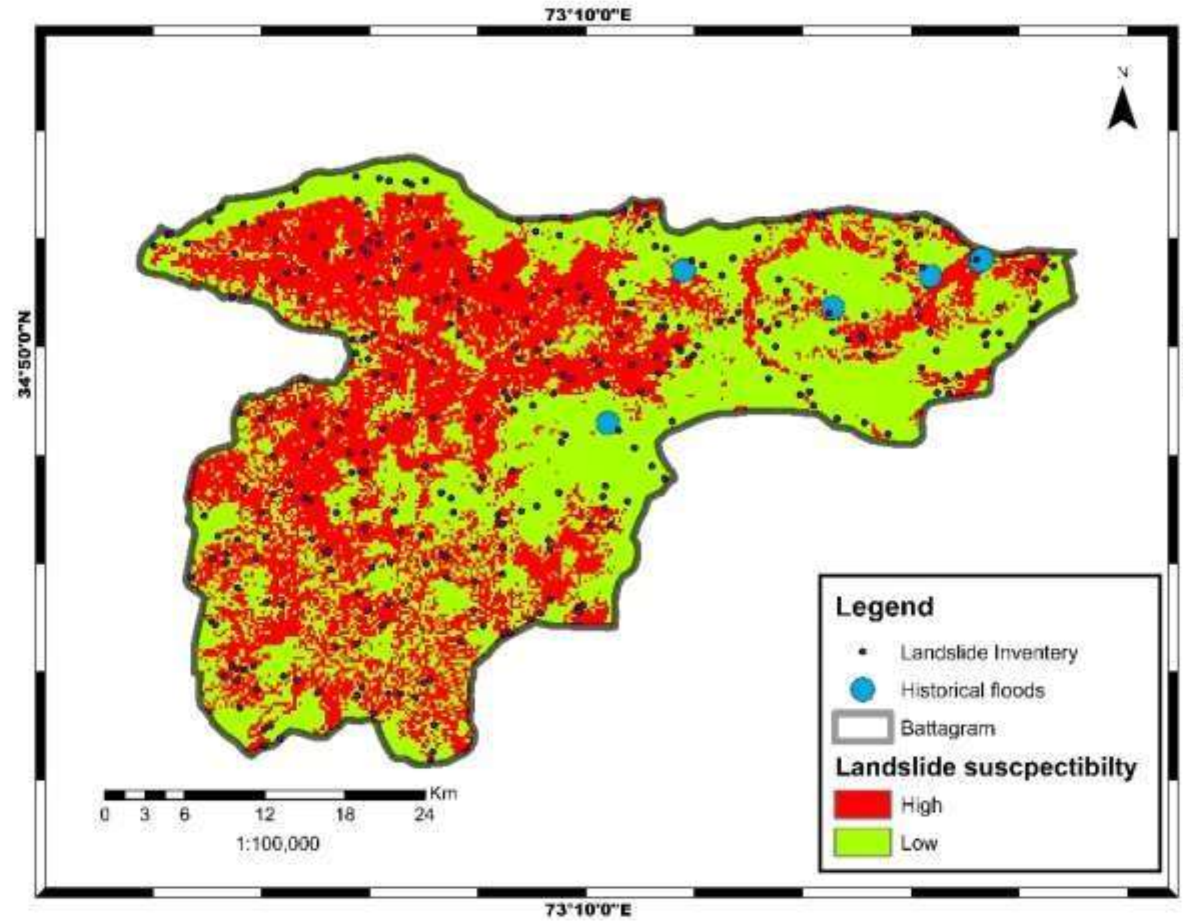


Figure 14: *The landslide susceptibility map by using Frequency Ratio*

Towards advance a landslide susceptibility map for learning zone, the LSM map is classed into two classes: very low and extremely high susceptibility (Fig. 15).

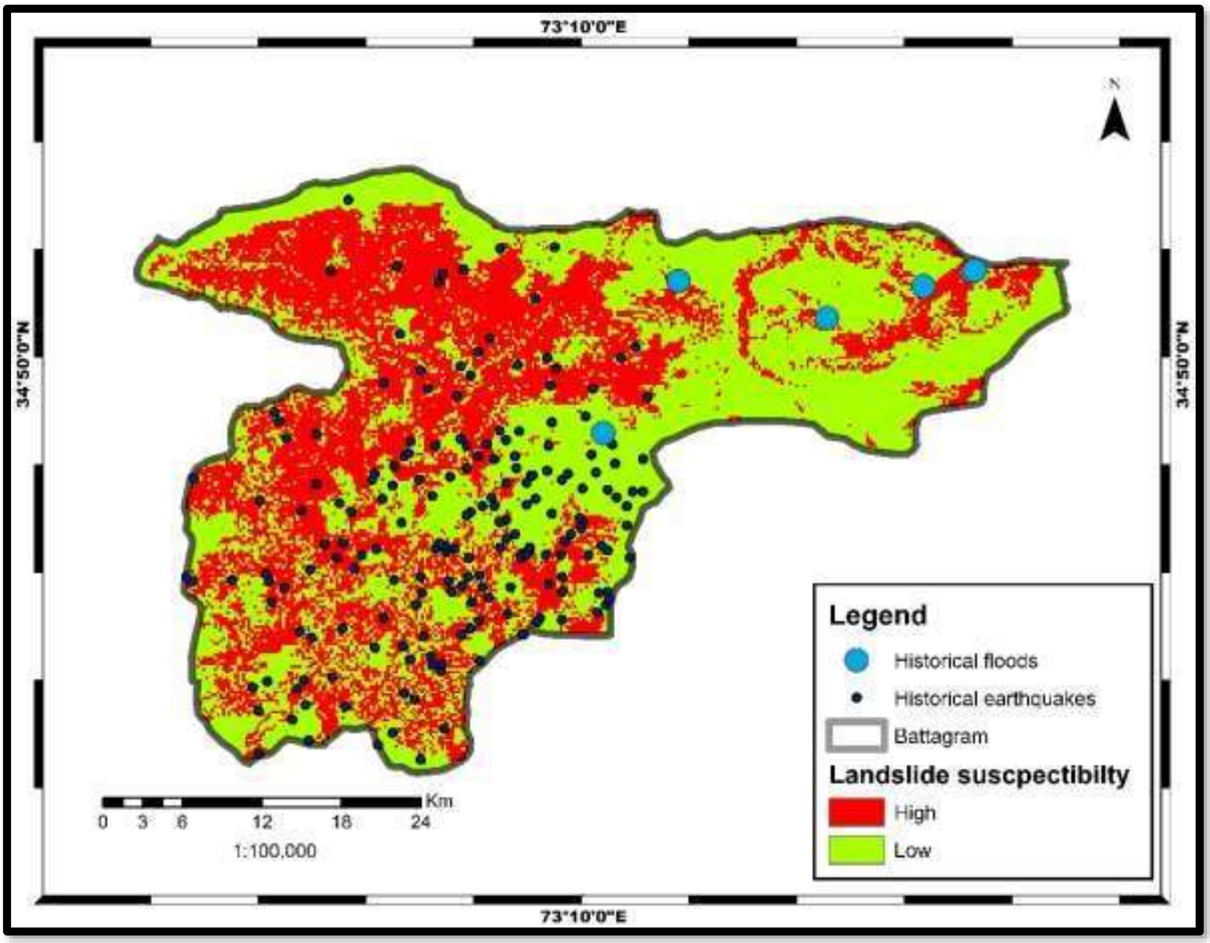


Figure 15: *Landslide susceptibility map induced from earthquake and flood*

According to the results, 44.67% of the range is in the very high class, followed by the high susceptibility class (40.94%), moderate class (11.61%), low susceptibility class (1.96%), and very low susceptibility class (0.79%). The LSM map (Fig. 15) gives rise to the success rate curve. The LSM map's index values for every pixel stayed as expected overall. The 1% cumulative intervals were used to reclassify these values into 100 classes. The landslide susceptibility map and the classified map used to overlap. According to the justification results, 70% of the pixels are correctly categorized as landslide pixels.

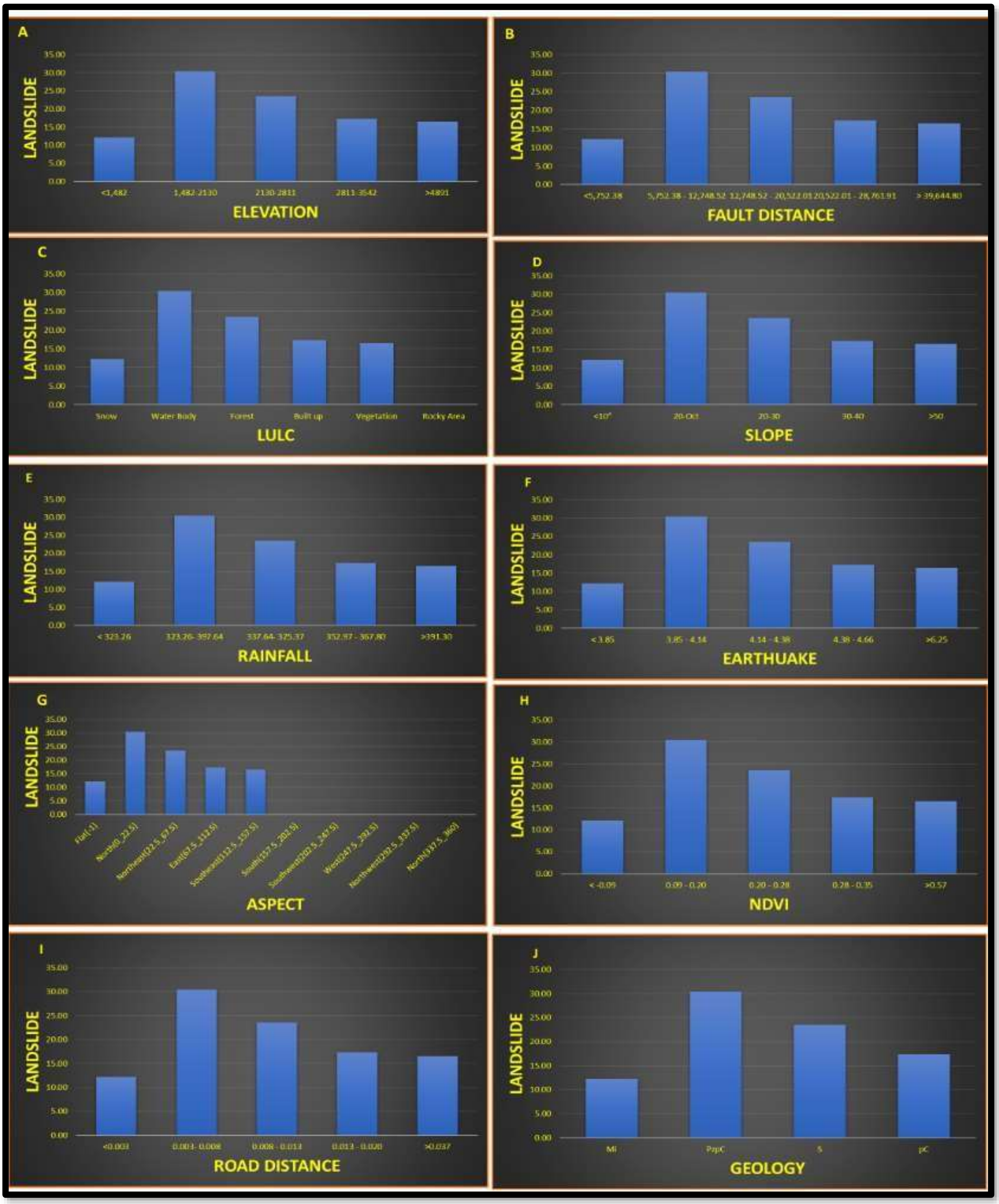


Figure 16: *The Relationship between landslide and all parameters*

Table 4: The calculation of frequency ratio for landslide susceptibility

Parameters	Class	Value	Class Pixcel	% Pixcel	Landslide Pixe	landsliidng Pix	FR
Elvevation	<1,482	1	381830	22.21	231	12.19	0.001
	1,482-2130	2	440629	25.63	577	30.45	0.001
	2130-2811	3	348330	20.26	446	23.54	0.001
	2811-3542	4	311525	18.12	328	17.31	0.001
	>4891	5	237177	13.79	313	16.52	0.001
			1719491		1895		0.006
NDVI	<- 0.09	1	175123	11.70	231	12.19	0.001
	0.09 - 0.20	2	180965	12.09	577	30.45	0.003
	0.20 - 0.28	3	399932	26.72	446	23.54	0.001
	0.28 - 0.35	4	486289	32.49	328	17.31	0.001
	>0.57	5	254335	16.99	313	16.52	0.001
			1496644		1895		0.008
Aspect	< 73.99603642	1	314573	18.29	231	12.19	0.001
	73.99 - 148.99	2	278285	16.18	577	30.45	0.002
	148.99- 216.91	3	376541	21.90	446	23.54	0.001
	216.91 - 287.66	4	352692	20.51	328	17.31	0.001
	> 359.82	5	397400	23.11	313	16.52	0.001
			1719491		1895		0.006
Earthquake	<3.85	1	6919	14.05	231	12.19	0.033
	3.85 - 4.14	2	10190	20.69	577	30.45	0.057
	4.14 - 4.38	3	13978	28.39	446	23.54	0.032
	4.38 - 4.66	4	13424	27.26	328	17.31	0.024
	> 6.25	5	4732	9.61	313	16.52	0.066
			49243		1895		0.212
Fault Distance	<5,752.38	1	10707	29.17	231	12.19	0.022
	5,752.38 - 12,748.52	2	9668	26.34	577	30.45	0.060
	12,748.52 - 20,522.01	3	6059	16.51	446	23.54	0.074
	20,522.01 - 28,761.91	4	6031	16.43	328	17.31	0.054
	> 39,644.80	5	4236	11.54	313	16.52	0.074
			36701		1895		0.283
LULC	Snow	1	205109	13.70	231	12.19	0.001
	Water Body	2	54424	3.64	577	30.45	0.011
	Forest	3	481830	32.19	446	23.54	0.001
	Built up	4	80989	5.41	328	17.31	0.004
	Vegetation	5	332400	22.21	313	16.52	0.001
	Rocky Area	6	341892	22.84	1895		0.000
			1496644				0.018
Rainfall	< 3.85	1	415847	27.71	231	12.19	0.001
	3.85 - 4.14	2	556394	37.07	577	30.45	0.001
	4.14 - 4.38	3	216290	14.41	446	23.54	0.002
	4.38 - 4.66	4	186865	12.45	328	17.31	0.002
	>6.25	5	125352	8.35	313	16.52	0.002
			1500748		1895		0.008
RD Distance	<0.003	1	24328	49.40	231	12.19	0.009
	0.003- 0.008	2	13073	26.55	577	30.45	0.044
	0.008 - 0.013	3	7080	14.38	446	23.54	0.063
	0.013 - 0.020	4	3596	7.30	328	17.31	0.091
	>0.037	5	1166	2.37	313	16.52	0.268
			49243		1895		0.476
Slope	<10°	1	494599	65.46	231	12.19	0.000
	20-Oct	2	251548	33.29	577	30.45	0.002
	20-30	3	5765	0.76	446	23.54	0.077
	30-40	4	1994	0.26	328	17.31	0.164
	>50	5	1666	0.22	313	16.52	0.188
			755572		1895		0.432
Geology	Mi	1	11381	21.95	231	12.19	0.020
	PzpC	2	1408	2.72	577	30.45	0.410
	[illegible]	3	17065	32.92	446	23.54	0.026
	pC	4	21990	42.42	328	17.31	0.015
			51844		1582		0.471

The landslide susceptibility map comprises of the predicted landslide area hence it can be used to decrease the potential hazard associated with the landslides in this study area. It means this model is 88.9% accurate to predict the probability of landslide and the model is 92.3% success to generate the prediction in the study area.

Table 5: The prediction ratio for all the factors

Slope (degree)	2.357866	235.79
Elevation(m)	2.17186737	217.19
Rainfall	1.03679384	103.68
Rd distance	2.95838643	295.84
Fault distance	1	100.00
nduse/land cov	3.24558626	324.56
Geology	4.56060049	456.06
Earthquake	1.06810309	106.81
NDVI	1.8171733	181.72

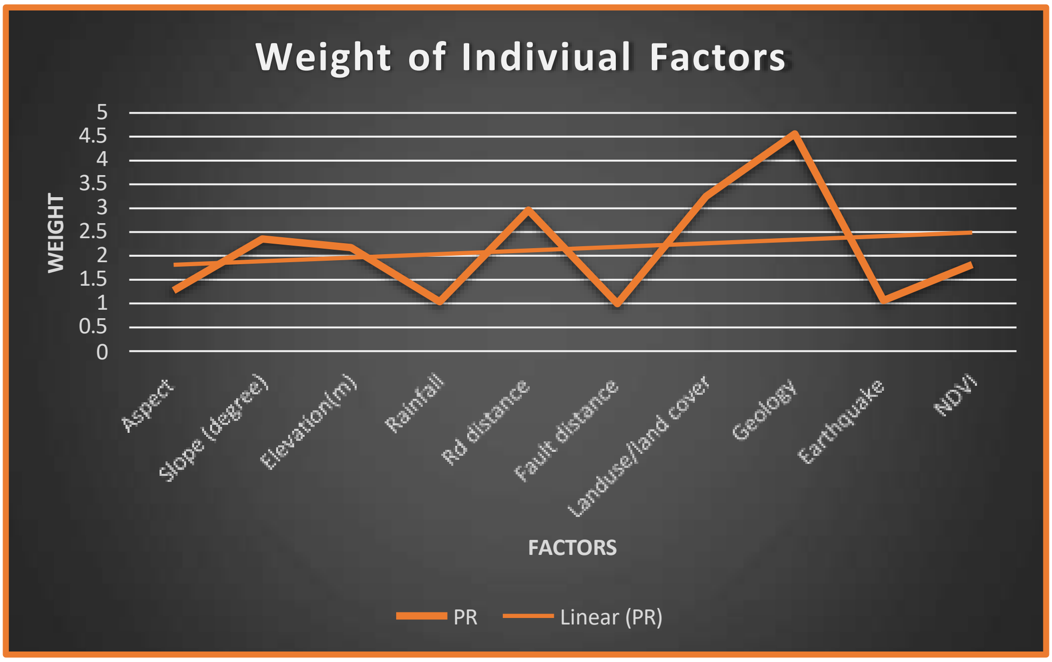


Figure 17: *Graphical representation of Prediction ratio*

Conclusion

The purpose of this work was to create a complete database of landslides caused by the Battgaram earthquake and rainfall by interpreting multitemporal images and correlating them with environmental, seismic, and rainfall parameters. These landslides resulted from a mix of rainfall- and earthquake-induced occurrences. It is difficult to assess how the climate affects landslides because the two phenomena only partially overlap in space and time. While rainfall is likely the most frequent cause of landslides, this study has identified earthquakes and floods as additional triggers for landslide risk. The northern portion of Battgaram is closely watching the extent of the flood and the activation of the earthquake in 2022, which increases the susceptibility of landslides. Examining the landslide inventory map made especially for the study area, it is evident that the majority of the region's active landslide locations are located in its higher-elevation sections. The findings lead to the following conclusions, which are proposed: The purpose of this study was to use geographic methods to create an LSM of the research region in order to lessen the effects of potential dangers. The weighted sum analysis of the study showed that 1.74178% of the area had very low susceptibility. The area of Muzaffarabad is divided into four susceptibility zones: high (2.5714%), moderate (36.0127%), low (14.2585%), and very high (5.41%). Specifically, 44.67% of the range falls into the very high class, followed by the high susceptibility class (40.94%), the moderate class (11.61%), the low susceptibility class (1.96%), and the very low susceptibility class (0.79%) in the frequency ratio model. In the current study, the GIS-based statistical models WSM and FR were utilized to calculate the correlation between dependent variables (the elements that cause landslides) and dependent variables (the events or inventories of landslides).

The purpose of this study was to assess the relationship between the occurrence of landslides and causal factors. The topography, geology, hydrology, climate, and geomorphology of these factors were listed. After applying the Weight Sum analysis method and transferring the weight data to the GIS environment, a landslide susceptibility map was produced. The results of the validation showed that the FR model is a reliable approach for the LSM. The susceptibility map was validated by comparing its positions with those of known landslides. 85.7% of the predictions were shown to be accurate. We conclude that the most authentic, adaptable, and dependable way to generate LSM is through statistical modeling based on GIS. The maps of landslide susceptibility that this study produced are crucial for local governance and sustainable urban development. Initial decision-making and policy planning may benefit from the data obtained from the created map. Furthermore, in order to be widely applied in more regional areas, more relative data must be obtained.

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Drought Risk Assessment of Muzaffargarh District by Using Geospatial Techniques

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Abstract

Drought is a major natural hazard characterized by extended periods of insufficient precipitation, posing serious threats to both ecosystems and human livelihoods. This study evaluates drought risk in Muzaffargarh District, Pakistan, by combining geospatial techniques such as remote sensing (RS) and geographical information systems (GIS). Landsat ETM+ and OLI imagery from 2002, 2008, 2013, and 2018 were used to compute the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). The study found that LST increased from 38.77 °C in 2002 to 42.54 °C in 2018, while NDVI values decreased from 0.989 to 0.576. This inverse trend confirms declining vegetation cover and rising surface temperatures, which are important indicators of increasing meteorological and agricultural drought risk. Regression analysis confirms a negative correlation between LST and NDVI ($R^2 = 0.4167$), indicating the region's vulnerability to climatic stress. The supervised classification of LU/LC data reveals significant urban expansion and vegetation loss between 2002 and 2018. The resulting drought risk maps identify increasingly dry zones, providing critical spatial insights for policymakers and stakeholders as they develop targeted and proactive drought mitigation plans.

***Keywords**:* Drought, GIS, LST, meteorological drought, NDVI, remote sensing.

Introduction

Drought is one of the most complex and devastating natural hazards, affecting millions of people worldwide, particularly in arid and semi-arid areas. It is characterized by a prolonged deficiency in precipitation, resulting in water scarcity, crop failure, and socioeconomic distress. (WHO 2021). Climate change has increased the frequency, severity, and duration of droughts, posing significant challenges for water resource management and food security (IPCC et al. 2023). Pakistan, as a predominantly agrarian economy, is especially vulnerable to droughts. Southern Punjab's Muzaffargarh District is not an exception; it has experienced ongoing dry spells that have negatively impacted livelihoods and agricultural productivity (Ahmad et al. 2020).

Traditional drought monitoring approaches frequently deficiency spatial resolution and fail to deliver timely warnings at the local level. The integration of geospatial techniques, with remote sensing (RS) and geographic information systems (GIS), has been established as a reliable and cost-effective technique for drought risk assessment (Nepal et al., 2021). These technologies permit unceasing monitoring of vegetation health, land surface temperature, soil moisture, and rainfall anomalies, all of which are key gauges of drought. The Normalized Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), and the Standardized Precipitation Index (SPI) are broadly used indicators to measure drought vulnerability and spatial degree (Amarasingam et al. 2022). In Muzaffargarh, a comprehensive drought risk assessment is vital for making knowledgeable decisions and planning. The district's varied agro-climatic zones, reliance on seasonal rainfall, and growing demand for water resources necessitate the usage of advanced geospatial tools for real drought monitoring and mitigation. This study purposes to assess drought risk in Muzaffargarh District by investigating multitemporal satellite data and climatic variables through geospatial techniques. The consequences are anticipated to provision local authorities and stakeholders in developing targeted drought preparedness and resilience strategies.

Research objectives

This study aims to:

- To evaluate the underlying factors contributing to drought risk in the study area through geospatial analysis.
- To track changes in vegetation health and surface temperature over time.
- To investigate how land use and land cover changes contribute to drought risk.

Study area

Muzaffargarh District is located in south-central Punjab province, Pakistan, at latitude 30°4′10″N and longitude 71°11′39″E. The district covers 8,249 km² and borders the Chenab River to the east and the Indus River to the west. The region is divided into four tehsils: Muzaffargarh, Jatoi, Alipur, and Kot Addu, with 111 union councils in total.

- The districts of Khanewal and Multan are located on the eastern side of District Muza ffargarh, across the Chenab; the district of Layyah borders the district on the north; an d the districts of Bahawalpur and Rahimyar Khan Border to the south. The districts of Dera Ghazi Khan and Rajanpur are located on the western bank of the Indus River, w hile District Jhang is located in the northeast.

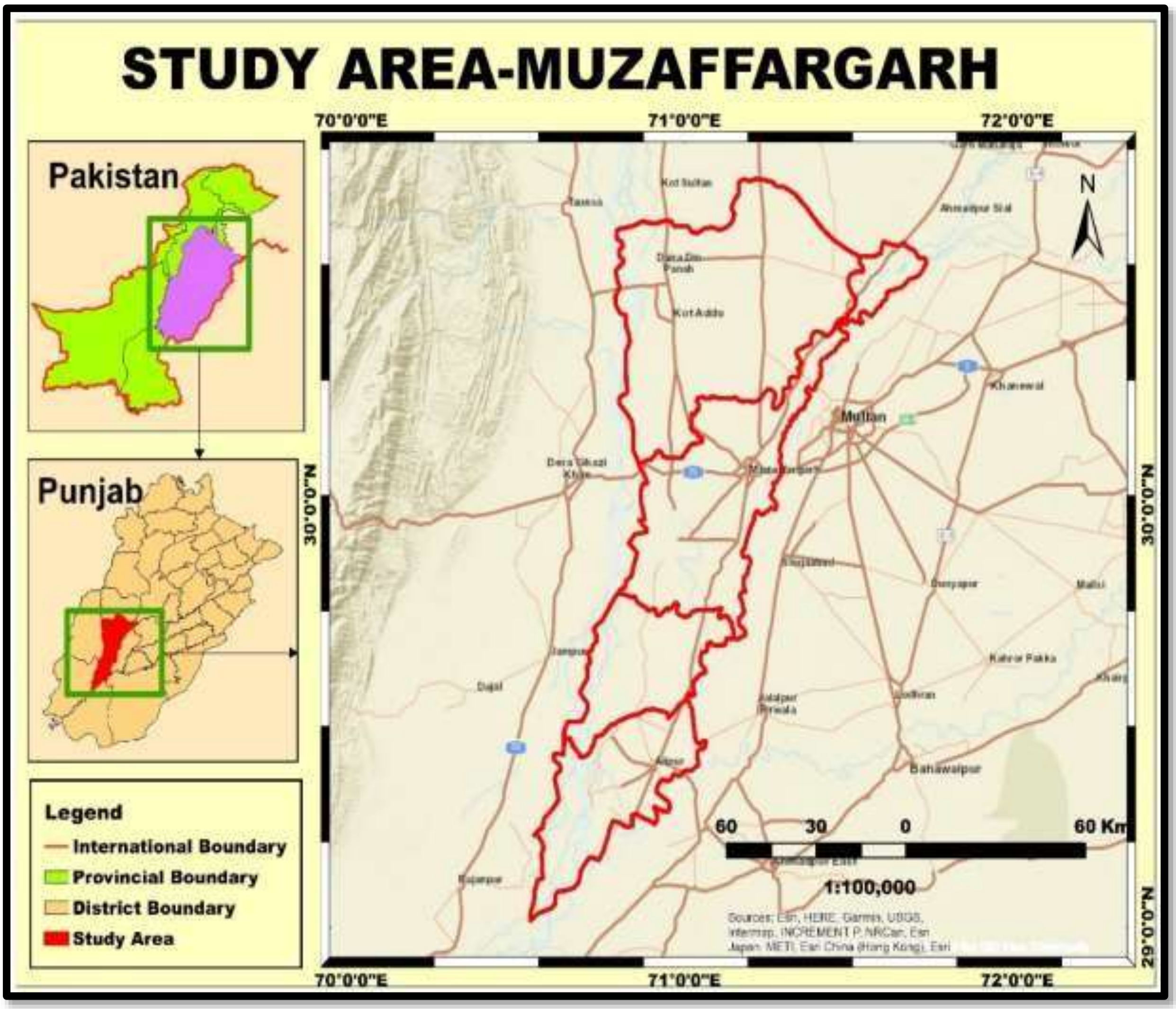

Figure 1: *Study Area Map*

(Source: USGS Earth Explorer)

Climate

Mostly the area of Muzaffargarh is dry and also consists of the barren lands and sand dunes known as the thal area, but the other portion of the area, whether flooded from the river or irrigated by inundation canals, is less dry.

- The climate of Muzaffargarh is arid, with scorching summers and moderate winters. The city has seen among Pakistan's most severe weather. The months of May through Septem ber are hot, but between mid-August and mid-September, a cool breeze might begin to bl ow, which would lower the temperature. In December and January, there are cold nights with heavy frost, which seriously damages vegetables, cotton, mangoes, and sugarcane.
- The temperature that was recorded was roughly 1°C at the lowest point and 54°C at the m

aximum.

- The maximum temperature graph displays how many days per month reach certain tempe ratures. Figure 2 shows that the maximum temperature that is of 40°C the Muzaffargarh is in June to July, the whole month in 2018.

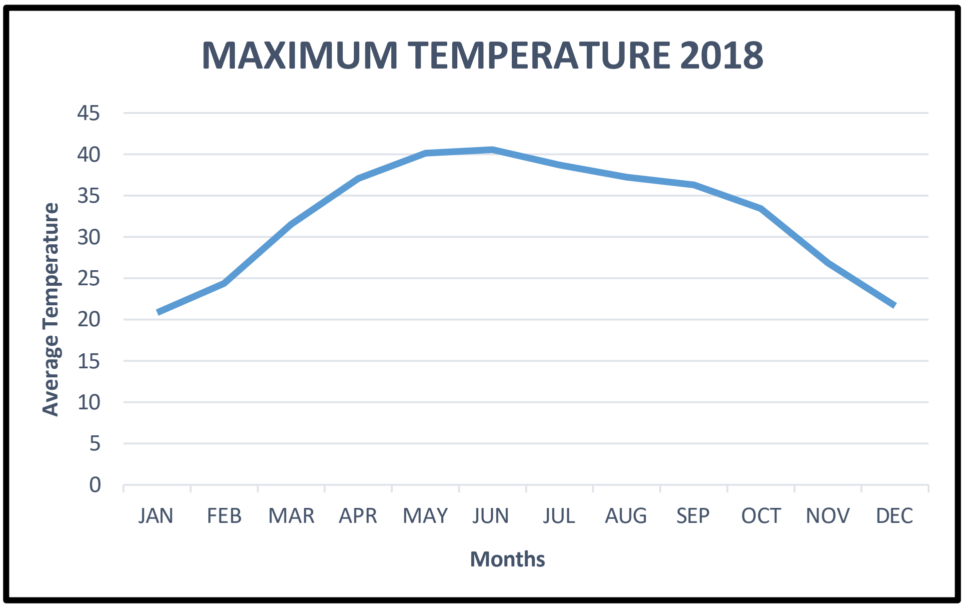

Figure 2: *Graphical representation of the maximum temperature in Muzaffargarh (2018)*

Material and Methods

The overview of used methodology used to work out the proposed research. Reliable indices to distinguish the spatial and temporal dimensions of drought existence and its concentration are necessary to evaluate the impact, and also for decision-making and crop research priorities for improvement. The methodological framework is illustrated in Figure 2.

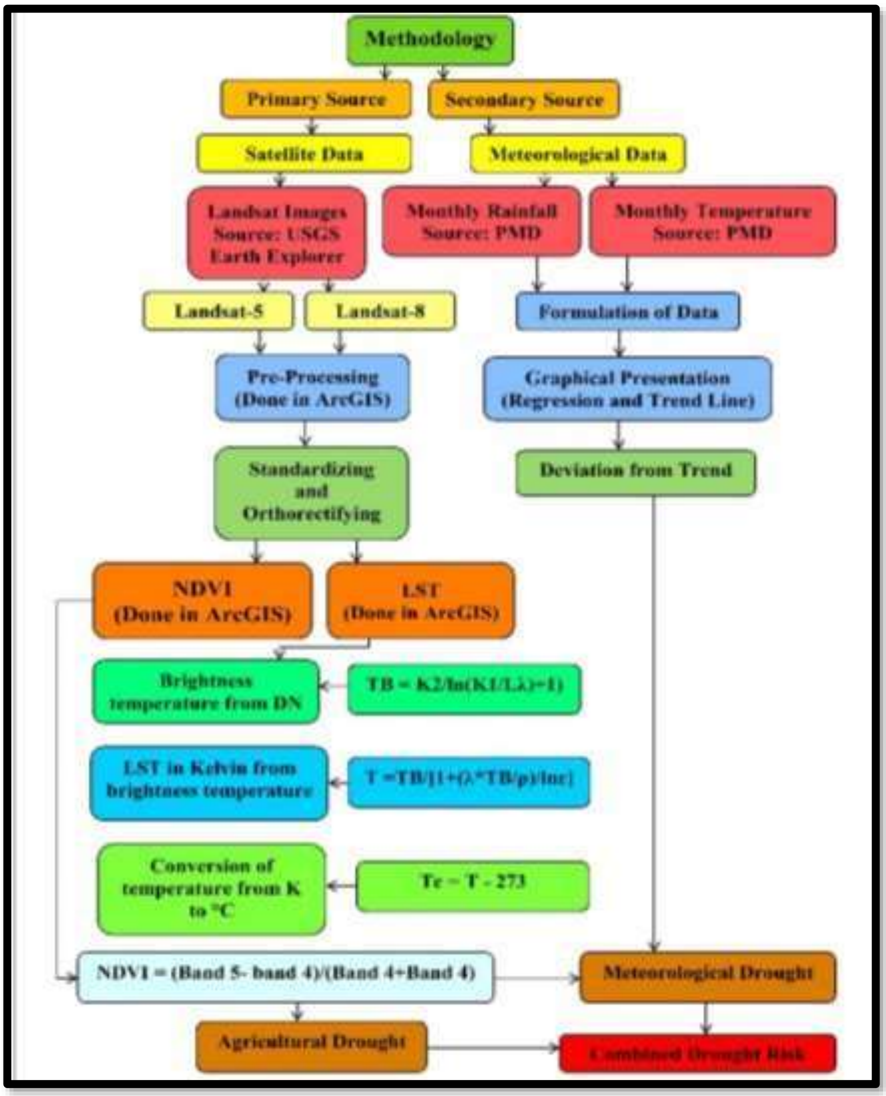

Figure 3: *Methodological Framework*

Dataset used

The satellite data, that has been taken from the United States Geological Survey (USGS) (http://earthexplorer.usgs.gov), Landsat 5 and 8 Enhanced Thermal Mapper (ETM+) and Operational Land Imager (OLI), images (path 150 rows 39, path 151 rows 39 and path 151 row 40) with the 30 m resolution, of July, for the years 2002, 2008, 2013 and 2018 as mentioned in Table 1 used for applying the analysis by using the Remote Sensing and Geographical Information System techniques. In this study, the secondary data source, as Pakistan Meteorological Department (PMD), brings meteorological data on monthly rainfall and monthly temperature, which has been collected for the period 16 years, ranging from 2002-2018.

Table 1. Detailed Information about satellite imagery. (Source: USGS Earth Explorer)

Satellite	Dates of Images	Resolution	Reference system/Path/Row
Landsat 5	14/07/2002	30m	WRS/150/39
Landsat 5	21/07/2002	30m	WRS/151/39
Landsat 5	21/07/2002	30m	WRS/151/40
Landsat 5	14/07/2008	30m	WRS/150/39
Landsat 5	05/07/2008	30m	WRS/151/39
Landsat 5	21/07/2008	30m	WRS/151/40
Landsat 8	12/07/2013	30m	WRS/150/39
Landsat 8	19/07/2013	30m	WRS/151/39
Landsat 8	19/01/2013	30m	WRS/151/40
Landsat 8	10/07/2018	30m	WRS/150/39
Landsat 8	01/07/2018	30m	WRS/151/39
Landsat 8	01/07/2018	30m	WRS/151/40

Data analysis

Satellite imagery was analyzed using key drought indices such as the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and supervised classification for Land Use and Land Cover (LU/LC). The Pakistan Meteorological

Department (PMD) provided secondary climatic data in addition to satellite data. Microsoft Excel was used to establish and examine the mean temperature and precipitation averages for the year. The line graphs were formed by applying regression analysis to these variables, which assisted in influential and identifying the study area's drought risk. A vigorous measure of the Earth's surface energy balance, land surface temperature (LST) is extensively recognised as a vital variable in the investigation of land-surface processes at both regional and global scales (Yadav et al. 2024). In this study, LST was performed by means of satellite thermal bands—Band 6 for Landsat 5, and Bands 10 and 11 for Landsat 8. The satellite imagery for Muzaffargarh, Pakistan, experienced knowledgeable preprocessing, which comprised mosaic generation and geometric correction.

Satellite data was transformed into real-world spatial coordinates during image processing by applying the WGS 1984 datum and the Universal Transverse Mercator (UTM) projection system. Table 2 shows the full sequence of image processing and analytical procedures used in this LST:

Step no. 1: Conversion of DN values to the spectral radiance by using the equation

$$\mathbf{L\lambda = ML{*}Qcal + Al}$$

$L\lambda$ is the cell value as radiance (Ebaid 2016). ML is the radiance multi-band value, Al is the radiance add band value, and Qcal is the thermal band used in it.

Step no.2: Radiance values from the TM 5 / L8 thermal band were then changed to radiant surface temperature, that is, top-of-atmosphere brightness temperature, using thermal calibration constants (Ebaid 2016) by the given equation:

$$\mathbf{TB = K2/ln(K1/L\lambda)+1)}$$

Step no.3: In the very last step in we got the outcomes that are the temperature, which was in kelvin, converted into Celsius (C°) through this equation:

$$\mathbf{T= T(K)-273.15}$$

Table 2. Processing steps, as well as the conversion of DN numbers to LST

Processing Steps	Formulas	Explanation
Conversion of DN (Digital Number) to At-Satellite Brightness	TB = K2/ln(K1/Lλ)+1)	• K1 Band specific thermal conversion constant (in watts/meter squared *ster*µm) • K2 = Band-specific thermal conversion consta nt (in kelvin) • Lλ =spectral radiance at sensor aperture meas ures (in watts/ meter squared *star*µm) • λ =wavelength of emitted radiance • ρ =h*c/σ (1.438*10^-²m-K)

Temperature.		• h=Plank's Constant (6.62*10^-34 j-s) • σ = Boltzmann Constant (1.38*10^-23 j/K) • c =velocity of light (2.998*10^8 m/s) • ε =emissivity, which is given at: ε = 1.009+0. 047 ln(NDVI)
Calculation of Land Surface Temperature in Kelvin	T=TB/[1+(λ*TB/ρ)/lnε]	• T = land surface temperature in Kelvin • Tc = land surface temperature in Celsius.
Conversion from Kelvin to Celsius	Tc = T – 273	

The Normalized Difference Vegetation Index (NDVI) is one of the most extensively used and reliable vegetation indices for monitoring plant health and assessing drought conditions (Whig et al. 2024). Tucker and Choudhury applied it to drought monitoring for the first time in 1987. In this study, vegetation-related features were extracted from the Muzaffargarh district 3-band satellite imagery using the NDVI technique.

NDVI = (NIR- RED)/(NIR+RED)

Or

NDVI = (Band 5 – Band 4)/(Band 4 + Band 5)

NIR signifies near-infrared reflectance, and RED characterizes red reflectance. This ratio demonstrates the difference between healthy vegetation, which strongly reflects NIR and absorbs RED, and stressed or non-vegetated surfaces, which do not exhibit this spectral behavior. Using this index on Landsat satellite imagery, variations in vegetation cover across space and time were successfully identified, allowing for a detailed assessment of vegetative stress and potential drought conditions in the region.

Variations in land use and land cover (LU/LC) pose a threat to our comprehension of environmental change on a global scale. In this study, supervised classification of LU/LC dynamics in the Muzaffargarh district was carried out using ArcGIS 10.5.

- The process began with the satellite images being organized. For each tile, multispectral images were formed by combining Landsat 5 bands 1–6 and Landsat 8 bands 1–11. After extracting the study area from the larger dataset, a mosaic process was carried out using a reliable spatial reference system.

- To confirm the land features in the study area, ground truthing was carried out by superimposing a base map in ArcGIS. Initiating the pertinent tool and generating training samples in polygonal form over the removed image tiles was the first step in supervised classification. Water, vegetation, and built-up areas were the three main LU/LC categories into which these samples were detached. After that, a GCS (Geographic Coordinate System) signature file encompassing the training data was saved.
- Importing the GCS signature file into the ArcGIS workspace was the last step by step. Applying the symbology of the layer, each land cover class was given a distinct color: brown for built-up areas, green for vegetation, and blue for water bodies. The inclusive distribution of land cover and its variations over time were accurately and clearly represented by this classification.

Results

Abundant geospatial analyses, such as the Index of Normalized Difference Vegetation (NDVI), Land Surface Temperature (LST), and supervised classification for Land Use/Land Cover (LU/LC) mapping, were performed using the Landsat satellite sequence. To confirm outstanding spatial resolution, all maps were made at a scale of 1:10,000. Agricultural and meteorological drought risks have been mixed to generate a composite risk map, which demonstrates that the study area is likely to knowledge compounded hazards due to the convergence of these drought categories.

Land cover change

In this study, LU/LC variations were analyzed using a supervised classification method, chiefly applying the Maximum Likelihood Classification (MLC) technique. The land cover was classified into three major groups: water, vegetation, and built-up areas, by normal remote sensing classification practices. The investigation of the Muzaffargarh district over 16 years (2002-2018) exposes a significant change in land use patterns.

The most notable change is rapid urbanization, which has resulted in a significant increase in built-up areas. This trend coincides with both population growth and the arrival of refugees in the region. As urbanization has increased, vegetative cover has decreased, indicating a significant shift in land use. These spatial changes are displayed by LU/LC maps created with ArcGIS 10.5. Although the built-up area has grown, vegetation still occupies a larger portion of the district. However, the consistent decline in vegetation suggests a possible change in local climatic conditions, particularly an increase in land surface temperature. This pattern demonstrates a direct relationship between land use changes and the risk of meteorological drought, which can lead to agricultural drought. The temporal LU/LC maps for 2002 and 2018 show in Figure 4 visual evidence of these changes, emphasizing the importance of sustainable land management in mitigating environmental risks.

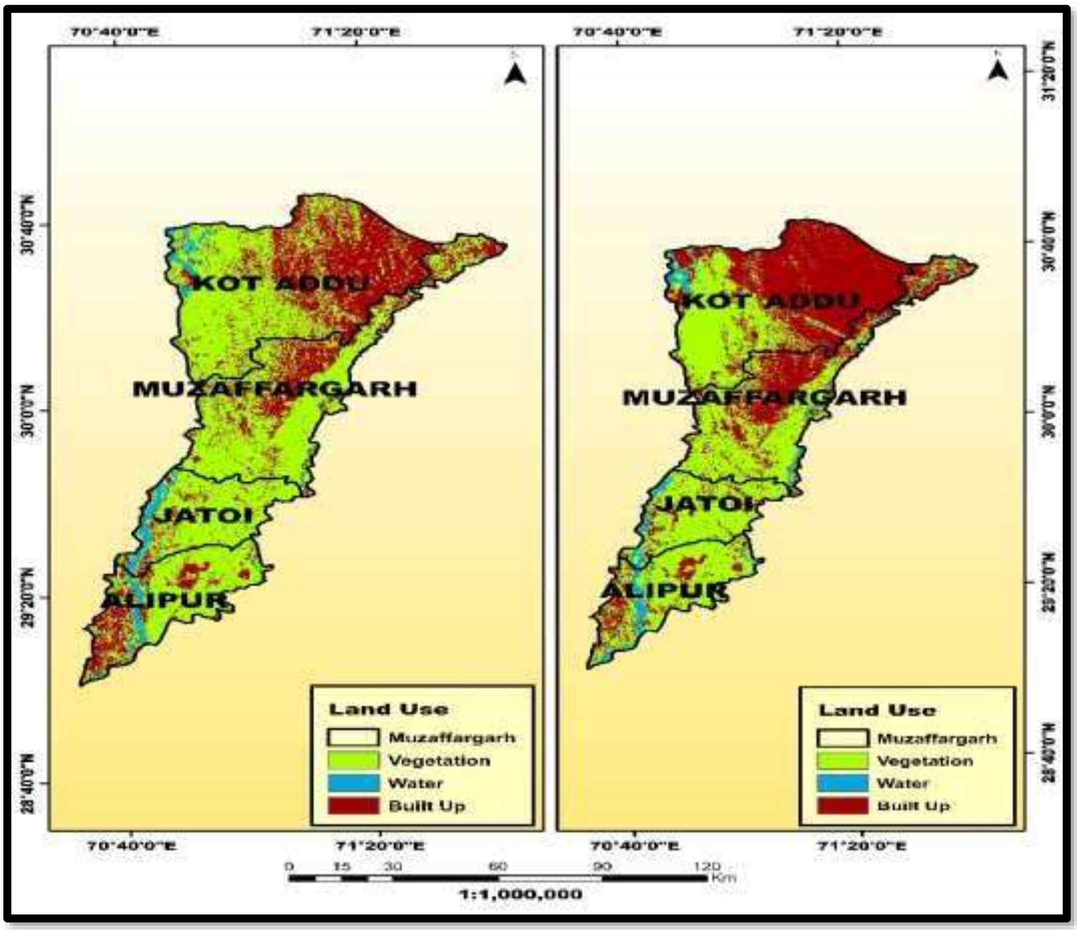

Figure 4: *Temporal Variation in Land Use Mapping (2002-2018)*

Land surface temperature (LST)

Globally, urban temperatures have been steadily increasing (Patel and Patel 2024). Several studies have used satellite-based measurements to accurately calculate Land Surface Temperature (LST) (Mustaquim 2024). The present analysis shows in Figure 5 a significant increase in maximum temperature from 38.77 °C in 2002 to 42.54 °C in 2018. The line Graph 1 and 2 depicts the trend in average maximum and minimum land surface temperature (MMaxT and mminT) for the years 2002, 2008, 2013, and 2018. This consistent temperature rise indicates an increasing risk of meteorological drought. Furthermore, the rise in LST has had a direct impact on vegetation health and coverage, accelerating the onset of agricultural drought.

Over the 18-year study period, the maximum Normalized Difference Vegetation Index (NDVI) value decreased significantly, from 0.989 in 2002 to 0.576 in 2018. This decrease reflects the declining vigor and extent of vegetative cover, particularly cropland, which is extremely vulnerable to climatic stress. A comparison of NDVI and LST maps reveals that the study area experienced increasingly dry conditions in 2018. The spatial correlation between rising surface temperatures and declining vegetation highlights throughout Table 3 the region's increased vulnerability to drought, emphasizing the importance of proactive mitigation strategies and sustainable land management practices.

Table 3. Summary of Land Surface Temperature (LST)

Year	LST Value (C°)	
	Maximum	Minimum
2002	38.77419	21.012
2008	38.7097	21.324
2013	39.4871	21.42
2018	42.5432	21.54

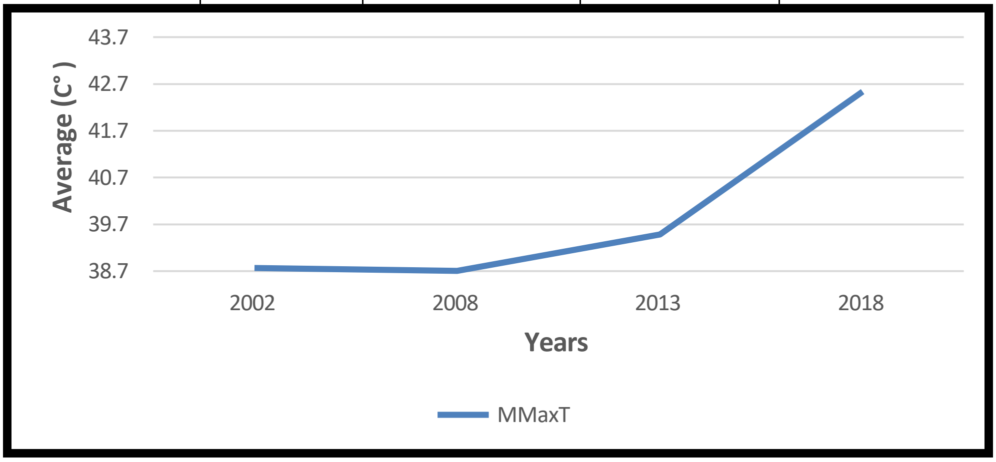

Figure 5: Temporal variation in maximum temperature of Muzaffargarh in the month of July (2002-2018). (Source: PMD)

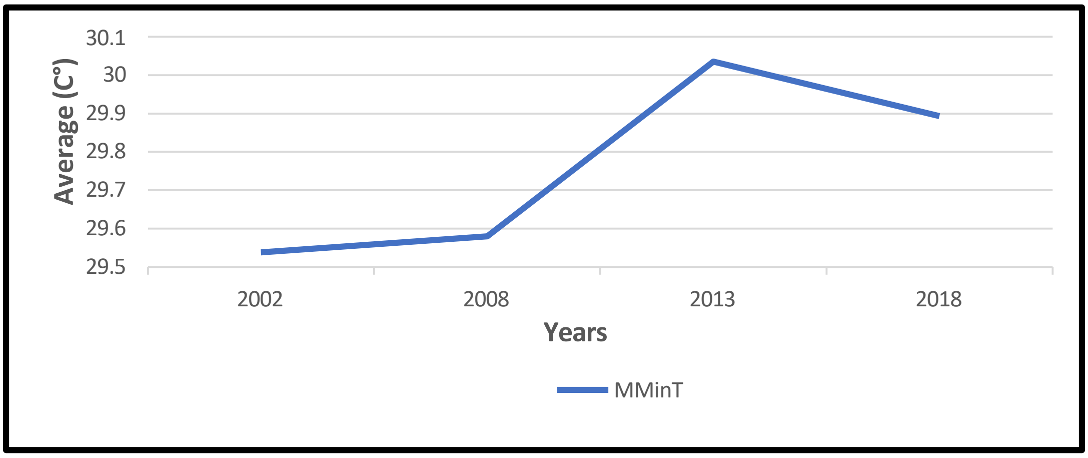

Figure 6: Temporal variation in minimum temperature of Muzaffargarh in the month of July (2002-2018). (Source: PMD)

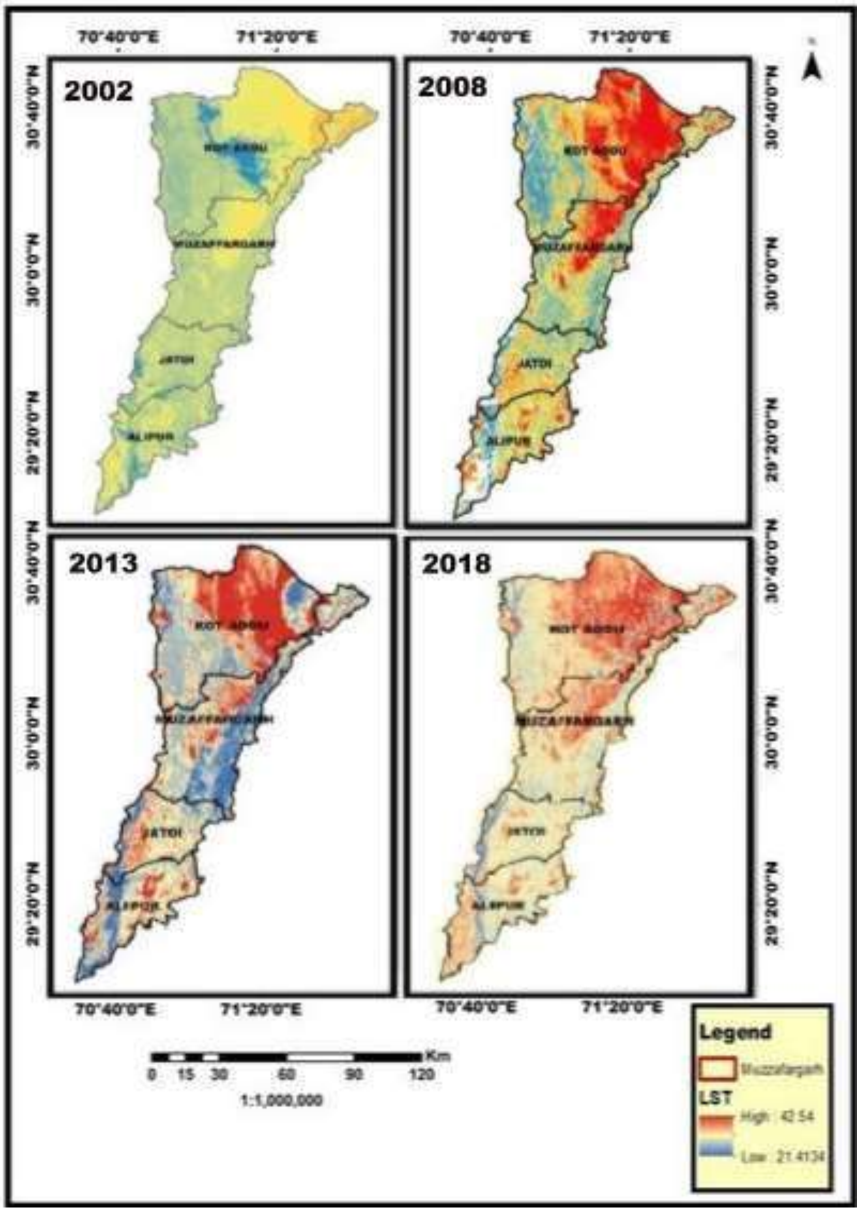

Figure7: *Temporal Map of Land Surface Temperature (LST) (2002-2018*)

Normalized difference vegetation index (NDVI)

NDVI was used to derive vegetation cover classes, allowing for the identification of spatial and temporal variations between 2002 and 2018. NDVI values fell dramatically during this time, from a high of 0.989 in 2002 to 0.576 in 2018, indicating, through Figure 6, a significant decline in vegetation health and density. This decline is primarily due to climate change, specifically rising atmospheric and land surface temperatures. According to international classification standards, much of the study area has shifted from moderate vegetation to increasingly dry conditions, as shown in Table 4. This shift indicates an increased risk of agricultural drought, which could harm crop productivity and local livelihoods. The observed trend emphasizes the critical need for climate-resilient agricultural practices and sustainable land use planning.

Table 4. Classification of NDVI

NDVI Ranges	Drought
<0	Extreme Drought
0-0.2	Dry
0.2-0.4	Moderate
0.4-0.6	Wet
>0.6	Extreme Wet

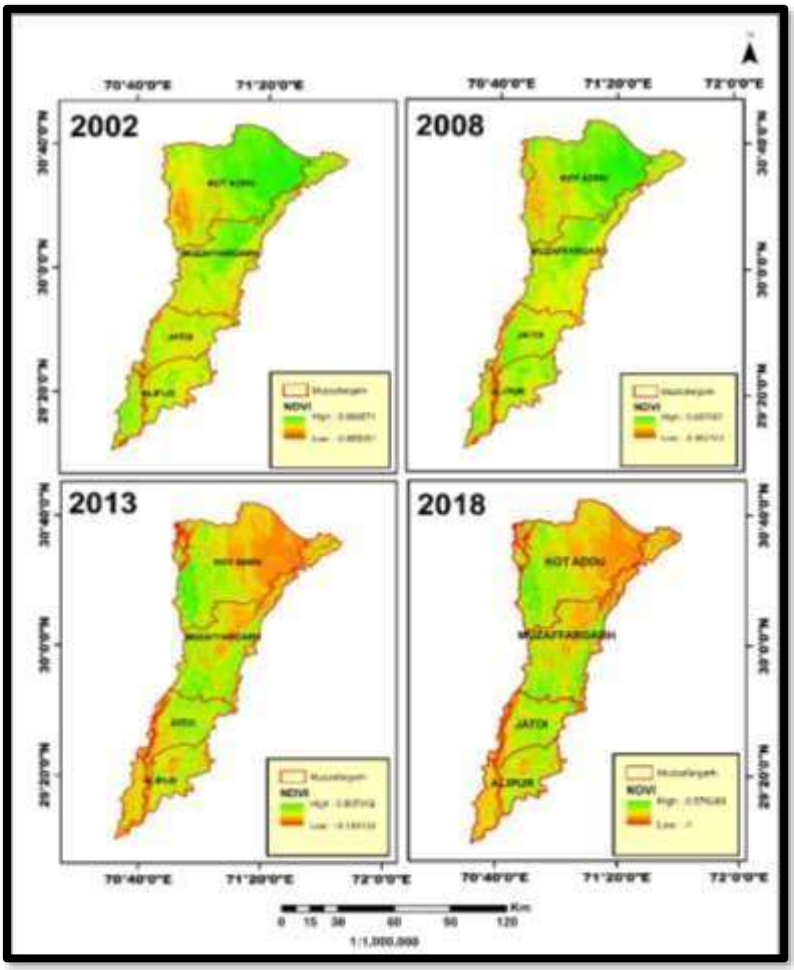

Figure 8: *Temporal Variation in Normalized Difference Vegetation Index (NDVI)*

The NDVI values in Muzaffargarh District indicate as well in Table 8, a clear decline i n vegetation health over time. The maximum NDVI values for 2002 and 2008 were relatively high (0.989 and 0.987, respectively), indicating dense and healthy vegetation cover. However, by 2013, the maximum value had fallen significantly to 0.507, with only a slight recovery to 0 .576 in 2018. Similarly, minimum NDVI values indicate increased vegetation stress, with the lowest value recorded in 2018 (-1.0). These trends indicate a consistent degradation of vegetat ion cover, most likely due to rising temperatures, urban expansion, and climatic stress, implyi ng an increased risk of agricultural droughts.

Table 5. Summary of Normalized Difference Vegetation Index (NDVI)

Year	NDVI	
	High	**Low**
2002	0.989071	-0.98305
2008	0.987097	-0.98214
2013	0.507312	-0.12913
2018	0.576289	-1

Correlation and linear regression analysis were performed between NDVI and LST anomaly. Graph 3 displays a clear view that there is an inverse correlation between land surface temperature (LST) and normalized vegetation index (NDVI). This directly indicates the risk of drought in this research target area. The graph demonstrates a negative linear relationship between temperature and NDVI, represented by the regression equation:

$$y=-0.0924x+4.4492$$

This means that for every 1°C increase in temperature, the NDVI drops by about 0.0924 units, indicating a decline in vegetation health.

- The coefficient of determination ($R^2 = 0.4167$) indicates a moderate negative correlation. Temperature changes account for approximately 41.67% of the variation in NDVI.
- The NDVI values decrease as the temperature rises from 38.77°C (2002) to 42.54°C (2018), indicating that vegetation cover and surface temperature are inversely correlated.
- This tendency supports the theory of increased drought risk, which holds that vegetation stress, a decline of greenness, and possible agricultural drought are caused by increasing temperatures.

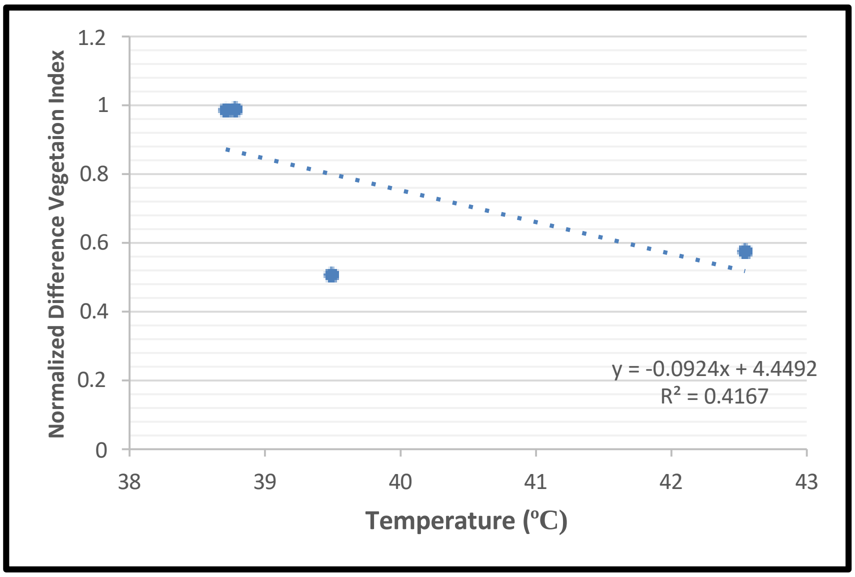

Figure 9: *Correlation between Land Surface Temperature and Normalized Difference Vegetation Index*
(Source: PMD)

Discussion

This study's objective was to measure the Muzaffargarh district's risk of agricultural and meteorological drought using geospatial methods. A mutual occurrence worldwide, droughts have distressing belongings on agriculture, ecosystems, and socioeconomic systems (WHO 2021). The absence of long-term, high-resolution rainfall data for the target area was a component of the study's restrictions. Nevertheless, this limit was addressed by using satellite-derived indices like the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and Land Use/Land Cover (LULC) classification. To professionally map and track situations of drought, a amount of studies have employed NDVI and LULC analysis (Mahajan and Dodamani 2015). Forest and shrubland areas have progressively decreased over time, according to historical trends in land cover shifts, while agricultural land, built-up areas, and water bodies have improved (Gandhi et al. 2015). In this study, a alike trend was detected, with supervised classification of LULC data and NDVI analysis revealing a gradual decline in vegetation cover from 2002 to 2018, representing increased agricultural drought vulnerability.

LST has been widely used in prior studies as a proxy for surface moisture circumstances and drought risk (Latha 2021). Our analysis reveals a rising trend in surface temperatures across the district, typically in recent years, which further supports the presence of meteorological drought. The inverse relationship between NDVI and LST, also engrained in earlier studies (Mahajan and Dodamani 2015; Sun and Kafatos 2007), was validated settled regression analysis in this research. The negative correlation experiential through the summer season strengthens the notion that improved surface temperatures contribute to vegetation stress and decline. Overall, the integration of NDVI, LST, and LULC data brings a comprehensive thoughtful of drought dynamics in Muzaffargarh. This approach not only enables spatial identification of drought-prone areas but also offers a scientific basis for developing risk mitigation strategies. Such multi-source geospatial analyses are energetic for effective drought monitoring, early warning systems, and adaptive land management planning under changing climatic circumstances (IPCC, 2023).

Conclusion

Prolonged precipitation deficiencies, or drought, pose thoughtful problems for agriculture and the situation. By pursuing agricultural and meteorological droughts using geospatial tools like the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), this study measures the risk of drought in the Muzaffargarh District. It has been demonstrated that declining rainfall lowers NDVI values, suggesting the beginning of drought and vegetation stress. From 2002 to 2018, research was led in Muzaffargarh, which is situated between the Chenab and Indus rivers. In accumulation to notable land use moves from vegetation to built-up areas, the results validate a steady rise in surface temperatures and a consistent decline in vegetation cover. This trend designates which drought vulnerability is increasing. Regression analysis demonstrates that LST and NDVI have an inverse relationship, highlighting surface temperature rise as a key factor influencing the risk of agricultural and meteorological drought.

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Flood Risk Reduction Using Integrated Community-Based Disaster Risk Management and Geo-Spatial Approaches in Gin River Basin, Sri Lanka

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Abstract

Floods present considerable risks to the sustenance of livelihoods, infrastructure, and social fairness within the Gin River Basin, Sri Lanka, necessitating an integrated methodology for efficient risk mitigation. This article investigates the implementation of Community-Based Disaster Risk Management (CBDRM) combined with geospatial techniques to reinforce community resilience and involvement in reducing flood hazards. Encompassing an area of 932 square kilometers, the research site displays various climatic conditions impacted by monsoons and diverse topography spanning from mountainous forested inclines to agricultural floodplains. The methodology involved the selection of 100 households and stakeholders for data collection through quantitative surveys and qualitative interviews, focusing on demographic characteristics, livelihood trends, flood impacts, and coping strategies. Data was acquired from both primary and secondary resources, encompassing governmental publications and hydrological observation stations. The Delphi method was employed to enhance the CBDRM model customized for the area. The investigation pinpointed crucial socio-economic variables influencing community engagement in flood risk governance. The outcomes of the study underscored the recurrent flood occurrences intensified by climate variations, underscoring the necessity for a multifaceted strategy encompassing both physical and non-physical interventions. The strategy for lessening flood risks integrates traditional local knowledge, participatory risk evaluations, and sophisticated geospatial technologies like OpenStreetMap for instantaneous flood delineation. Proposed physical interventions involve the establishment of new sluices, refurbishment of pump houses, and the erection of flood embankments, while non-structural actions emphasize prompt warning systems, land utilization supervision, and community enlightenment. This holistic approach accentuates the significance of community responsibility, regional proficiency, and sustainable developmental techniques in augmenting flood resilience. The findings aim to enhance the wider conversation on disaster risk reduction and provide practical solutions for managing flood hazards in the Gin River Basin.

***Keywords**:* CBDRM, demographic, DELPHI, flood hazards, flood resilience

Introduction

The Millennium Development Goals (MDGs), adopted globally in 2000, highlight the importance of addressing vulnerability, disaster management, and risk assessment in development (WMO, 2017). Disasters, both large and small, can undo years of progress, severely impact livelihoods, and increase the risk of extreme poverty, disease, and poor health. Floods, in particular, are frequent hydrological disasters causing significant economic damage, threatening human lives, and disrupting infrastructure. Their impacts on businesses, public services, and the environment exacerbate social and economic inequalities, affecting community resilience and participation in flood-risk management. Effective community involvement in disaster risk reduction (DRR) requires understanding the socio-economic factors influencing participation, such as poverty, education, and access to services (Ashvin et al., 2021).

This paper attempts to address the importance of enhancing community resilience is underscored by Sri Lanka's experience in DRR over the past two decades. Despite traditionally high resilience, government and civil society efforts have primarily focused on preparedness and recovery, affecting attitudes and knowledge about disaster risk (David, 2021). Community-based institutions play a crucial role in managing flood risks, with indigenous knowledge providing valuable coping strategies. For instance, in Bangladesh, communities adapt by raising houses and storing emergency provisions. Sri Lanka, frequently affected by floods, experiences significant disruptions and damage during monsoon seasons (Pakneshan et al., 2023). Understanding the magnitude and frequency of floods is essential for effective planning and management. Models like the disaster-resistant and disaster-resilient communities emphasize minimizing vulnerability and enhancing community participation in DRR efforts (Chamal et al., 2023).

Research objectives

The main objective of this study is to determine Flood Risk Reduction using integrated Community-Based Disaster Risk Management and Geo-spatial Approaches in GIN River Basin, Sri Lanka. The sub-objectives of the study are to analyze the flood risk reduction in the Gin River area, prepare a flood risk reduction plan using integrated community-based disaster risk management (CBDRM) and geospatial approaches, and to align the CBDRM with a suitable existing model of flood risk reduction.

Study area

The study area, as delineated by latitudes 6°18'-6°24'N and longitudes 80°19'-80°35'E, encompasses the Gin catchment, situated between longitudes 80°08'E to 80°40'E and latitudes 6°04'N to 6°30'N, covering an estimated area of 932 square kilometers. The climatic conditions in this region are shaped by the influence of the southwest monsoon (May to September) and the northeast monsoon (November to February), interspersed with inter-monsoon showers during the remaining months. Precipitation levels exhibit variation in accordance with elevation, ranging from more than 3500 mm annually in the upper regions to below 2500 mm in the lower areas. (Salajegheh, 2013) The catchment area, entirely situated within the wet zone, showcases mountainous forested slopes in the higher elevations, while the middle and lower parts feature human habitation, agricultural activities, and forested areas. Thawalama, positioned in the mid-section of the catchment, primarily comprises human settlements and cultivated lands within the expansive floodplain of the Gin River (Wickramaarachchi, 2016). This zone borders the Sinharaja Rain Forest, a designated natural world heritage site, and incorporates anthropogenic practices like tea and rubber cultivation, domestic gardens, and regenerated forests.

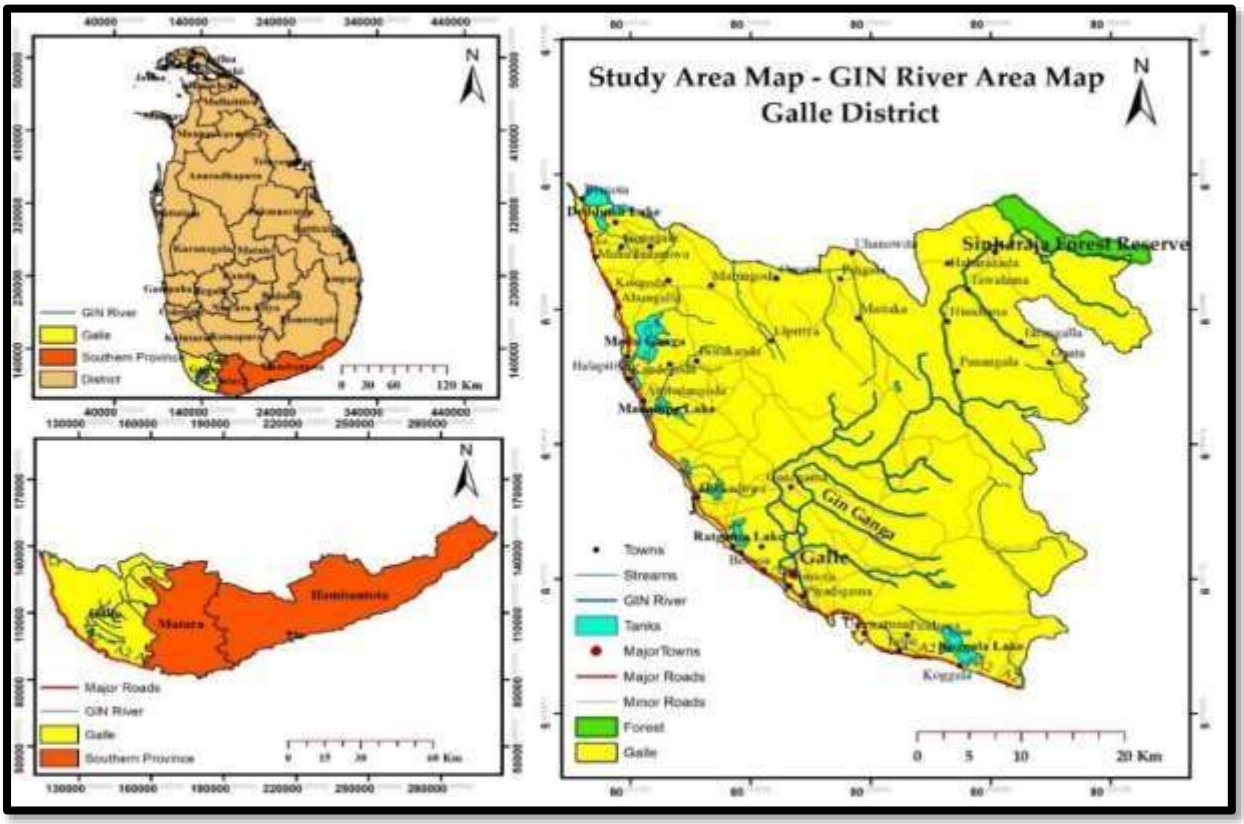

Figure 1: Study Area Map

Topography

The geographical features of the locality are defined by steep-sided, northwest-oriented strike ridges and valleys, characterized by basement rocks comprising highly resistant Precambrian metamorphic formations. The flow patterns of tributary streams are influenced by geological formations, where smaller streams rely on seasonal precipitation, whereas larger streams exhibit perennial flow. The Gin River basin, classified as a fifth-order stream, spans an area of 947 square kilometers with a river length of 112 kilometers, originating from elevated terrains exceeding 1300 meters (Kumari et al., 2018).The data for this research endeavor was obtained from the hydrological monitoring station at Thawalama (6°20'33"N, 80°19'50"E), covering an upstream catchment area of 470 square kilometers. (Dennis et al., 2019). The average annual precipitation within the catchment region is around 3,200 mm.

Material and Methods

The methodology involved purposively selecting 100 households, institutions, community leaders, and practitioners at household, district, and community levels due to time and financial constraints. Both quantitative and qualitative approaches were used to study community-based disaster risk management (CBDRM), focusing on disaster preparedness and recovery. Data collection methods included narrative literature review, secondary data (e.g., government reports), and primary data (e.g., interviews, focus group discussions, key informant interviews, and field observation). The Delphi technique was employed in three stages to refine the final CBDRM model for the Gin River basin (Hua et al., 2020).Quantitative data was gathered through household questionnaires covering demographics, livelihood patterns, flood impacts, vulnerable groups, and coping strategies. Qualitative data was collected via key informant interviews with district-level stakeholders, NGOs, religious institutions, and community representatives, discussing topics such as livelihood patterns, income sources, flood impacts, vulnerability causes, coping strategies, and development options (Ekeu-Wei, (2018).

Data Analysis

The disaster risk reduction method consists of six consecutive steps that can be used either in advance of or during a disaster to lower risks in the future. Each stage develops from the one before it and leads to additional action. The stages in the disaster risk reduction process are given in the figure below:

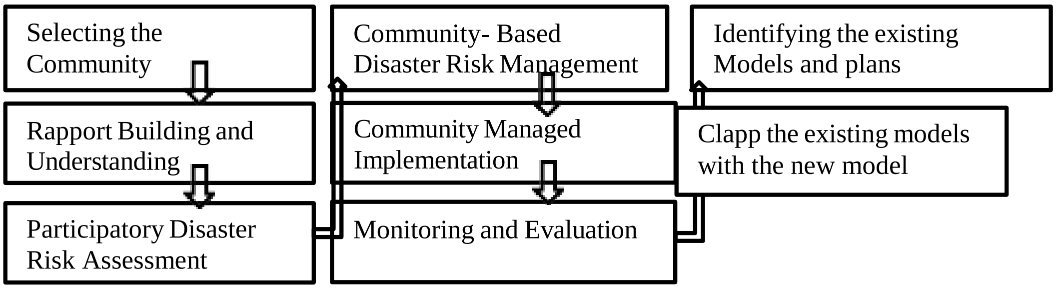

Figure 2: Disaster Risk Reduction Process (Adpc 2006)

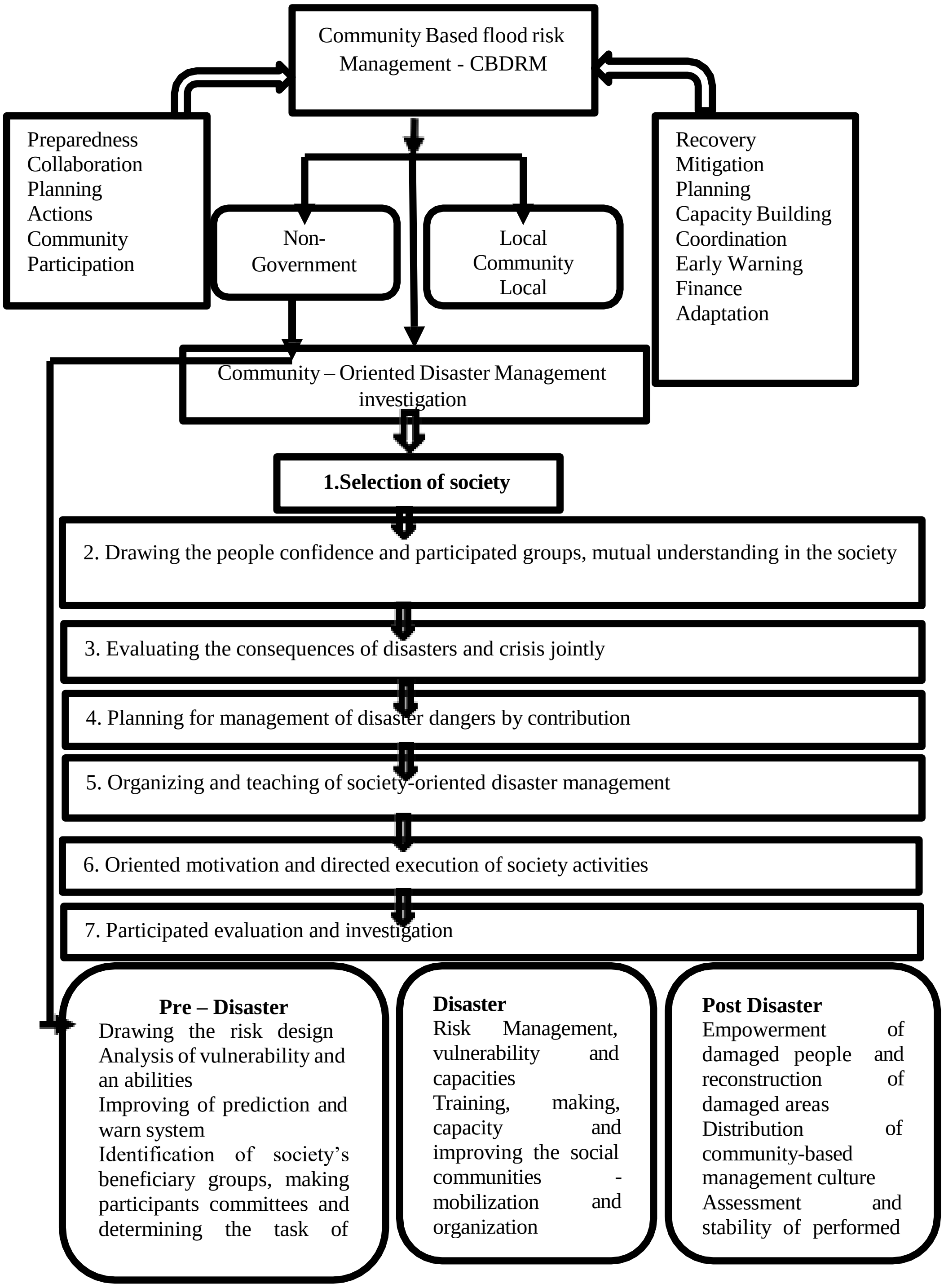

Figure 3: Methodological Framework

Results

However, the area is prone to recurring flood events, posing significant challenges to both the local communities and infrastructure. As climate change exacerbates weather patterns, the vulnerability of this region to flooding has become more pronounced, necessitating comprehensive studies and interventions to mitigate these risks (JMMU et al., 2020).

Several research endeavors have underscored the multifaceted aspects of flood risk within the GIN River basin. These studies often investigate the complex interplay of environmental factors, land use practices, hydrological patterns, and anthropogenic influences contributing to the heightened flood vulnerability. They explore diverse methodologies encompassing hydrological modeling, spatial analysis, and socio-economic assessments to understand the dynamics of flood occurrences and their impacts on the region. Furthermore, the GIN River basin has witnessed various efforts aimed at flood risk reduction and management. These initiatives span a spectrum from structural interventions such as embankments and reservoirs to non-structural measures like community-based preparedness and early warning systems. The effectiveness of these strategies, their sustainability, and their alignment with local socio-economic contexts form pivotal focal points in the ongoing discourse on flood risk reduction in this region (Kanchana et al., 2020).

This paper aims to synthesize and critically analyze existing research on flood risk reduction in the GIN River area of Sri Lanka. By examining the current state of knowledge, identifying gaps, and evaluating the efficacy of mitigation strategies, this study seeks to contribute to the ongoing dialogue on enhancing resilience against flooding in this ecologically rich and socially vibrant region.

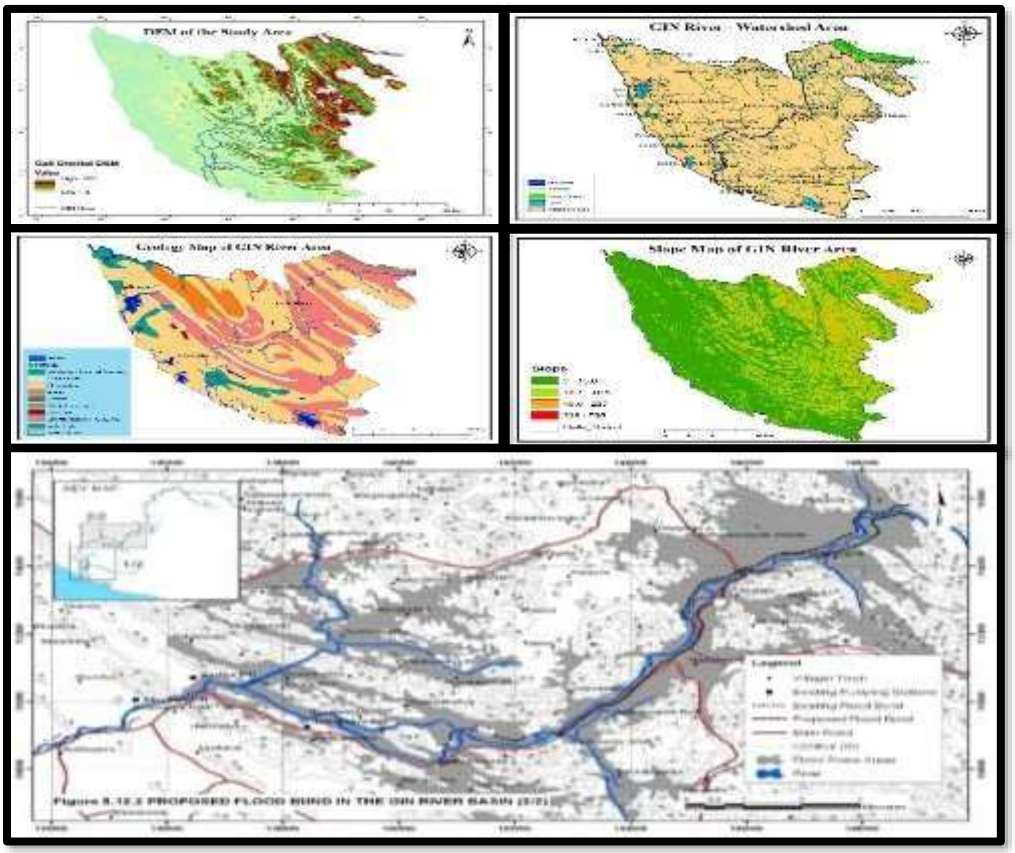

Figure 4: Gin River Area Dem, Gin River Watershed Area, Gin River Slope Map, Gin River Area Geology Map, Flood Prone Areas In Gin River Map

Society Participation

As per the definition provided by the World Health Organization (WHO) in 2002, community participation is characterized by individuals actively engaging in decision-making processes, identifying pertinent issues, and executing development policies and services (WMO. 2017). This approach enables individuals to exert influence on the design of development initiatives, decision-making processes, and the allocation of resources. Participation involves collaborative decision-making and societal supervision, covering all essential activities required to address present needs. It capitalizes on the inherent capacities of individuals, granting them the ability to effectively oversee their health and manage their lives through the acquisition of knowledge, skills, and self-assurance (Sadegh Nejad, 2009). To participate people in society, the different roles are determined for people which are as fallow:

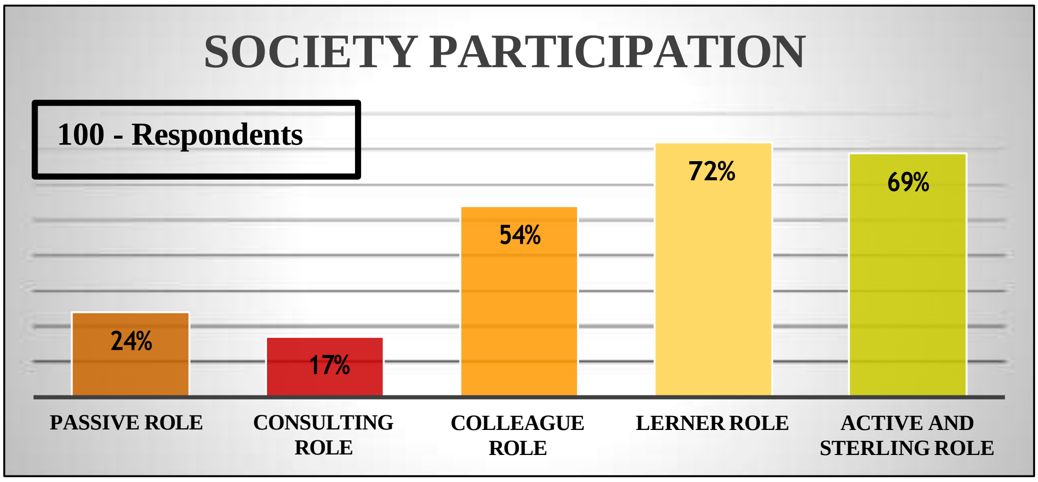

Figure 5: Society Participation (Source- Compiled by Author, 2022)

- **Passive role:** fallowing and obeying of rules and plans of decision makers and lawmakers
- **Consulting role:** using of people views
- **Colleague role:** people cooperation in management processes
- **Lerner role:** learning knowledge and necessary skills for people interventions
- **Active and sterling role:** people cooperation as a partnership (Jahangiri, 2010)

In flood analysis within the GIN River area, various socio-economic factors significantly impact both the vulnerability of communities to floods and the subsequent recovery and resilience-building efforts (Rojanamon et al., 2009).

Community-based flood disaster risk management is crucial in Sri Lanka to enhance resilience and preparedness against the frequent flood hazards that pose a threat to the nation. The damage inflicted on structures and infrastructure by floods underscores the necessity for integrating disaster risk reduction (DRR) mechanisms within the current systems. Despite the advocacy for sustainability by the Green Building Council of Sri Lanka, the complete integration of DRR into its framework remains incomplete. Consequently, Community Disaster Management Committees (CDMC) are being formed in at-risk areas such as the Gin River region. (Perera, B, H, N., Wickramaarachchi, N, C., 2022) These committees offer DRR information, carry out vulnerability assessments, and provide training for effective disaster preparedness and response. Furthermore, there is a development of multi-stakeholder networks to facilitate the exchange of knowledge between government bodies and flood-prone communities.

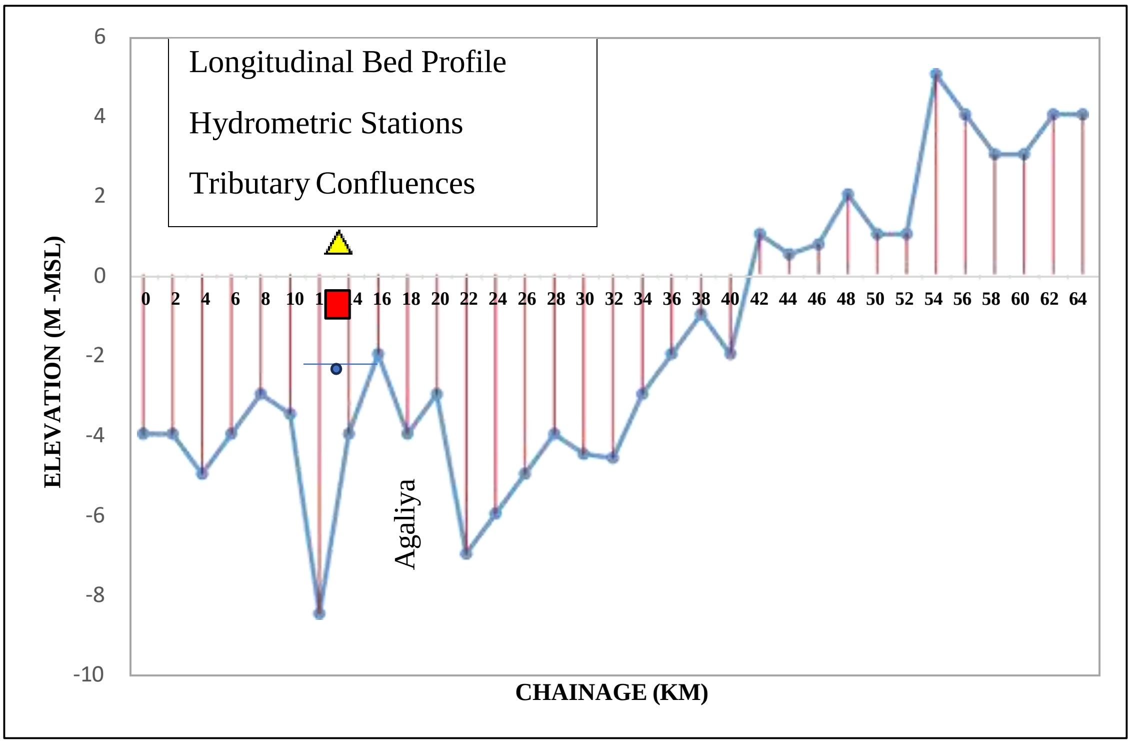

Figure 6: Longitudinal Profile of Gin River (Source: LHI, 2021)

Diverse methodologies are being utilized to effectively involve communities in flood disaster risk management. These methodologies encompass Participatory Risk Assessment (PRA), Vulnerability and Capacity Assessment (VCA), community hazard mapping, and the establishment of community-based early warning systems. Additional strategies include simulation drills, workshops for capacity enhancement, formulation of community-based disaster management plans, and mobilization of local resources. Attention is also given to gender and social inclusivity, the reinforcement of local institutions, nurturing partnerships, promoting sustainable livelihoods, and engaging communities in recovery and rehabilitation endeavors. These strategies underscore the significance of community ownership and empowerment, utilizing local expertise to bolster flood disaster resilience in Sri Lanka.

Existing flood management Master Plan Gin River Basin

Structural Measures

Table 1: Proposed Major Structures in Master Plan (Gin River)

	Kind of structure	Major dimensions
Short Term	1. New sluices	9 nos.
	2. Rehabilitation of existing pumps	10 pump houses
	3. Mound dike	A=51,000 m^2 (3 sites)

Plan	4. Flood bund	Left bank (L=8,360 m, H=5.4m) Right bank (L=7,620m, H=5.3m)
Long Term Plan	5. Flood bund (heightening)	Left bank (L=8,360 m, H=6.6m),Right bank (L=7,620m, H=6.3m)
	6. New pump house	8 nos.

Non-structural Measures (To proceed in parallel with the short-term plan)

Table 2*:* Non-Structural Measures to be promoted (Gin River) (Source: JICA Study Team)

Measures	Major Items
1. Early warning and monitoringsystem	- 8 rain gauge stations - 5 hydrometric stations
2. Restriction of further development in urban area	- Management and monitoring of land use - Prohibiting housing development in flood prone area - Flood zoning with hazard mapping,
3. Promotion of water-resistantarchitecture	- Heightening of building foundation - Construction of column-supported - Housing, change to multi-storied housing - Water proofing of wall/housing materials, etc.
4. Promotion of flood fightingactivities	- Information dissemination in the communities - Evacuation to safer area, - Removal of properties in house/building, etc.
5. Resettlement	- Mound dike
6. Institutional strengthening ofimplementing agency	- Consensus building for project implementation - Integration with urban development and land use development plans

Flood Risk Reduction Plan Using the Cbdrm and Geospatial Approaches

A plan for reducing the risk of floods has been examined in Sri Lanka using the Community-Based Disaster Risk Management (CBDRM) and geospatial methods. The focus of the research was to identify areas that are vulnerable to flooding and develop models to evaluate the levels of flood risk. The studies integrated different criteria, such as the built environment, physical environment, and socio-economic environment, to categorize vulnerability and assess the levels of risk (Reaves, 2013). Open-Source applications, like OpenStreetMap (OSM), were employed to gather on-site information and identify areas that are inundated by floods. (Dr.Sanjar Salajegheh, 2013) Advanced models were utilized to assess the advantages of local infrastructure adaptation measures and determine the costs of not responding to changing flood risks (Gireesan, 2013). The spatial variations of drought and flood hazards were also analyzed in the Northern Region of Sri Lanka. These studies offer valuable insights and tools for the development of effective plans to reduce flood risks using CBDRM and geospatial approaches in Sri Lanka.

Creating a flood risk reduction plan for the Galle District in Sri Lanka using integrated Community-Based Disaster Risk Management (CBDRM) and geospatial approaches involves a comprehensive and collaborative process. Here's a general outline of the steps Researcher identified by the outputs (Pacific et al., 2008).

Step 1: Understand the Context

Risk Assessment: Conduct a detailed risk assessment of flood-prone areas in the Galle District. This includes identifying vulnerable communities, assets, infrastructure, and natural features that are at risk.

Step 2: Engage Stakeholders

Stakeholder Mapping: Identify and engage key stakeholders, including local communities, government agencies, NGOs, academic institutions, and private sector entities.

Step 3: Data Collection and Analysis

Geospatial Data Collection: Gather geospatial data such as elevation, land use, drainage systems, and flood history. This data will be essential for creating flood hazard and vulnerability maps.

Step 4: Community Participation

Participatory Mapping: Involve local communities in mapping flood-prone areas, safe shelters, evacuation routes, and critical infrastructure. Their knowledge is crucial for accurate planning.

Step 5: Risk Mapping

- Flood Hazard Mapping: Use geospatial data to create flood hazard maps indicating areas at risk of flooding based on elevation and historical flood patterns.
- Vulnerability Mapping: Combine socio-economic data (population density, poverty rates, etc.) with flood hazard maps to identify vulnerable communities and assets

Step 6: Risk Assessment

Integrated Risk Assessment: Combine hazard and vulnerability information to assess the overall flood risk in different areas of the district.

Step 7: Strategy Development

- Community-Based Strategies: Collaborate with local communities to develop strategies tailored to their needs. This could include early warning systems, community training, evacuation plans, and resource mobilization.
- Infrastructure Improvement: Identify critical infrastructure in flood-prone areas and develop plans for upgrading or relocating them.

Step 8: Early Warning Systems

Community Early Warning Systems: Design and implement community-based early warning systems that utilize both modern technology and local knowledge.

Step 9: Capacity Building

Training and Workshops: Conduct capacity-building workshops to enhance community members' skills in disaster preparedness, response, and first aid.

Step 10: Monitoring and Evaluation

Implementation Monitoring: Continuously monitor the implementation of the flood risk reduction plan and gather feedback from the community.

Regular Review: Regularly review and update the plan based on new data, lessons learned, and changes in the flood risk landscape.

Step 11: Collaboration and Coordination

Stakeholder Coordination: Ensure effective collaboration among all stakeholders involved in the plan's implementation.

Step 12: Public Awareness and Education

Community Outreach: Conduct public awareness campaigns to educate the community about flood risks, safety measures, and the importance of their participation.

Step 13: Documentation and Reporting

Figure 7: Identified Flood risk reduction plan for the GIN River Area

Communities and institutions involved in disaster management were forced to take proactive measures to lessen the impact of disasters due to the rising trend of disasters. The Sri Lankan government and other DM actors have begun to recognize the Community Based Disaster Risk Management (CBDRM) method as a fundamental tactic for increasing community capacity and resilience. The Government Road Map and the National Disaster Management Plan have designated Sri Lankan Red Cross Society as one of the primary actors in delivering CBDRM measures (Mohamed et al., 2023).

In accordance with the framework established by the government, SLRCS CBDRM interventions concentrated on conducting participatory risk profiling through evaluations of hazard, vulnerability, and capability, followed by the creation of community risk reduction plans, forming community groups to serve as village disaster management committees, training and outfitting local reaction teams, Identifying and implementing small-scale, community-managed mitigation activities, conducting simulation exercises and drills, installing signboards to indicate safe evacuation routes, executing DM awareness campaigns, and distributing information, education, and communication materials are just a few examples (Miyami et al., 2022).

The CBDRM program includes a school programming that is put in place to foster a culture of readiness within the school community. This entails the creation of a school-based disaster management unit, the creation and training of safety teams, the creation of plans and maps for the reduction of disaster risk at the school level, the execution of disaster mitigation and preparedness operations at the school level, and the conducting of practice drills.

Combining the Gin River Cbdrm Process with Existing Cbdrm Approach Model

The harmonization of the GIN River Community-Based Disaster Risk Management (CBDRM) approach with the participatory methodologies of the Participatory Learning and Action (PLA) model presents a compelling opportunity to fortify community resilience, instigate sustainable solutions, and cultivate an all-encompassing flood risk reduction strategy within the GIN River basin of Sri Lanka. (Wickramaarachchi, 2016) The GIN River CBDRM approach, tailored to the region's specifics, lays the foundation by engaging local stakeholders, leveraging community insights, and pinpointing flood vulnerabilities unique to the basin. (Kodikara et al., 2019). This initiative champions community involvement and context-sensitive strategies to mitigate risks.

Conclusion

In conclusion, the objectives set forth to analyze flood risk reduction in the GIN River area have paved the way for a holistic approach towards managing and mitigating potential flood hazards. By employing integrated Community-Based Disaster Risk Management (CBDRM) techniques alongside geospatial methodologies, a comprehensive flood risk reduction plan has been crafted. This plan considers the unique vulnerabilities of the GIN River area and harnesses suitable existing models of flood risk reduction, thereby fostering a proactive and adaptive strategy aimed at enhancing resilience and ensuring the safety of the communities within this region against the threat of floods.

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Assessment of Risk Factors, Disease Control, and Health-Seeking Behavior of Diabetes Mellitus among Urban Slum Populations

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Abstract

This cross-sectional descriptive study aims to specify the trend, major risk factors, and control of Diabetes mellitus (DM) patients in urban slum areas. A significant progression in adult populations globally has made it a major public health issue and a disaster of recent times. Lack of awareness, social constraints, and absence of community participation to address this public health issue contributed to a socio-economic burden on society. The study concluded the trends, major risk factors, and behavior regarding Diabetes Mellitus. A total of 164 males and 211 females were included in the study with a median age of 53.03 years. Following demographic information, the risk factors, duration of DM presence, practice regarding control, type of treatment taken, and the medical advice to manage the disease were observed as variables of the study. Risk factors such as hypertension 65%, dyslipidemia 41%, obesity 29%, and ischemic heart disease 33% were observed significantly. A high ratio of 62% among the study population did not control the disease properly. Only 35% of people knew the presence of the disease for 6-15 years. Only 26% of participants visited a general physician for medical advice regarding DM. Diabetes mellitus needs to be addressed due to lack of awareness, poor perception, and behavior among the diabetic community of urban slum areas. Further study on a large scale, considering a larger sample size and expanding the community area, may be helpful to establish guidelines to fight against this public health disaster.

Keywords. Diabetes mellitus, prevalence of diabetes, diabetic complications, diabetic awareness, urban slums communities

Introduction

Diabetes Mellitus (DM) is a non-communicable chronic disease also termed hyperglycemia, which is a raised blood glucose level in the body. This is because of the condition referred to as insulin resistance, in which insulin is not produced or does not work properly to convert glucose into energy. The main types of DM are listed as type 1, type 2, and gestational diabetes (Khali & Azar 2024; Solomen & Chew, 2017)**.** This is estimated at present that about 537 million (3 in 4) of the adult world population are living with DM, and this number is specifically rising so predicted that 643 million in 2030 and 783 million by 2045, as stated by IDF Diabetes Atlas. This scenario is more alarming in low and middle-income countries than in high-income countries. Another big challenge to global health is that DM is more prevalent globally due to the fact to remain the condition is uncontrolled or untreated (Mishra & Pandey, 2024)**.** According to IDF, the prevalence of DM in the adult population in Pakistan, by 2021 is about 12-13 million (12.3%, 1 in 8 adults) and expected to rise to around 18-19 million (15.4%, 1 in 6 adults) by 2045.

This alarming condition made Pakistan a more targeted point regarding DM progression among the general adult population (Basit & Fawad, 2018). The adult diabetic population nearly 44.7% are living as undiagnosed and this is a cause of a global burden of socioeconomic scenario and needs to be addressed regarding effective prevention, early detection, and proper management of diabetes (Wali, Rafique, 2020; Tokhirovna, 2024). There are several risk factors of DM, are known as non-modifiable risk factors including family history, age, and ethnic background, but modifiable risk factors are a sedentary lifestyle, smoking dietary behavior, cardiovascular issues, hyperlipidemia, excessive alcohol consumption, and mental stress (Wang & Li,2021). Complications of DM include serious conditions such as microvascular conditions such including diabetic retinopathy, diabetic nephropathy, and diabetic neuropathy, as well as macrovascular conditions, such as cardiovascular issues, stroke, and peripheral arterial diseases. Additionally, the population suffering from DM is expected to get infections and slower wound healing **(**Casqueiro & Casqueiro, 2012).

In a community-based study conducted in Nepal, hypertension was recorded as the leading risk factor for DM, in the list of global disease burdens of a public health issue of underdeveloped countries found as 29.4%, in this study, while 25% of individuals suffered from hypertension and < 50% were known about their disease[i]. In the Chinese population, the rate of hypertensive conditions evolved to 26-29% among the adult population (Swedish Council on Health Technology Assessment, 2008). As a genetic and environmental factor of diabetes, obesity has been found a considerable increase in ratio worldwide (Ruze & Liu, 2023). Obesity and DM have a significant ratio of 29% among our study population mentioned already in the study. DM was also established as a strong risk factor for cardiovascular diseases and available research data explained the high prevalence of CVD as a result of both Type 1 and Type 2 DM and a cause of atherosclerosis as well as heart attack (Heather & Hafstad, 2022). Arterial fibrillation was also established as increasing in prevalence all over the world and a significant risk factor of sudden death in the Type 2 DM population of the older age group

> 75 years of age Mozaffarian, Kamineni, 2009; Volgman, & Nair, 2022). The study conducted by the American Diabetic Association settled a standard protocol to address the behavior, treatment, and comorbid conditions, and in older patients over the age of 65 years, this was established that in kidney diseases, the patient must be evaluated regarding kidney functions, also (Pecoits-Filho & Abensur, 2016).

Longer duration of uncontrolled and untreated DM represents the evidence of more complications resulting from DM (Park, & Cho, 2024). Better diet control established good glycemic control as a result of the best strategy to control Type 2 DM among the adult population, and in the middle age group including the overweight and obese population were best-treated population of higher body mass index which was moderately control of the DM scenario (Chiavaroli & Lee, 2021). The diabetic population has little knowledge about the disease, and 94% of people know about the disease, but only 17% know about the risk factors and preventive measures of DM. The knowledge about the disease was recorded higher among the diabetic population those have diabetes in their relatives and families (Tellawy & Alfallaj, 2021).

Hypertension is a condition with DM type 2 and interlinked with each other, so the prevalence is increasing worldwide due to arteriosclerosis so be considered as an emerging cardiovascular disease (Balakumar & Maung, 2016). Moreover, data expressed that the association between high blood pressure and DM more significant cause of many other cardiovascular complications, so needs to be conscious for the treatment and control of hypertension and diabetes both together (Przezak, Bielka, & Pawlik, 2022). Dyslipidemia is another comorbid condition to be considered in patients with DM, due to the raised value of triglycerides and low high-density lipoprotein cholesterol (HDL-C), which is more prevalent and evident. The finding showed that cardiovascular diseases are also associated and have a high prevalence in the diabetic population (Kaze, & Santhanam, 2021) Ischemic heart diseases like cardiomyopathy, myocardial infarction, and heart attack have high mortality rates with DM type 2, and adopting a standard protocol to monitor diabetes and heart issues on regular basis (Shrivastava & Ramasamy, 2013), (Heather, & Hafstad, 2022). Duration of occurrence of DM is a more prevalent factor about 25% among the population of older age group as a main health burden, so has a higher risk of increasing in frequency in the next decades. This is now established from the data that normally the older age group of population has the more complications because in this group the duration of DM is directly associated with the growing age, eventually greater the age longer the duration of diabetes if present (Huang &

Laiteerapong, 2014; Izzo, Massimino, & Riccardi, 2021). The control of DM is directly associated with the lack of awareness of the disease, and lifestyle also has an impact on the control of DM. An active lifestyle may be very helpful in coping with the effects and complications of diabetes. Research showed that about 23% population takes care of and shows good response to the medication for the treatment of DM (Shrivastava & Shrivastava, 2013). The adherence rate also has a direct impact on treating diabetes among the population with pharmacological ways such as oral medication or insulin, so clinical depends upon the uptake of the machines as medical advice enhances good clinical outcomes (Alharbi & Alaamri, 2023).

The biology of type 2 DM is one of the risk factors, and the absence of enough production of insulin or insulin produced by the pancreas not being able to work properly. Accumulation of fat in the liver due to static lifestyle resulting in physical inactive behavior. Poor hygienic environment, social isolation, sleep disturbance, air, and noise pollution are the strong risk factors of DM. Smoke, green area elimination, burden of traffic cause severe stress, enhancing the disease condition. (Dendup & Feng, 2018). Strong associations of rapid population growth, unhealthy air quality index, urbanization, and thickly populated areas, specifically urban slums, are at high risk of developing worse condition of DM .among adult and especially in old age group in general population (Hankey & Marshall, 2017).

Materials and Methods

This cross-sectional study was conducted among the general population involving 375 individuals with a simple random sampling technique and calculated by the formula,

$$n= Z^2 \text{ (p q) } /d^2$$

$$= Z^2 \text{ p } (1\text{-p})/d^2$$

$$= (1.96)^{2\,\times}\ 70.4\ (100\text{-}70.4)/5^2$$

$$= 30.96 \times 70.4\ (29.6)\ /25$$

$$= 8252\ /\ 25$$

$$= 330$$

With a 10% attrition rate, 330 +33 = 363

For convenience, 375 individuals were included in the study.

All new and follow-up patients residing in urban slums of Lahore visiting Gulab Devi Teaching Hospital Lahore, with known patients of DM type 2, were included in the study for a dilated retinal examination in the eye department. A self-structured questionnaire was used to collect the data, and all patients for the study were interviewed with informed consent. After data collection, data were analyzed on SPSS version 26. Categorical variables were computed and presented in tables, charts, and graphs. In the descriptive analysis, frequency tables were generated. Cross tabulation and association of variables were done by chi-square test, P – P-value < 0.05 was considered as significant. ANOVA was used to analyze the difference between the mean of groups, and an independent sample t-test was used to analyze the difference between the means of two unrelated groups.

Results and Analysis

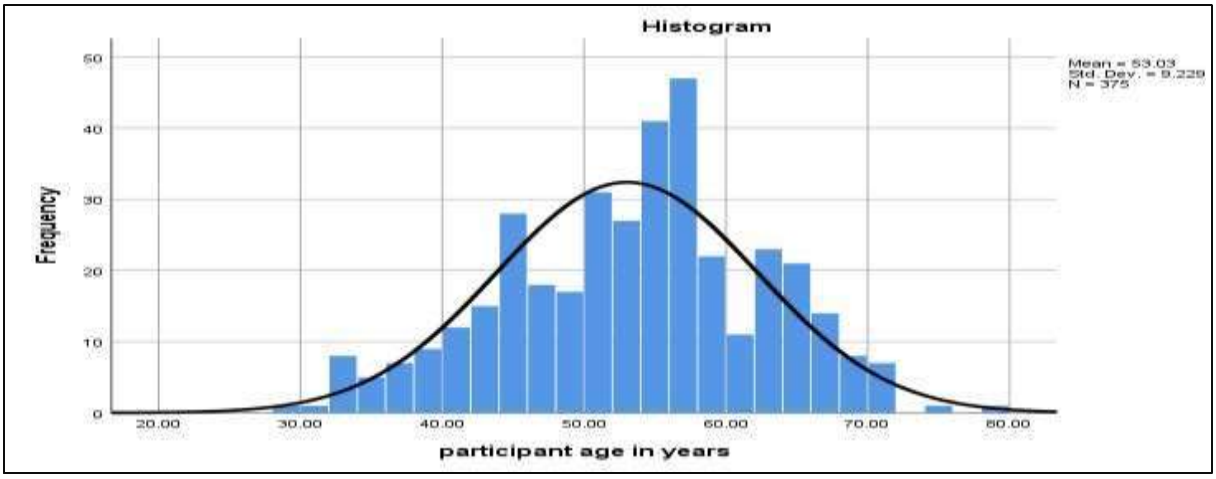

Figure 1: Age Distribution of the Participants

Figure 1 shows the age and gender of the study population and explains that the median age was 53.03 years, with a standard deviation of 9.23. The total number of participants included in the study was 375.

Table. 1 Demographic Presentation of the Participants

	Category	*f*	%
Gender	Males	164	43.73
	Females	211	56.26
Educational Status	Illiterate	132	35.2
	Primary9o78	72	19.2
	Secondary	113	30.13
	Graduate	58	15.46
Profession	Govt. Job	31	8.26
	Private job	35	9.33
	Labor	34	9.06
	Retired	39	10.4
	Housewife	176	46.93
	Unemployed	60	16

Out of 375 participants in the study, 164 (43.73%) were males, and 211(56.26%) were females. The ratio of females was higher than that of males. The educational status of the participants was as follows: 132 (35.2%) illiterate, 72 (19.2%) primary level, 113 (30.13%) secondary level, and 58 (15.46%) were graduate.

The professional status of participants was recorded as Govt. Job 31 (8.3%), Private Job 35 (9.3%), Labor 34 (9.1%), Housewives 176 (56.9%), Retired 39 (10.4%), and Unemployed 60 (16.0%) (Table 1).

Table 2 Major Risk Factors of Diabetes Mellitus

Risk Factors	*f*	%
Hypertension	244	65.06
Dyslipidemia	155	41.33
Obesity	109	29.06
Ischemic Heart Disease	123	32.8

This table explains the co-morbidities of DM, as hypertension was evident in 244 (65.1%), dyslipidemia in 155 (41.3%), obesity in 109 (29.1%), and ischemic heart diseases in 123 (32.8%) (Table 2).

Table 3 Duration of Diabetes Mellitus

Duration in years	*f*	%
3-5	81	21.6
6-10	129	34.4
11-15	128	34.13
16-20	30	8.0
>20	7	1.86

Table 3 shows the duration of the diabetes best known by the individual was observed in the category of 3-5 years 81 (21.6%), 5-10 years 129 (34.4%), 11-15 years 128 (34.1%), 16-20 years 30 (8.0%), and more than 20 years 7 (71.9%).

Table 4 Control of Diabetes mellitus

Control	*f*	%
Very Strict	16	4.26
Strict	126	33.6
Not Strict	230	61.33

Table 4 explains the behavior towards the control of the DM, and data was recorded as individuals who control the disease very strictly were 16 (4.26%), strictly 129 (34.4%), and not strictly 230(61.33%).

Table 5 Type of Treatment Adopted by Individual

Treatment taken	*f*	%
Pills	244	65.06
Insulin	71	18.93
No medication	60	16

The table 5 shows the practice regarding taking any treatment to control the disease as 244 (65.06%) were on oral medication, 71 (18.93%) were insulin-dependent, and 60 (16.0%) were not taking any treatment to control the disease.

Table 6 Visit to General Physician

Visit to Physician	*f*	*%*
Regular	97	25.86
Not Regular	267	73.6
Never	11	2.93

The table 6 shows that participants 97 (25.86%) visited regularly, 267 (73.6%) not regularly, and 11 (2.9%) never visited to physician to take advice for the disease.

Discussion

Awareness and socio-economic status are both directly influencing factors of increasing diabetes in the adult population. (Saeed & Saleem, 2018). In our study, we concluded that the individuals involved in the study were of a median age of 53.03 years with a standard deviation of 9.23, which predicts the condition that the prevalence was significant in the old age group. It was also observed that the ratio of female patients was high at 53% as compared to female participants were 43%. Our data established a higher ratio of 35.2% in the illiterate category, the category of the primary level was 19.2%, and secondary level was 30.1%, the graduate level was recorded as 15.5%. Socio-economic and literacy status were considerable factors in this study. The profession also affects the behavior and practice to control and prevent non-communicable diseases as the busy schedule in many professions, awareness and self-care strategies are the main factors established in studies. (Agha & Usman, 2014) The professional status of participants was recorded in our research, as Govt. Job 31 (8.3%), Private Job 35 (9.3%), Labor 34 (9.1%), Housewives 176 (56.9%), Retired 39 (10.4%), and Unemployed 60 (16.0%). In this study, the highest ratio was recorded among housewives (56.9%), and the second largest group was recorded among the unemployed population. The larger group of housewives was the dominant group of participants in the study.

The comorbidities were experienced in this study, including hypertension 244 (65.1%), dyslipidemia 155 (41.3%), obesity cases 109 (29.1%), and ischemic heart diseases 123 (32.8%). In a study done on Madrid's general population, the comorbid conditions were found to be hypertension 70%, dyslipidemia 67%, and obesity 32%, in the study. (Barrio-Cortes & Mateos-Carchenilla, 2024). This study showed the equal proportions of results as suggested by other researchers. The results found that the duration of DM was also a significant factor in the emergence of many complications. The data has been recorded in this research regarding the duration and presence of the disease as among the categories of 3-5 years 81 (21.6%), 5-10 years 129 (34.4%), 11-15 years (128 (34.1%), 16-20 years 30 (8.0%), and more than 20 years 07 (1.9%). The highest ratio among the group 11-15 years was 34% among the population under observation during the study conducted in this study. Meta-analysis established in a survey declared that the duration of DM is evident due to glycemic conditions among the diabetic population (Stolar, 2010; Hemmelgarn, 2011).

The data regarding behavior among the study population has been recorded to control the diabetic condition as very strict control 4.26%, strict control 129 (34.4%), and not strict control 230 (61.3%), and as in the low-income population, the control of DM type 2 is behavior dependent, so knowledge and practices to overcome diabetes and its complications are significant among diabetic population (Papatheodorou, Banach, 2018). A study established that general health awareness, lifestyle changes, and following the right treatment plan remained good to control diabetes (Gruss & Nhim, 2019). The findings of this study also showed the situation of practice and behavior of the participants regarding control of DM type 2. Our research expressed that only a small group controls the condition, and 61% of individuals were not serious regarding their disease due to lack of knowledge. A larger group was on oral medication, taking medication by mouth 65%, insulin 18.93%, and 16% were not taking any treatment.

The study also witnessed that 11 (2.9%) participants did not visit a general physician, 267 (71.2%) visited but not regularly, while only a small group 92(25.9%) visited regularly for medical advice or treatment. Lack of knowledge and awareness hinders the perception of taking advice on medical care about diabetic control (Nagelkerk, Reick & Meengs, 2006). his is also stated by data that practitioners face difficulties in treating a patient of DM due to a lack of knowledge about the disease. Healthcare providers make decisions while considering DM to treat the patient, so decision-making is very important for the treatment with pills, insulin, or both (Chimoriya & MacMillan, 2024)Furthermore, medical advice acceptance is very crucial for diabetic control as the treatment plan or strategy prescribed by the health care practitioner leads to better control and prevents complications in advanced age if the disease remains untreated or uncontrolled (Najafipour & Farjami, 2021).

The control and prevention of diabetes is a public health concern for the community all over the world as well as regional situations. The practice and perception of controlling the disease is not ideal, and the presence of the undiagnosed or untreated disease is the cause of many complications (Hamid, Akash & Rehman, 2021). Our study strongly overlooked the status regarding complications as a result of untreated or uncontrolled DM type 2 and found a very crucial scenario in which only 15% of participants visited a specialist doctor to take advice regarding any complication introduced as a result of diabetes. This is also evidence of a lack of knowledge regarding diabetes and its complications. The group of participants who did not visit a specialist for an expert opinion regarding complications was as crucial as other groups. This group is also at risk of diabetic complications.

Recommendations

- Establishing a public health issue, specifically among the diabetic community, needs to be considered as a public health disaster due to the increasing mortality rate and compromising quality of life among the diabetic population.
- Lack of awareness is a barrier to controlling and managing the scenario regarding behavior, perception, and practices among the community.
- Further studies may lead to follow-up guidelines to address the issue on a larger scale and benefit the population of other areas.

Limitations of the study

Lack of awareness and socio-economic factors remained the limitations, while follow-up visits. A small sample size was considered for the study, but further research may be continued in the future involving a large sample size, expanding the scope of study at the community level. Due to its significance and severity, this public health issue must be treated as a disaster.

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Analyzing the Impact of Covid-19 on Climatic Condition in Pakistan Using Geospatial Approach

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Abstract

Coronavirus affected the usual trends of environmental factors, globally. This study is an attempt to assess the impacts of COVID-19 on climatic conditions in Pakistan using a geospatial approach. The secondary data is used in this study. For analysis of climatic conditions satellite data of selected climatic factors (wind speed and LST) was collected from openly available websites. The climatic data were downloaded from the MODIS MERRA-2 sensor from EOSDIS Worldview NASA in NC4 File format of wind speed and data of LST from USGS Earth Explorer. The data were processed by using geospatial approaches, such as interpolation (IDW), zonal statistics, and weighted sum. By doing statistical analysis the variations in climatic conditions are assessed. The findings revealed that during the lockdown period variations were observed in climatic conditions due to limitations on anthropogenic and industrial activities. During the lockdown period of the COVID-19 pandemic not only the cases were under control but positive changes in climatic conditions were also observed. During the lockdown period of the pandemic, negative standardized anomalies in LST and wind speed were observed compared to prior years 2018 and 2019. Restriction on anthropogenic activities produces positive changes in environmental conditions.

Keywords: climatic conditions, covid-19, LST, wind speed, lockdown and geospatial approaches.

Introduction

A little cluster of cases of the disease now known as COVID-19 or coronavirus was first detected when a few patients with early symptoms of pneumonia were admitted to hospitals in the Chinese city of Wuhan on December 29, 2019 (Price et al., 2020). Globally WHO (World Health Organization) reported 28,276 confirmed cases with 565 deaths as of February 6, 2020, including at least 25 countries (Wu et al., 2020). Coronavirus was announced as a general public health emergency of International Concern in January 2020 (Bhatnagar et al., 2021) and coronavirus had turned into a global health concern of prime significance, influenced more than

400 million people with 5.7 million confirmed deaths by January 10, 2022 (Praharaj et al., 2022). Coronavirus is a positive single-stranded RNA genome encompassed by an envelope and its diameter ranges from 60nm to 140nm (Singhal, 2020). This disease has expanded expeditiously to the world and poses huge economic, environmental, health, and social challenges to the whole human population (Chakraborty and Maity, 2020).

In Pakistan first case of COVID-19 was reported on February 26, 2020, due to entry of infected pilgrims from Iran (Raza et al., 2021). A constant increase was observed in total cases of coronavirus until 12th June. 273,113 total confirmed cases were reported until 25th July 2020 (Ahsan-ul-Haq et al., 2022). The mortality rate was low in Pakistan as compared to other countries like Italy, Iran, Spain, and the USA (Amin et al., 2020). The spread of this pandemic can only be controlled by taking preventive measures. Pakistan imposed its first lockdown after three weeks since the first case reported when the total number of cases was greater than 880 (Farooq et al., 2020). The government of Pakistan did not impose a complete lockdown precipitously around the country but instead imposed it systematically (Khan et al., 2021). In Pakistan, the first lockdown was imposed on 23rd of March 2020, within the province of Sind, accompanied by a nationwide lockdown from 25th March, 2020. However, the lockdown policy varied from sector to sector such as the residential and industrial sectors. Therefore, divided the lockdown period into different stages, P1 the earlier stage from January to February, P2 before the lockdown period from the 1st of March to the 22nd of March 2020, P3 lockdown period from the 23rd of March to the 15th of April 2020, P4 loosed lockdown period from 16th of April to 30th of April 2020 and P5 selected lockdown period from 1st of May to 15th of May 2020. P4 refers to a partial or loose lockdown period when industries were not operating (Ali et al., 2021).

The association between coronavirus and climatic factors was ambiguous, which was demonstrated by both positive and negative impacts (Amnuaylojaroen et al., 2021). The positive environmental variations were reported because of the lockdown period during the COVID-19 pandemic (Evangeliou et al., 2021). COVID-19 had many positive impacts on air pollution and climatic conditions. A decrease in anthropogenic activities led to a significant decline in air pollution (Khan et al., 2021). The lockdowns during the COVID-19 pandemic brought larger changes in land surface temperature between rural and urban areas due to a reduction in anthropogenic activities (Sahani et al., 2021). The anomalies in land surface temperature during the lockdown period of COVID-19 were first studied over the worst virus-affected areas of North America and Europe. The studies discovered huge negative changes in night-time land surface temperature in Europe (0.11°C to -2.6°C) also significant changes were observed in both day and night time LST across North America from March to May in the pandemic year 2020 contrasted to the average of years before pandemic from 2015 to 2019, which can be partly due to the effects of lockdown period during COVID-19. The reduction in LST was associated with a negative change in air temperature (-0.46°C to -0.96°C). On the other side, the increase in daytime LST was observed throughout most regions of Europe due to a decrease in solar radiation by barometrical aerosols. The negative changes in LST at night time may be associated with reduced anthropogenic activities. In North America, studies discovered a significant negative change in LST of both day and night time during the lockdown period (Parida et al., 2021).

The changes in wind speed are mainly due to land use and land cover changes (Navinya et al., 2020). An increasing trend was observed in wind speed during the pandemic between 10th March 2020 and 21st July 2020. After that time period, a decline was observed in wind speed. In Pakistan, fluctuations were observed in wind speed from 10th March 2020 to 04th October 2020 (Ali et al., 2021). The overarching goals of this research are to analyze changes in LST and wind speed during the lockdowns of the pandemic by using satellite data. However, the present study is based on previous literature and elucidates the impact of COVID- 19 on climatic factors across the Pakistan and also helps to interpret the significant changes in climatic factors during the lockdown period and the reasons behind these significant changes in the study area by using geospatial approaches.

Study Area

The study area named Pakistan is located in the western zone of South Asia geographically extends from 30°22'31.2" N latitudes. It denotes Pakistan's location in the Northern Hemisphere and ranges from 69°20.707' E longitudes which represent the eastern location of Pakistan (Salma et al., 2012). Pakistan is comprised of four provinces Punjab, Sindh, Baluchistan, and KPK, and Islamabad Capital Territory. Additionally, there are two other administrative states Azad Jammu Kashmir (AJK) and Gilgit Baltistan as shown in Figure **1**. Pakistan is a land of mountains, plains, deserts, and coastal belt. The area of Pakistan is 796,095 square kilometers (Mohsin, 2020). Pakistan enjoys a wide range of seasons. Pakistan lies in the temperate zone, above the tropic of cancer. Pakistan has a bimodal distribution of rainfall. Pakistan is a developing country with a fragile health system and the financial condition of

Pakistan is also not better, the impacts of the virus were more in Pakistan as compared to developed countries. The potential risk of COVID-19 risk was more in Pakistan because of Pakistan's Population dynamics and demographics (Noreen et al., 2020). This study also analyzes the impacts of the COVID-19 pandemic on the climatic factors of Pakistan and helps to create a pandemic overview in Pakistan.

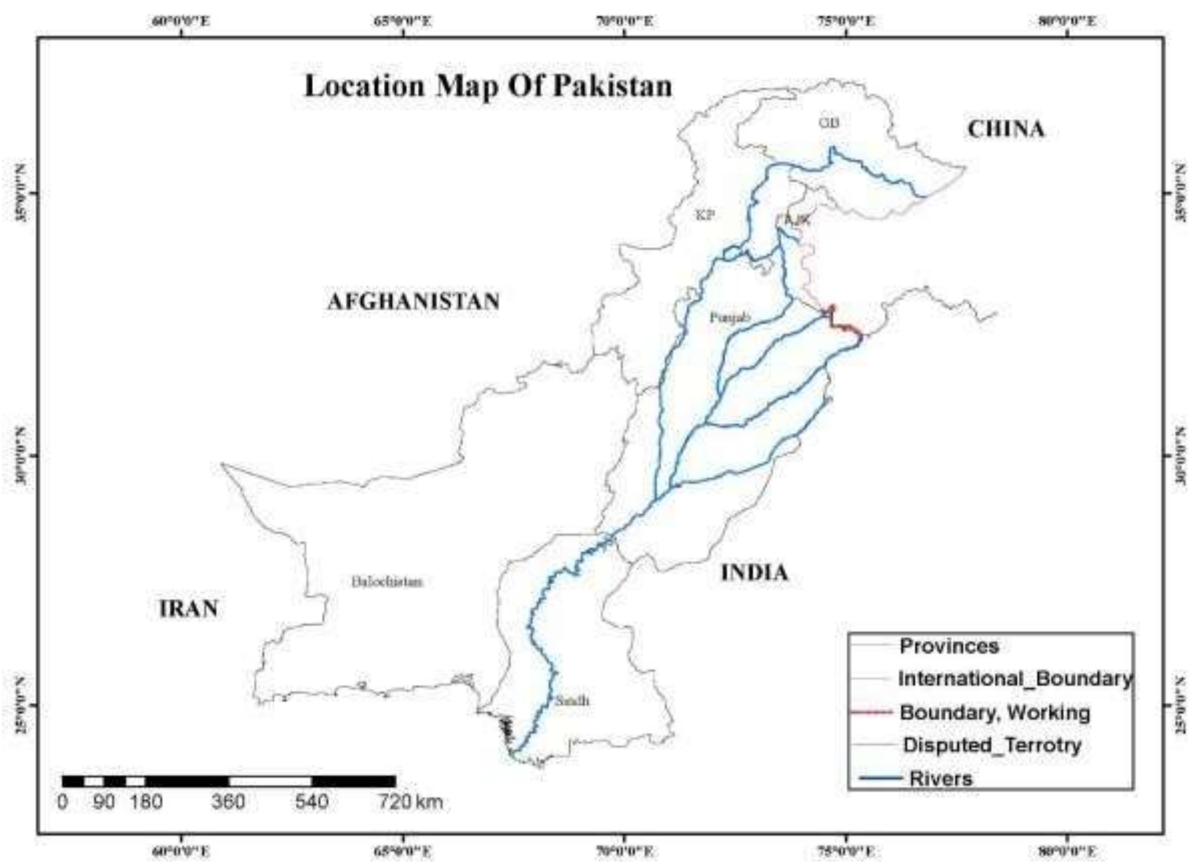

Figure 1: Study Area Map of Pakistan

Datasets used

To achieve the objectives of this study secondary data sources were exploited. For this study, satellite data and COVID-19 data were used. The data was collected through remote sources. Data has been downloaded manually from different websites. The monthly data of selected environmental factors (LST and wind speed) was downloaded from January 2018 to March 2022 and of preceding years 2018 and 2019 of pandemic and during COVID-19 pandemic. This data was collected from satellites images namely MODIS MERRA-2 sensor from EOSDIS Worldview NASA in NC4 file format of wind speed and data of LST from USGS

Earth Explorer to analyze the changes in environmental condition. In this study, the satellites images of climatic data of Pakistan were downloaded of preceding years 2018 and 2019 as a proxy for conditions and compared them with data for the period 2020, 2021 and 2022 under lockdown conditions. And province wise COVID-19 monthly data set of total cases assembled from open source website covid.gov.pk from March 2020 to March 2022 of COVID-19 this time period was considered for statistical data analysis because the first case of COVID-19 in Pakistan was reported on 26th February 2020. Table **1, 2 and 3** summarized the COVID-19 data which was used in this research and collected from open source website covid.gov.pk.

Table 1: Monthly COVID-19 data of Total Cases

COVID-19 Total Cases 2020							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK
March	54	708	0	253	158	184	6
April	343	6340	6053	2627	1049	339	66
May	2589	26240	28245	10027	4393	711	255
June	12912	76262	84640	26598	10476	1489	1093
July	150333	93057	121039	34056	11743	2134	2084
August	15649	96832	129469	36118	12879	2903	2299
September	16611	99479	137106	37811	15281	3787	2731
October	19970	104271	145851	39564	15920	4261	4133
November	30406	119578	174350	47370	17187	4658	6933
December	37888	138608	215679	58701	18168	4857	8277

Table 2: Monthly COVID-19 Total Cases of 2021

COVID-19 Total Cases 2021							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK
January	41418	157796	247249	67214	18823	4909	9019
February	44373	172054	258266	72424	19049	4956	10243
March	58557	223181	265680	88099	19576	5033	12805
April	75498	303182	283560	118413	22369	5310	17187
May	81257	340110	318579	132822	25218	5588	19250
June	82706	346301	337674	138068	27178	6138	20343
July	87699	356920	382865	144264	30432	8156	24501
August	99516	394738	432637	162402	32248	9919	32228
September	105516	431666	457928	174017	32926	10328	34157
October	106921	440259	470175	178074	33263	10390	34478
November	107722	443185	475820	180075	33484	10412	34556
December	108666	445107	482029	181402	33638	10429	34662

Table 3: Monthly COVID-19 Total Cases of 2022

COVID-19 Total Cases 2022							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK
January	128429	480421	543170	194887	34417	10703	38339
February	134404	501544	568277	216174	35345	11499	42978
March	135072	505003	575257	219026	35472	11702	43261

The data of wind speed (m/s) was extracted from MEERA-2 2d_lfo_Nx which is monthly mean data collection and for Land Surface Temperature (Kelvin) (LST) data collected from USGS Earth Explorer in HDF format. For the conversion of radiance Kelvin values to LST, first digital number (DN) obtained from USGS of the image were calculated and their average was taken out and multiplied with 0.02 and then radiance was subtracted from 273.15 (Javid et al., 2019). The data has been prepared by using the ArcGIS 10.3.1 software and MS Excel. The COVID-19 data was analyzed by using Microsoft Excel Spreadsheet and presented in the form of tables. The COVID-19 and climatic data both were processed by using Arc GIS. After that Inverse Distance Weighted (IDW) was used for visualization and to show the trends of COVID-19 data and variations of climatic factors. IDW is type of deterministic method of interpolation that estimates cell values by averaging the value of given sample data points in the neighborhood of each processing cell. Finally, zonal statistic implemented to show districts wise visualization of both COVID-19 and climatic data. Furthermore, maps were produced to show spatial distribution across Pakistan by using Arc Map Tools. The weighted sum analysis approach provides the ability to weight and combine series of raster inputs to create an integrated analysis. The weighted sum multiplies all the input raster values by specified weight. Statistical Analysis was performed to show changes in environmental factors at district level of Pakistan. By using this method, a generalized visualization of variation in climatic conditions in areas of Pakistan due to COVID-19 is shown.

Results

In this research impacts of the COVID-19 pandemic on climatic conditions are assessed and also how the lockdown period during the pandemic caused variations in environmental conditions. In this study it has already been mentioned cause of this pandemic, preventive measures were taken such as wearing masks, social distancing, limiting transport, closure of industries, and lockdowns were imposed to control the spread of COVID-19, lockdowns not only minimized the spread of COVID-19 but also brought positive changes in environmental conditions. In this study analysis are performed at both level district and province level. Tables represent impacts of lockdown on environmental conditions at district-level and images across the country. In Pakistan the first lockdown was imposed in the month of March 2020 to June 2020 known as strict lockdown. In the month of July 2020, the government again imposed a partial lockdown. In May 2021 the government again imposed a lockdown known as Eid lockdown. By June 2021 COVID-19 had hit Pakistan hard. Until March 2022 the most affected province by coronavirus was Sindh with 575257 total reported cases. And the least affected was GB with 11702 total cases. The total cases in March 2022 were 251334. The lockdown not only controlled the spread of COVID-19 cases but also caused changes in climatic conditions. Figure 2 depicts how during strict lockdown the cases of COVID-19 were under control. When the government loosened the lockdown, an increasing trend was observed in total cases in different parts of the country. Figure 3 **Error! Reference source not found.**shows how COVID-19 during the partial lockdown affected the country. Figure 4 depicts how COVID-19 affected Pakistan after the month of October 2020. Similarly, Figure 6 and 7 show the terrible increase in COVID-19 cases. And Figure 8 presents how pitifully coronavirus affected the Pakistan till March 2022.

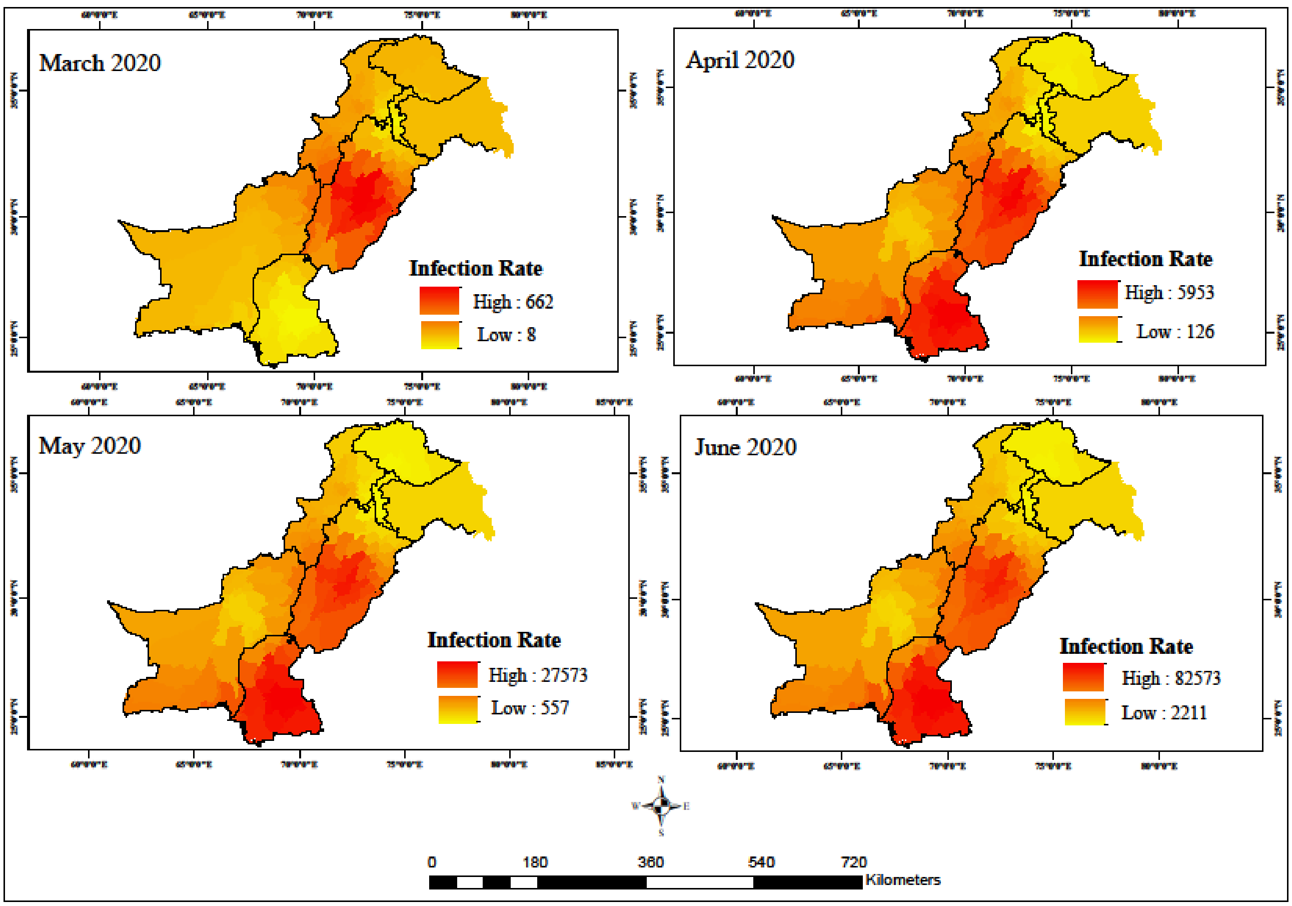

Figure 2: Spatial Distribution of Total Cases of Covid-19 during Strict Lockdown Period

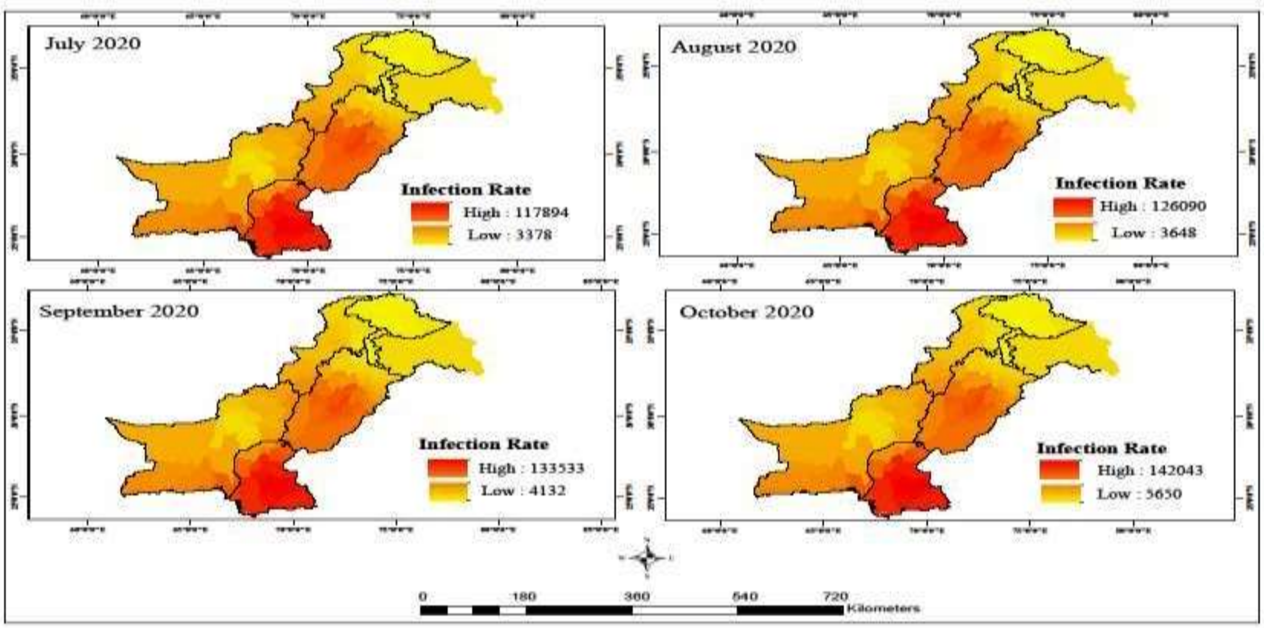

Figure 3: Spatial Distribution of Total Cases of Covid-19 during Partial Lockdown Period

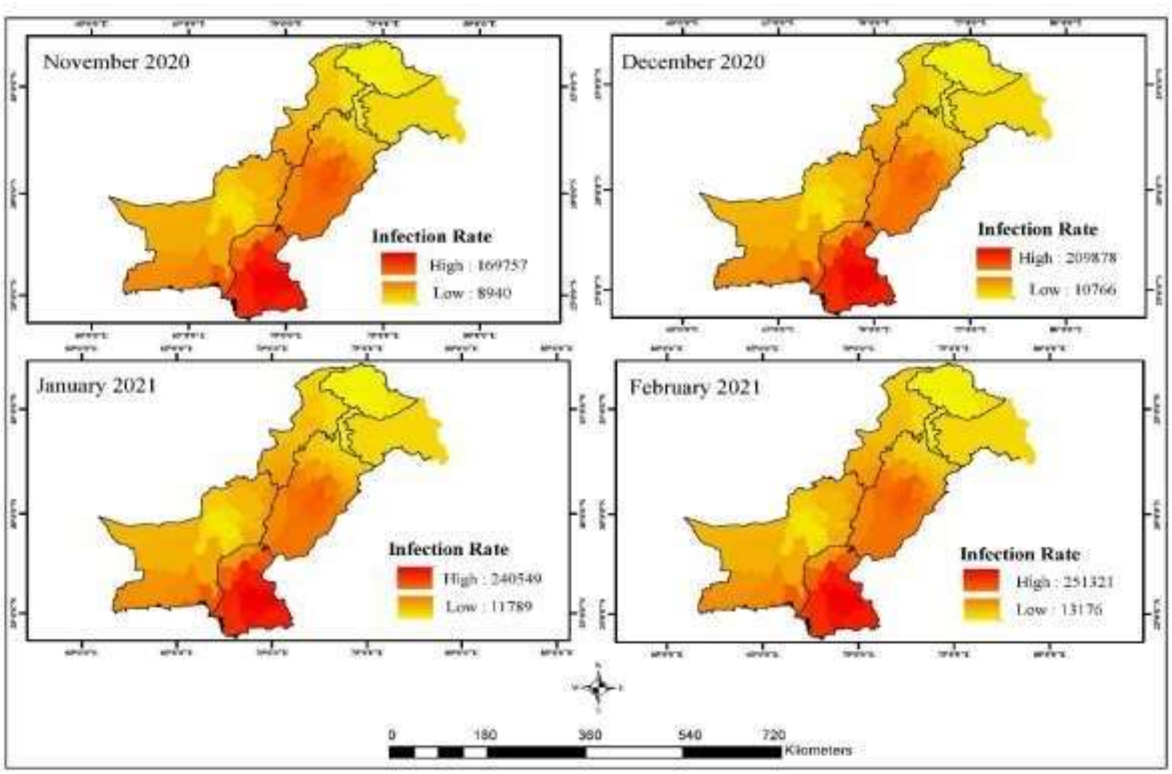

Figure 4: Spatial Distributions of Total Cases of Covid-19 after Lockdown Period

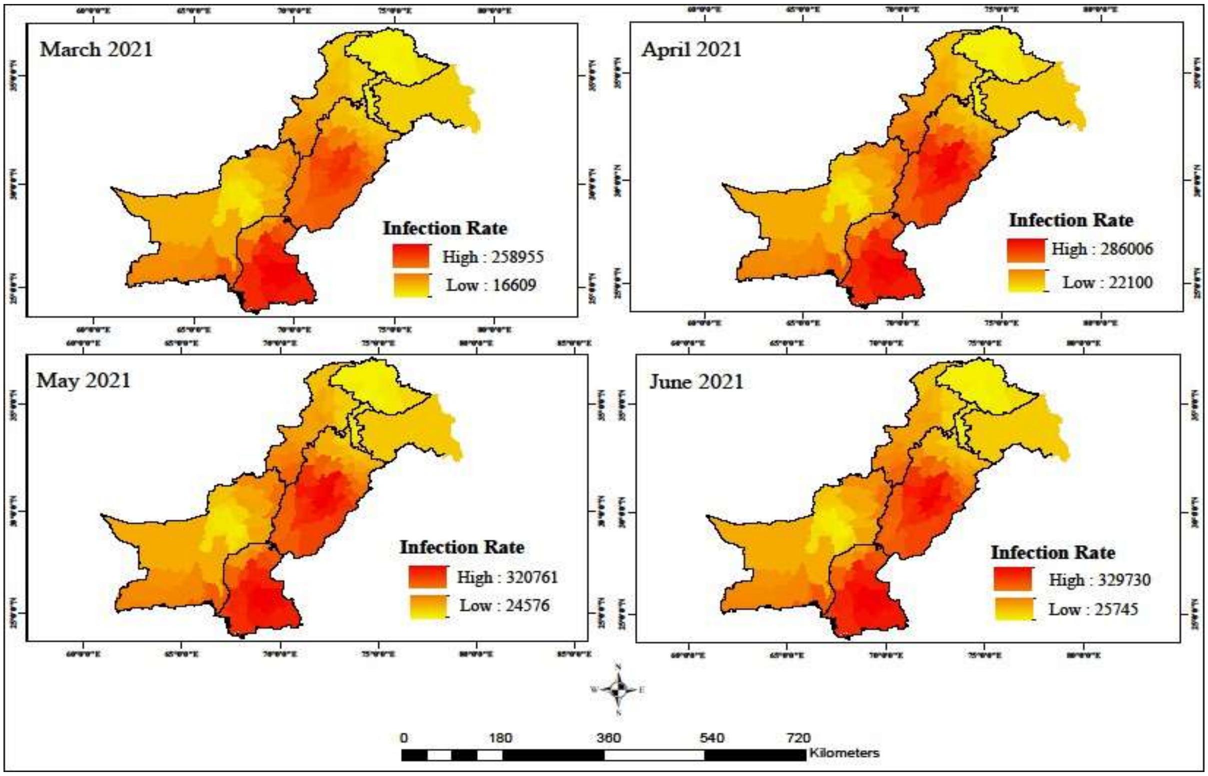

Figure 5: Spatial Distribution of Total Cases of Covid-19

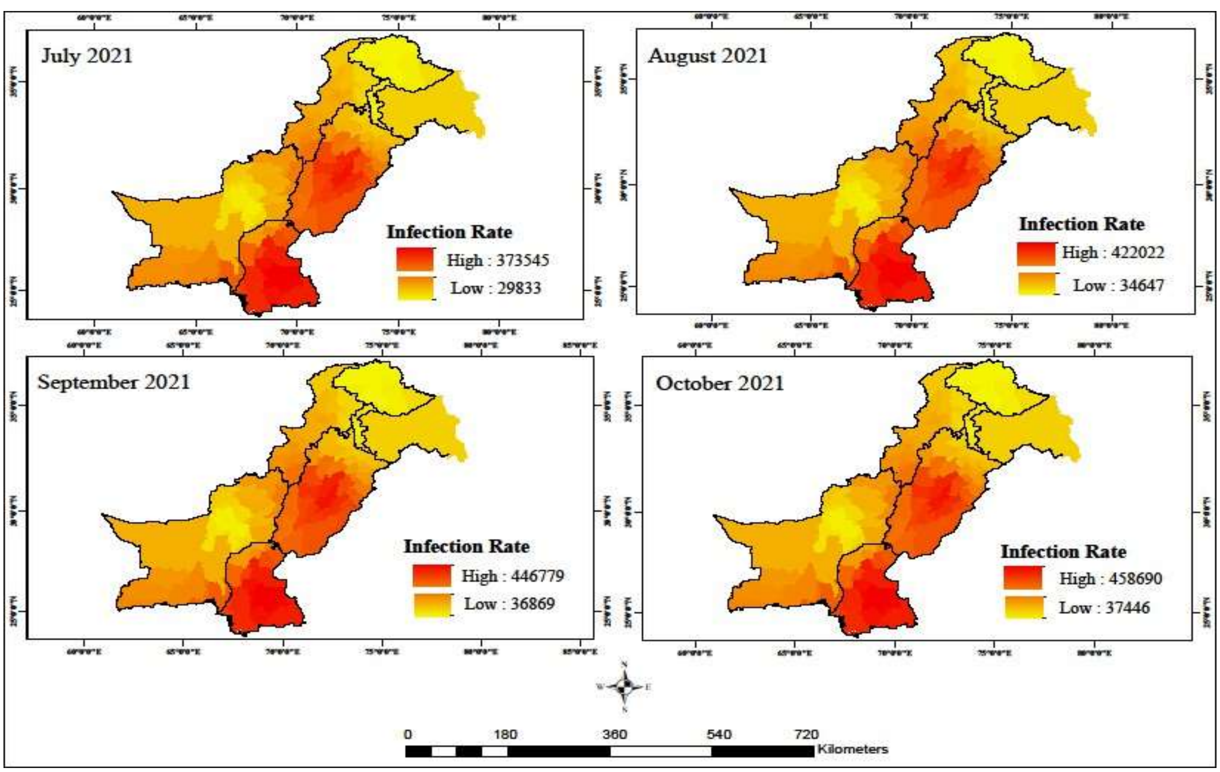

Figure 6: Spatial Distribution of Total Cases of Covid-19

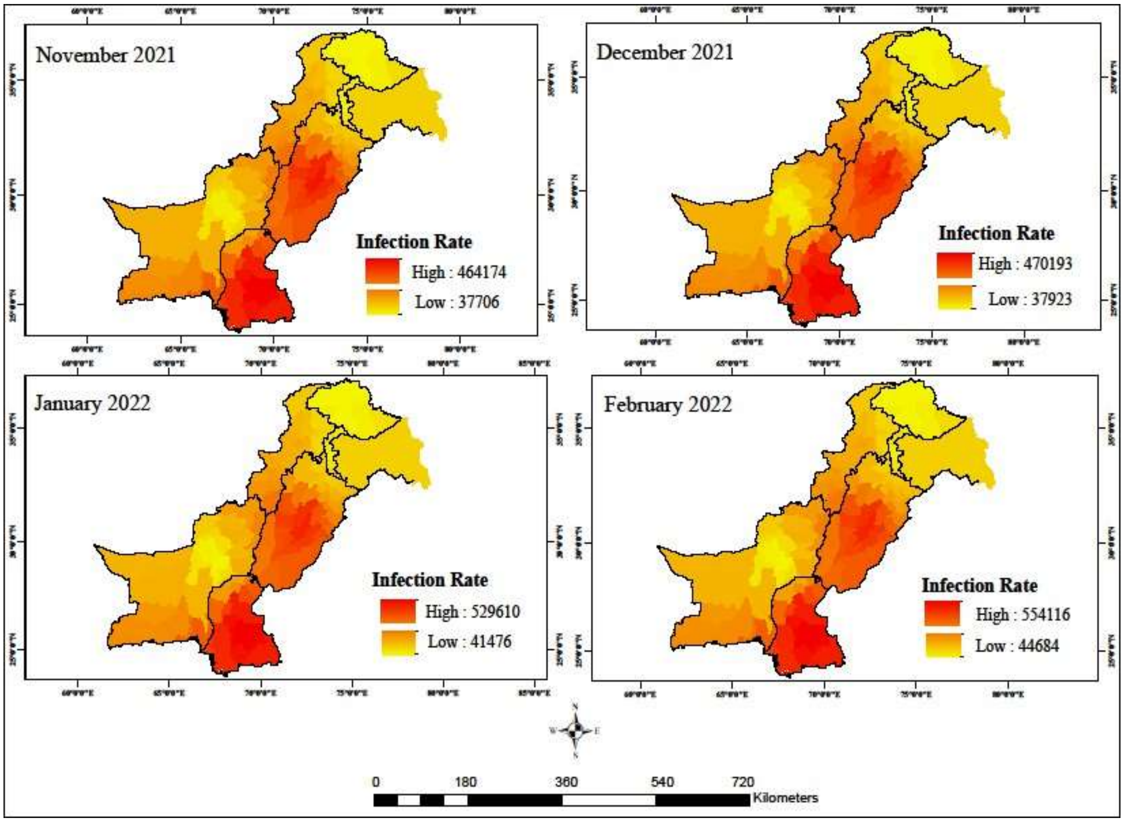

Figure 7: Spatial Distribution of Total Cases of Covid-19

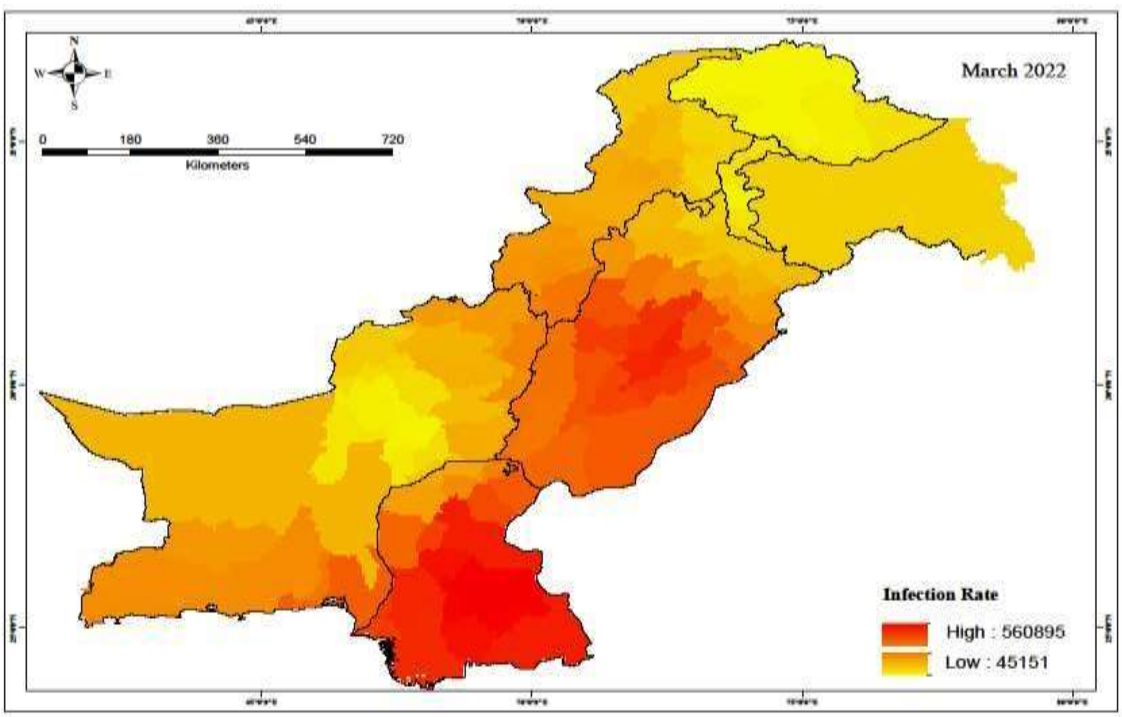

Figure 8: Spatial Distribution of Total Cases of Covid-19

A substantial variation in climatic factors was observed over Pakistan during the lockdown period. The results show a clear distinction between climatic factors before and after the lockdown period over the country. In the COVID-19 pandemic during the lockdown period decreasing trend was observed in the monthly district-wise mean of wind speed. In March 2020, the monthly average wind speed decreased to 4.23m/s from 4.38m/s and 4.36m/s compared to March 2018 and March 2019 respectively. A similar trend was also observed during the lockdown period of April 2020. There was a decline in the monthly district-wise average wind speed from 4.66m/s in April 2018 and 4.55m/s in April 2019 to 4.28m/s in April 2020. Figure 9 and 10 represent the spatial distribution of wind speed before the lockdown in March and April 2018 and 2019. Figure 11 shows the spatial distribution of wind speed during the lockdown period of March and April 2020. The monthly district-wise mean wind speed decreased. In May 2020 wind speed was 4.85m/s which decreased from 4.97m/s and 4.91m/s respectively prior to the years 2018 and 2019. Figure 16 shows the spatial distribution of wind speed during the lockdown period of May 2020 and Figure 14 and15 portray the spatial distribution of wind speed before the lockdown period of May 2018 and 2019. In June 2020, the wind speed also decreased due to lockdown from 5.26m/s in June 2018 and 5.14m/s in June 2019 to 4.58 m/s in June 2020. A similar trend was also observed during the 2021 lockdown in the month of May 2021.

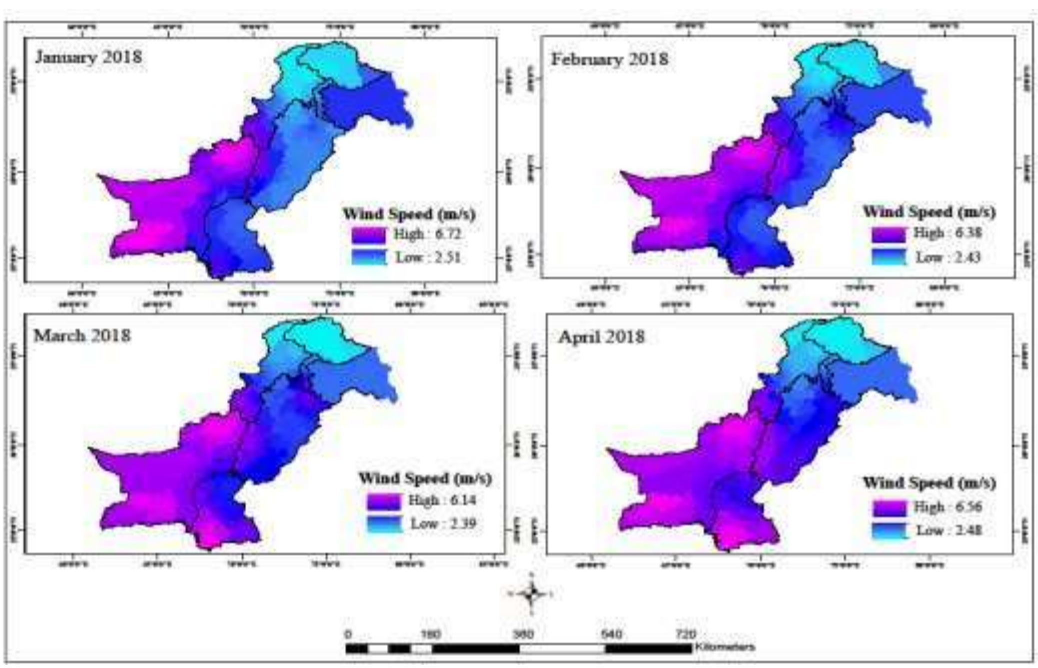

Figure 9: Spatial Distribution of Wind Speed in 2018 before Covid-19 Pandemic

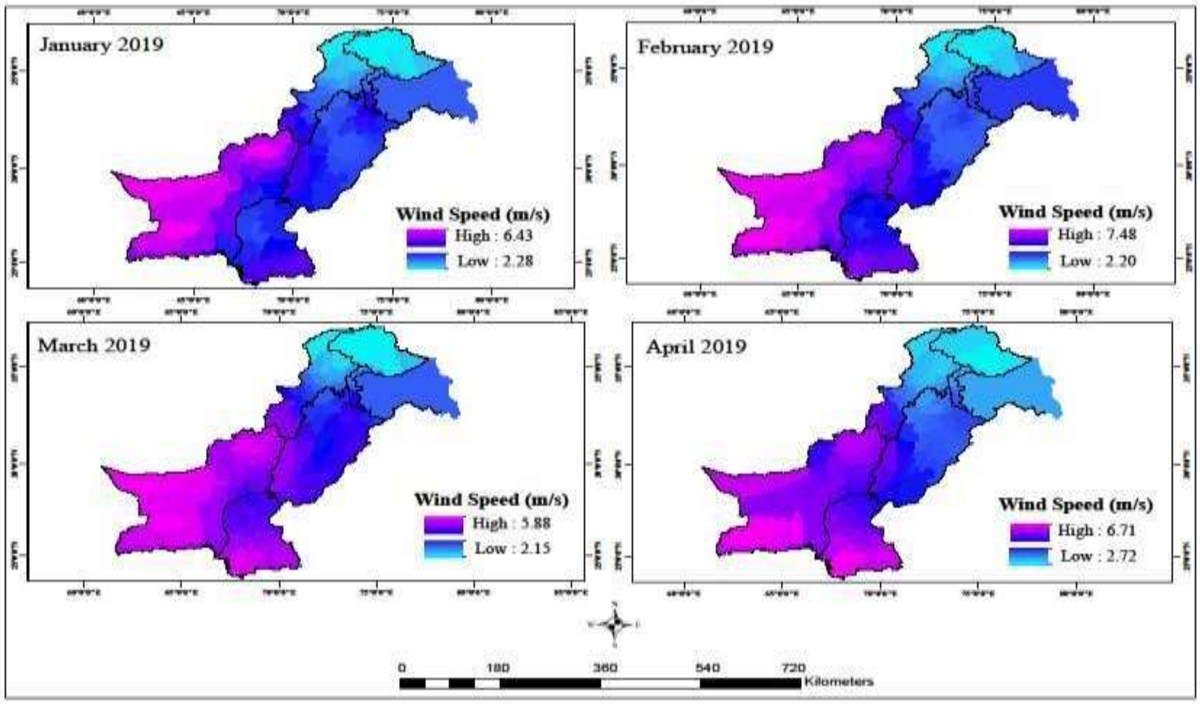

Figure 10: Spatial Distribution of Wind Speed in 2019 before Covid-19 Pandemic

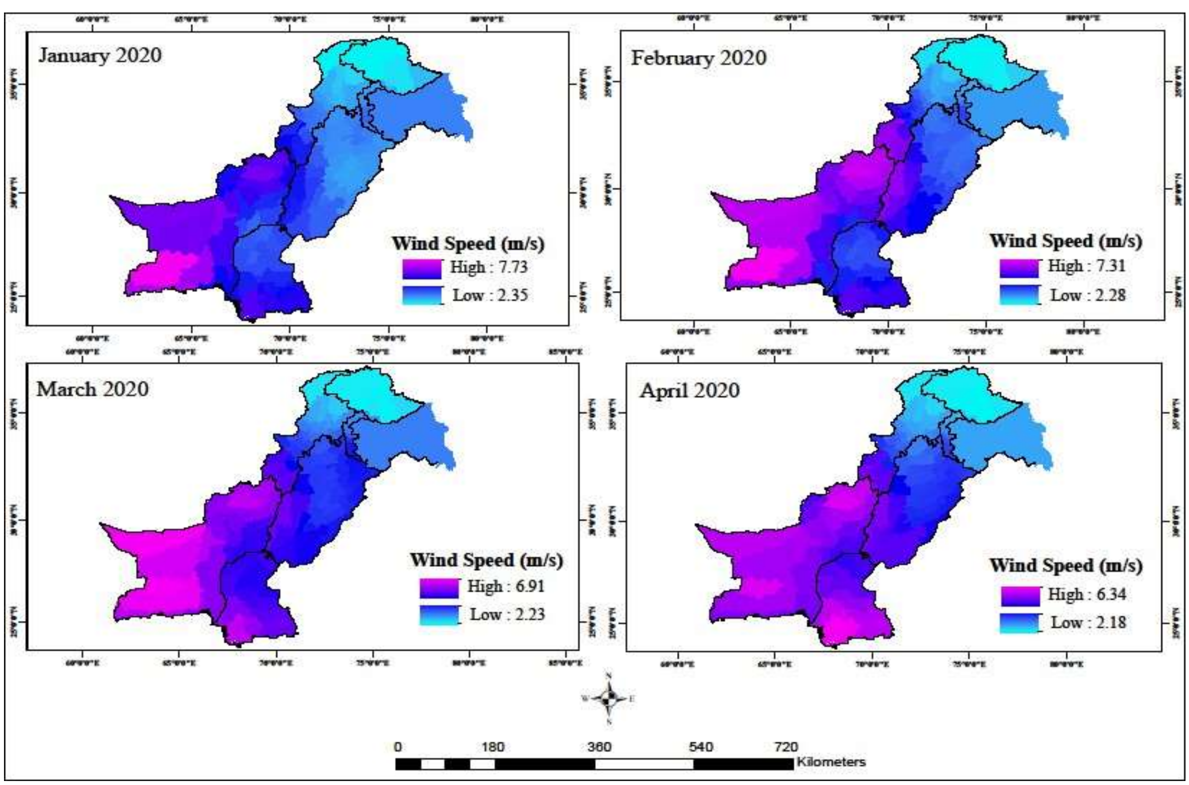

Figure 11: Spatial Distribution of Wind Speed during Pandemic 2020

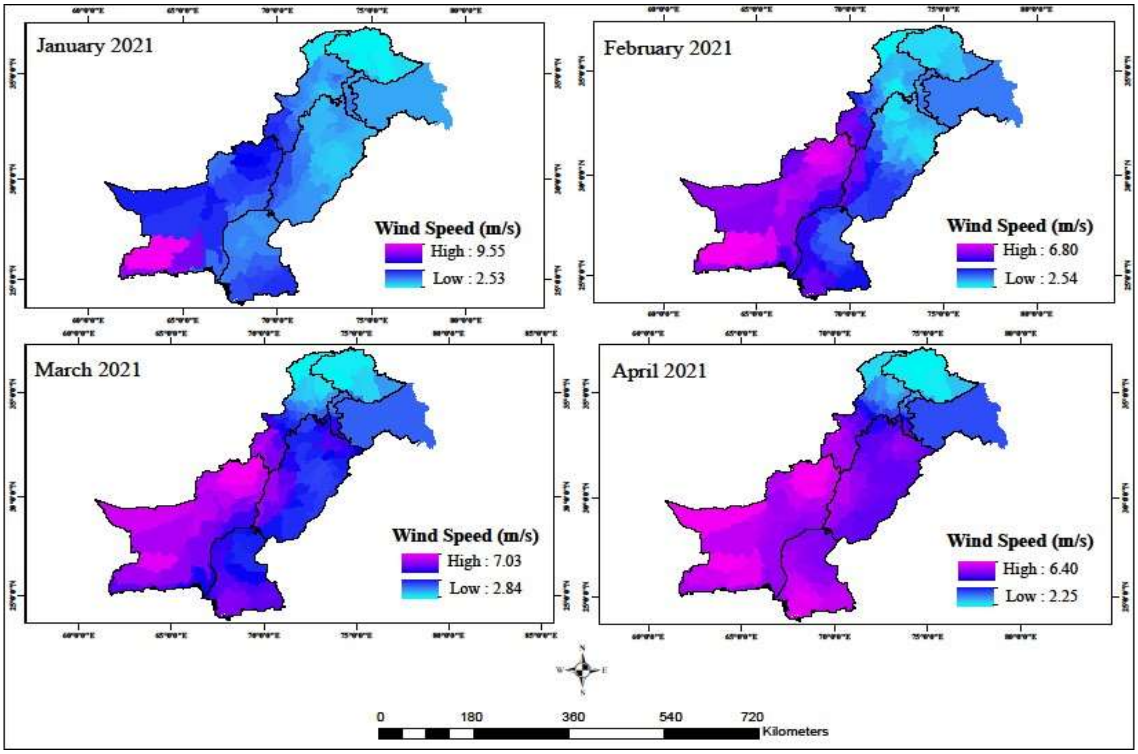

Figure 12: Spatial Distribution of Wind Speed during Pandemic 2021

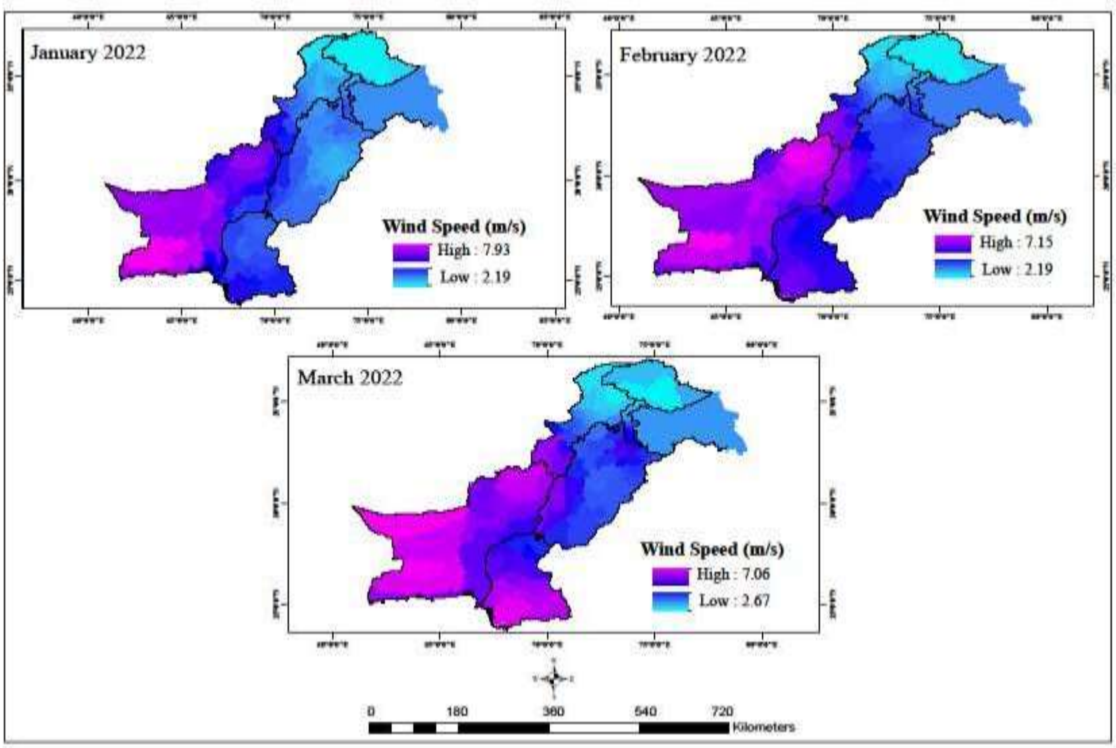

Figure 13: Spatial Distribution of Wind Speed during Covid-19 Pandemic 2022

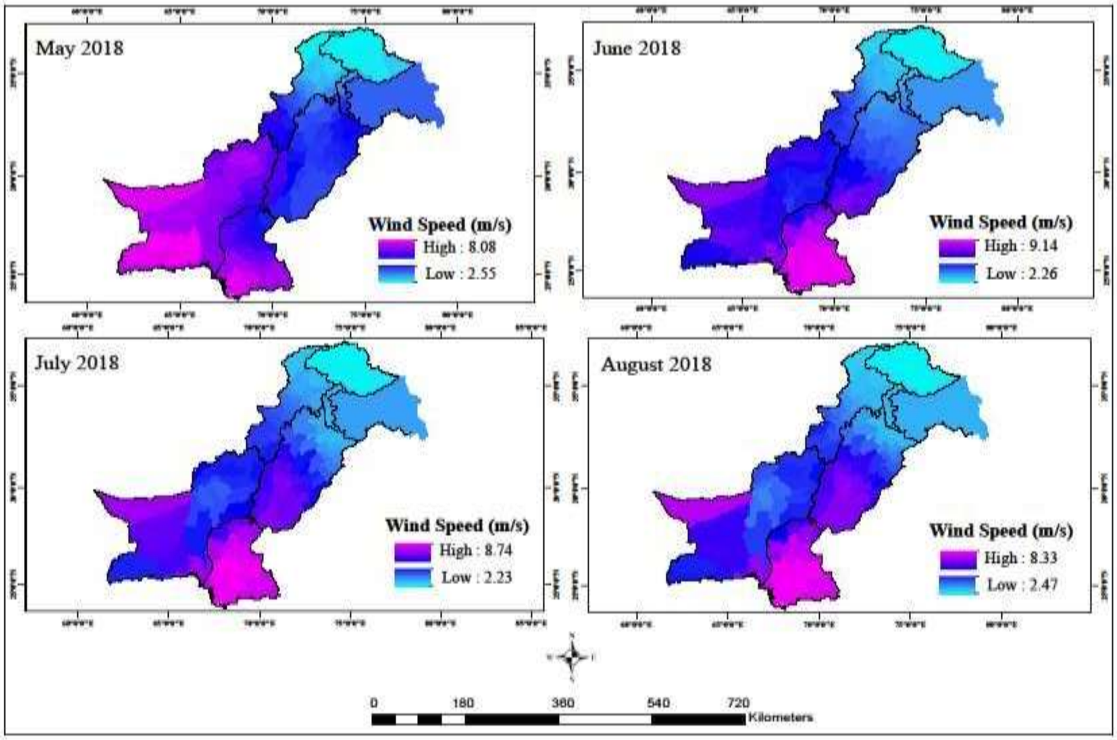

Figure 14: Spatial Distribution of Wind Speed 2018 before Covid-19 Pandemic

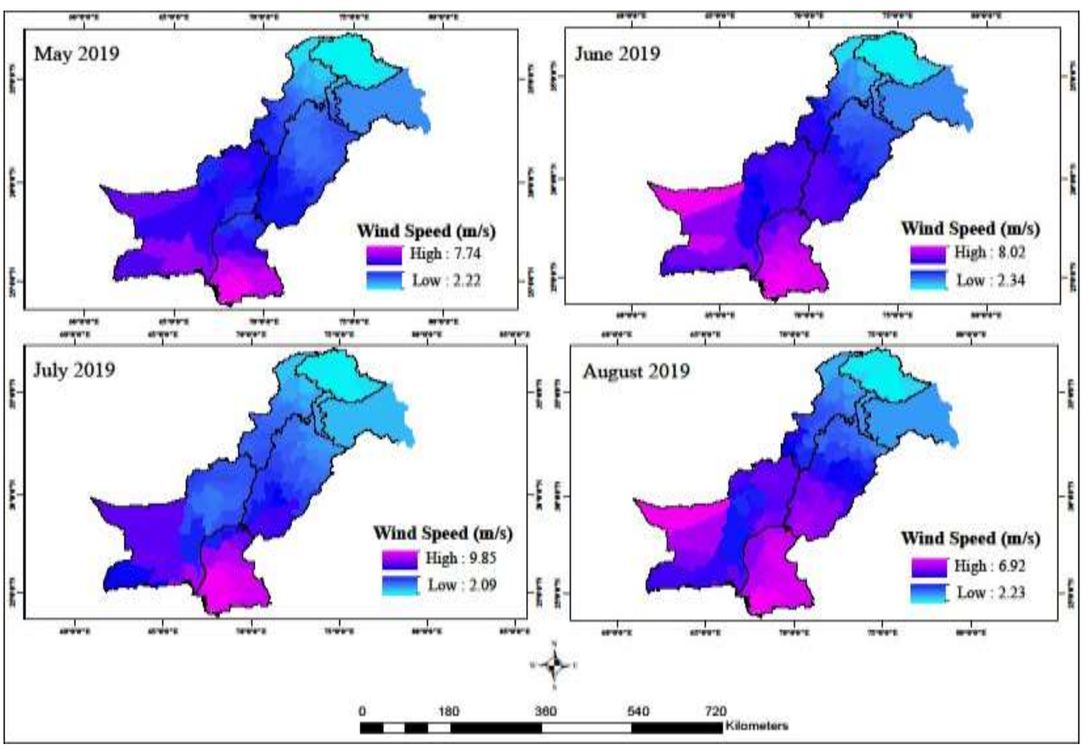

Figure 15: Spatial Distribution of Wind Speed 2019 before Covid-19 Pandemic

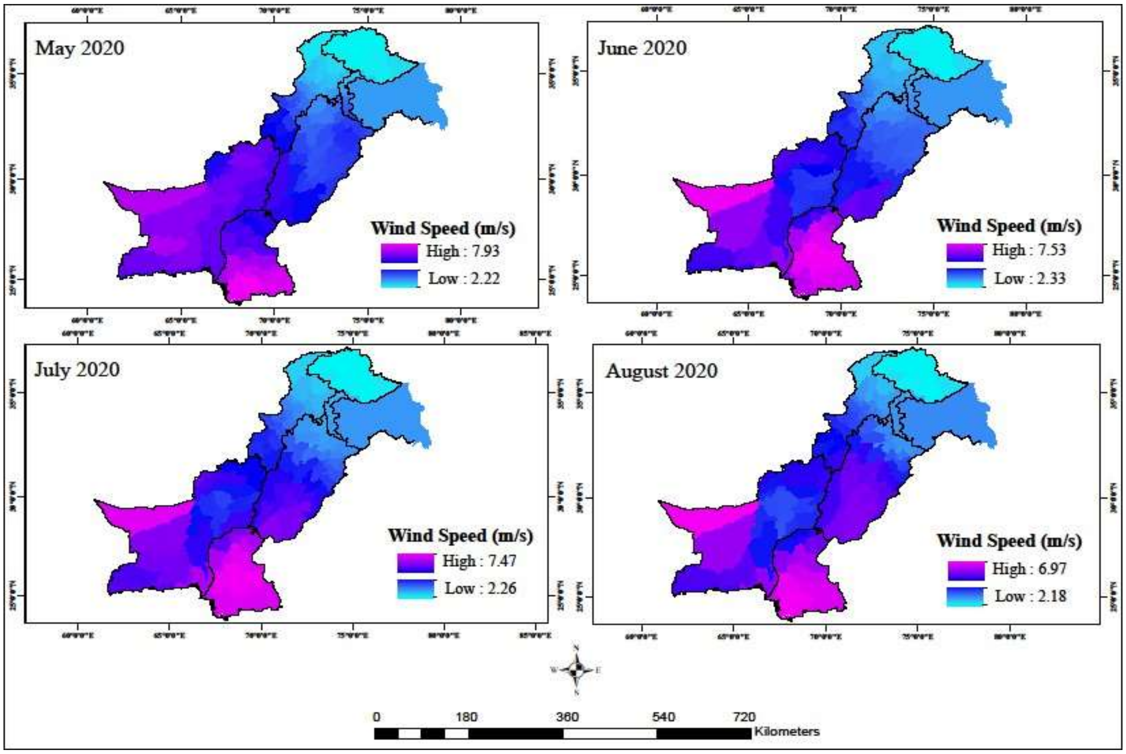

Figure 16 Spatial Distribution of Wind Speed 2020 During Covid-19 Pandemic

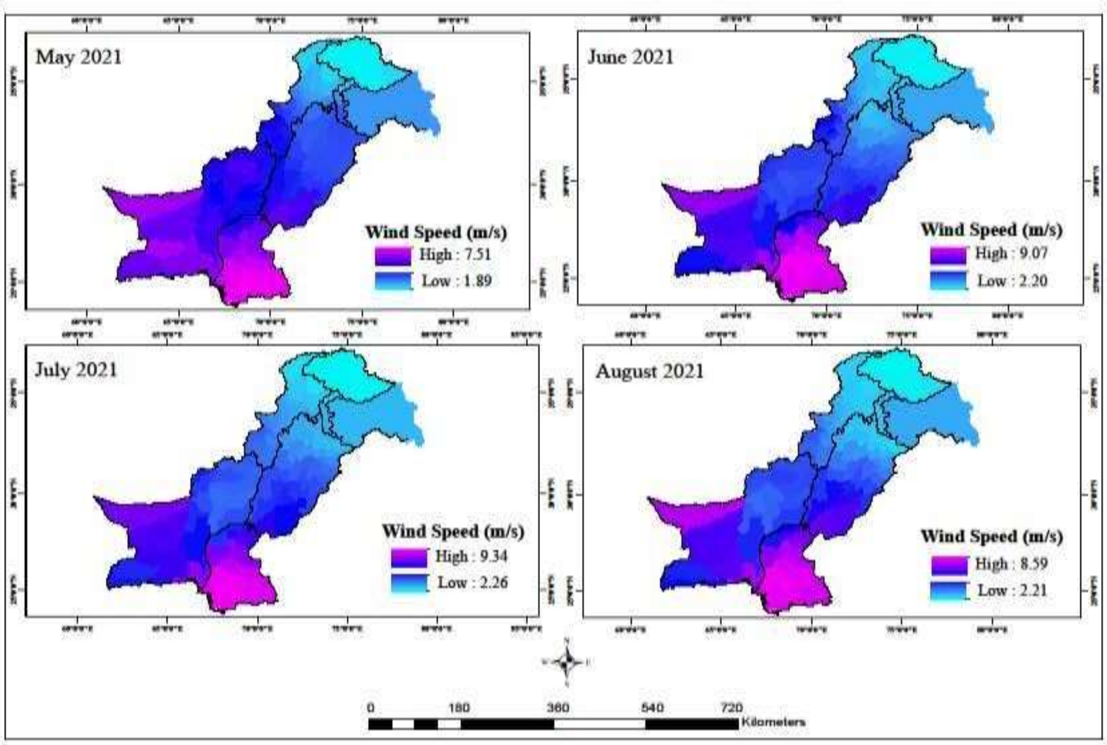

Figure 17: Spatial Distribution of Wind Speed 2021 during Covid-19 Pandemic

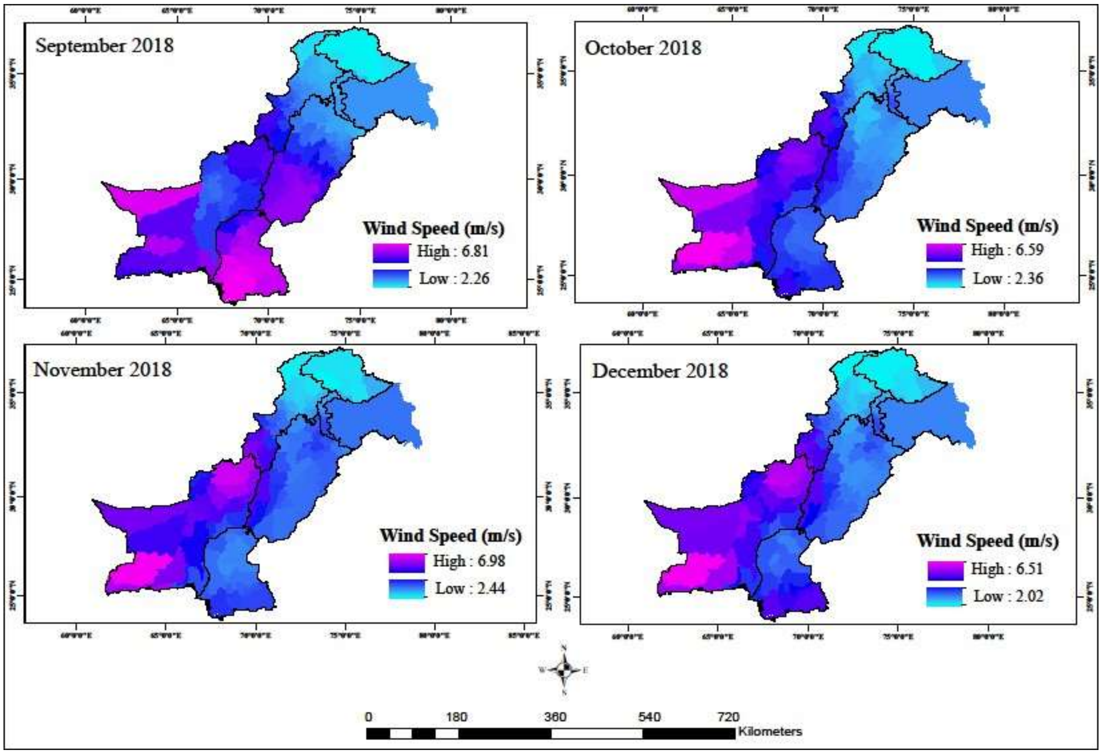

Figure 18: Spatial Distribution of Wind Speed 2018 Before Covid-19 Pandemic

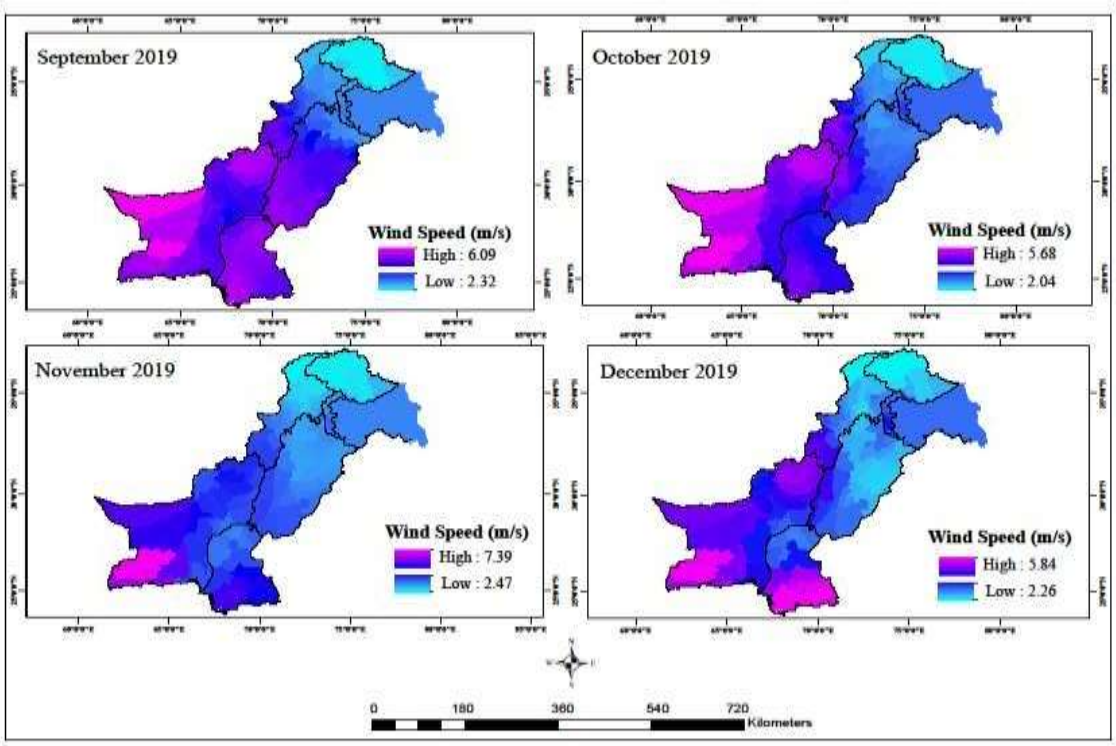

Figure 19: Spatial Distribution of Wind Speed 2019 before Covid-19 Pandemic

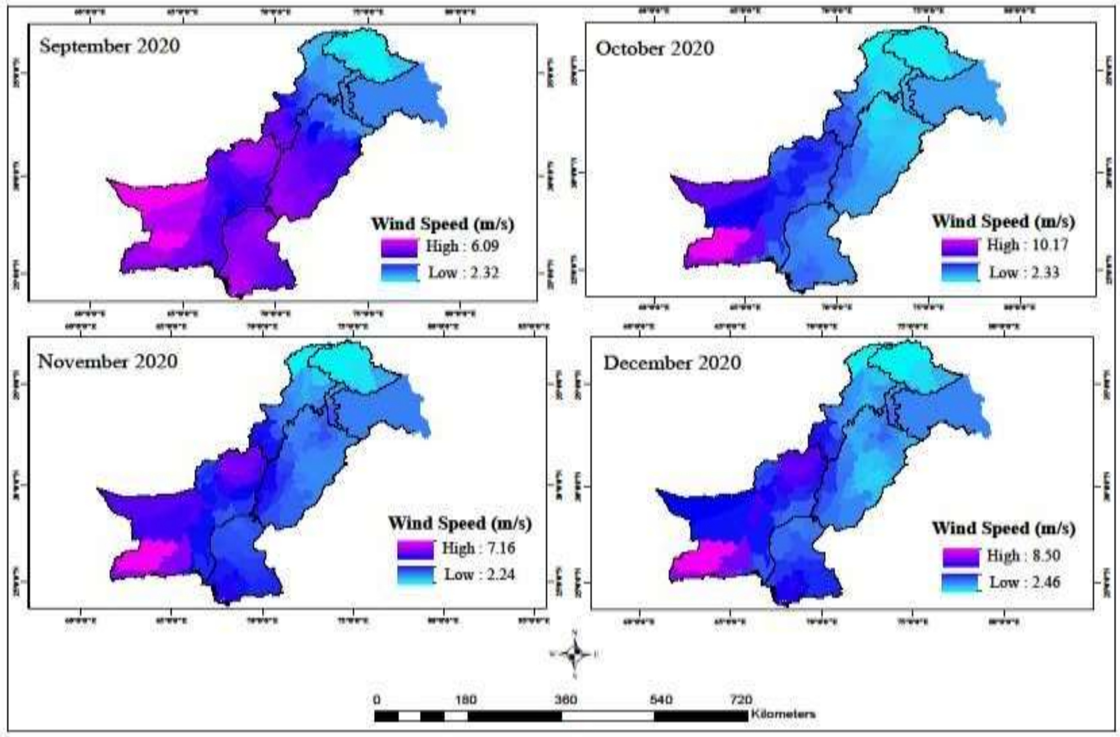

Figure 20: Spatial Distribution of Wind Speed 2020 during Covid-19 Pandemic

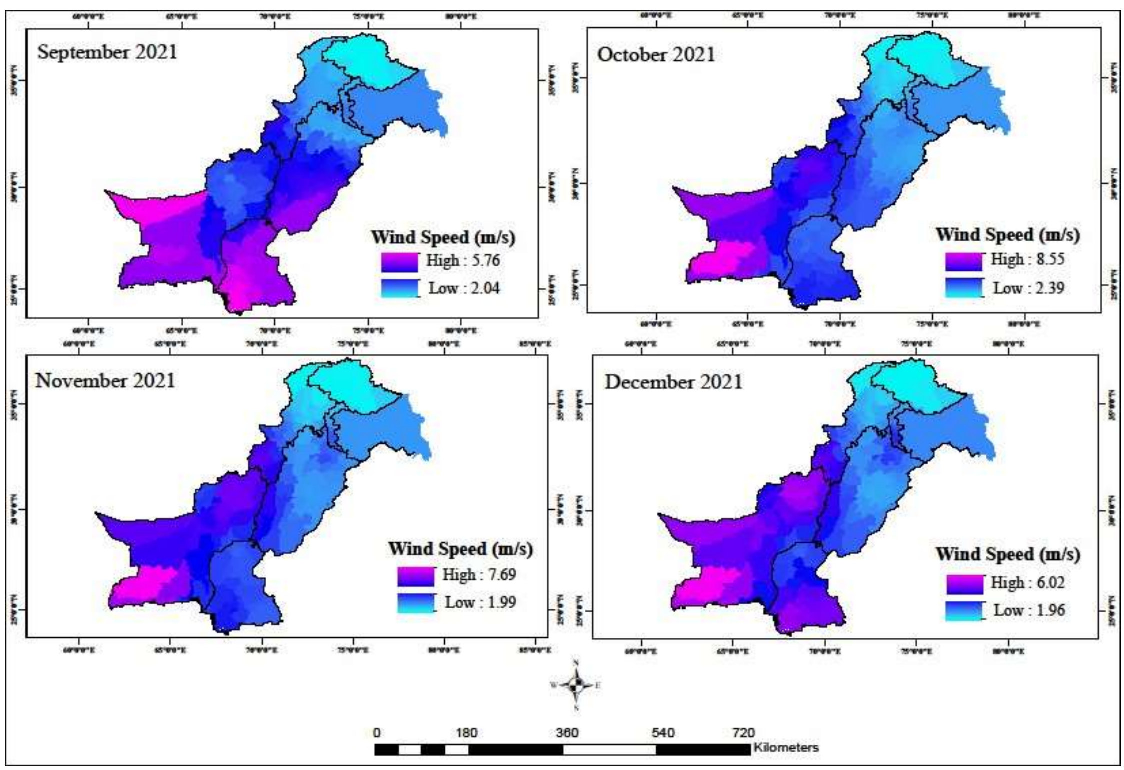

Figure 21: Spatial Distribution of Wind Speed 2021 during Covid-19 Pandemic

Table 4 : Statistics of Wind Speed During Lockdown

Wind Speed (m/s)	2018	2019	2020	2021
March	4.38	4.36	4.23	4.86
April	4.66	4.55	4.28	4.76
May	4.97	4.91	4.85	4.52
June	5.26	5.14	4.58	4.91

Figure 14 and 15 show wind speed distribution before the lockdown period of May 2018 and 2019. The monthly district-wise mean wind speed decreased in May 2021 (decreased to 4.52m/s May 2021 from 4.97m/s in May 2018 and 4.91m/s in May 2019. Figure 17 depicts the spatial variation of wind speed during the lockdown period of May 2021. After June 2020 again contrasting variation was observed in the values of wind speed this was because of the loosening of the lockdown. From the obtained results variations in wind speed were very clear during the lockdown period. Figure 9, 10, 14, 15 18 and 19 depict the spatial distribution of wind speed before the COVID-19 pandemic of 2018 and 2019 respectively. Figure 11, 12 16, 17, 20 and 21 show the spatial distribution of wind speed during the COVID-19 pandemic 2020 and 2021, sequentially. Similarly, Figure 13 shows wind speed district-wise distribution during the COVID-19 pandemic from January to March 2022. During the pandemic years 2020 and 2021 the annual average wind speed increased compared to the previous year 2019. Table 4 represents district–wise average of wind speed during the lockdown period of the pandemic.

The reduction in LST during the lockdown period was observed over Pakistan. The results of this study revealed that a 5°C reduction in the district-wise average of LST over Pakistan was observed in the month of March 2020 against the month of March 2018 (from 28°C in 2018 to 23°C in 2020) and as compared to the March 2019 the decline was 1°C (from 24°C in 2019 to 23°C in 2020). Figure shows the spatial distribution of LST over the country during the lockdown of March 2020 compared to 2018 and 2019 March before the lockdown period in Figure 22 and 23 respectively. The decline in LST was also observed in the month of April 2020. Figure 24 portrays the distribution of LST during the lockdown period of April 2020. The month of April 2020 showed a 2°C negative anomaly in LST against April 2018 (from 33°C in 2018 to 31°C in 2020) and as compared to the 2019 the decline was 1°C (from 32°C in 2019 to 31°C in 2020). Figure 22 and 23 depict the spatial distribution of LST before lockdown in April 2018 and 2019 sequentially. The decline in LST was also noticed in the month of May 2020 and LST had shown a negative anomaly of 1°C compared to the May of 2018 and 2019 (from 38°C to 37°C in both years 2018 and 2019). Figure 29 depicts the spatial distribution of LST during the lockdown period of May and June 2020. Figure 27 and 28 depict the distribution of LST before the lockdown period of May and June of 2018 and 2019 respectively. A decrease in the month of June 2020 was also noticed. The LST decreased 1°C in June 2020 compared to previous years 2018 and 2019 (from 38°C in June 2018 to 37°C in June 2020 and similarly in June 2019 from 38°C to 37°C). The same pattern was also remarked for LST in the month of May 2021 because of the lockdown and LST had shown a negative anomaly of 1°C as compared to 2018 and 2019 (from 38°C to 37°C in both years 2018 and 2019). Figure 30 shows the spatial distribution of LST during the lockdown period of May 2021. The drop in LST could be associated with lockdown or generally cooler weather. After the month of June 2020, we again started to observe the increase in LST because of the loosening of the lockdown that increased the anthropogenic activities. Figure 22, 23, 27, 28 31 and 32 depict the spatial distribution of LST before the COVID-19 pandemic period.

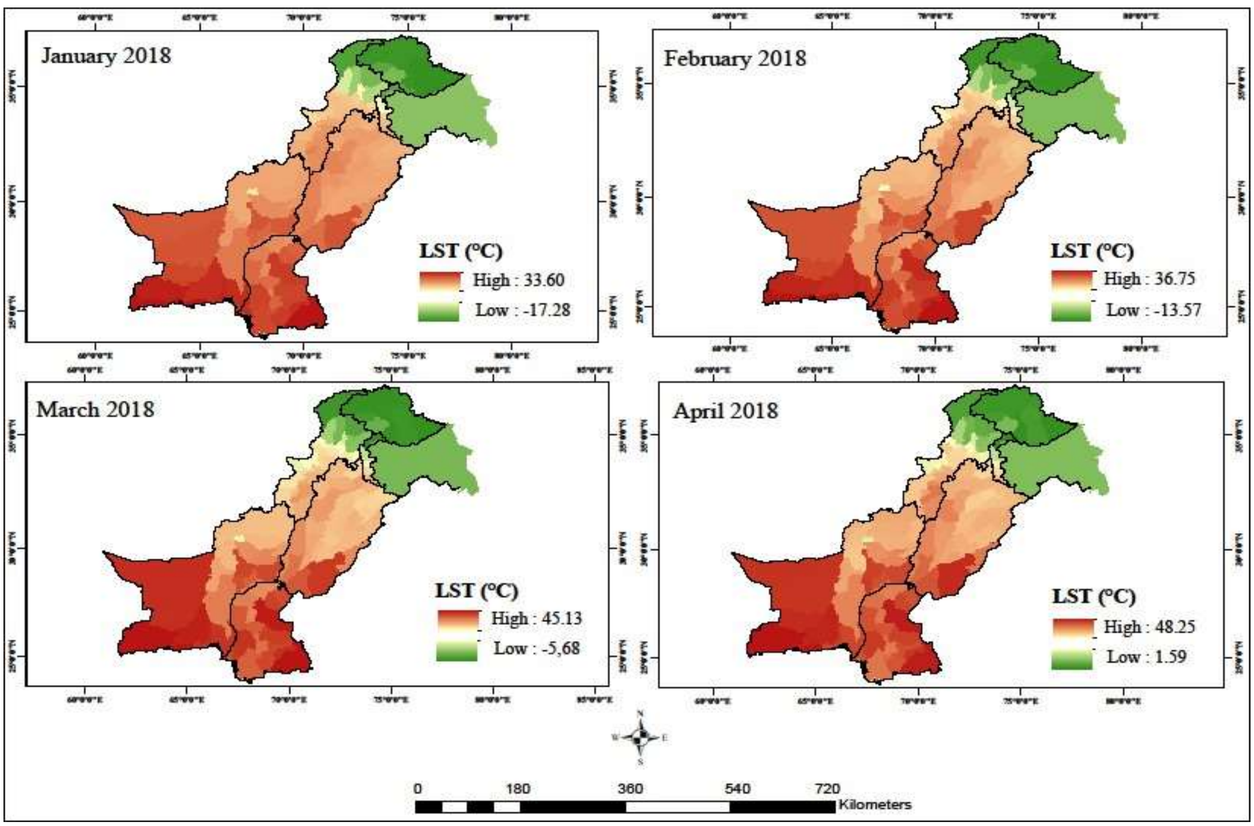

Figure 22: Spatial Distribution of LST before Covid-19 Pandemic 2018

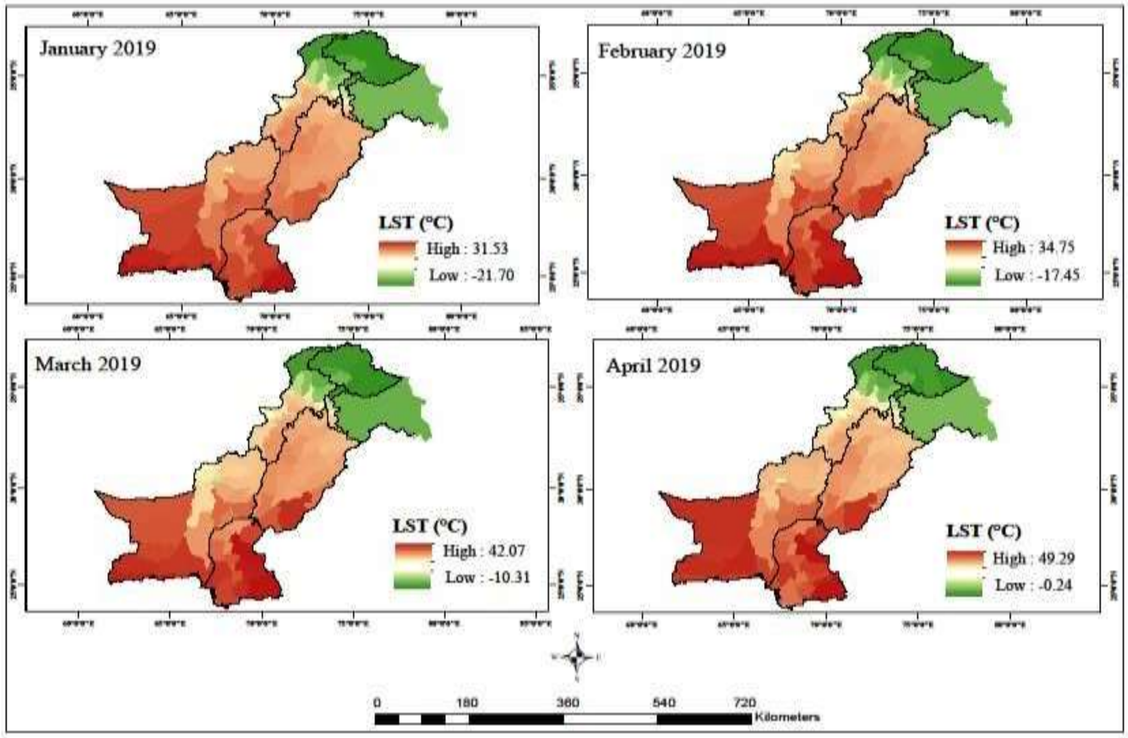

Figure 23: Spatial Distribution of LST Before Covid-19 Pandemic 2019

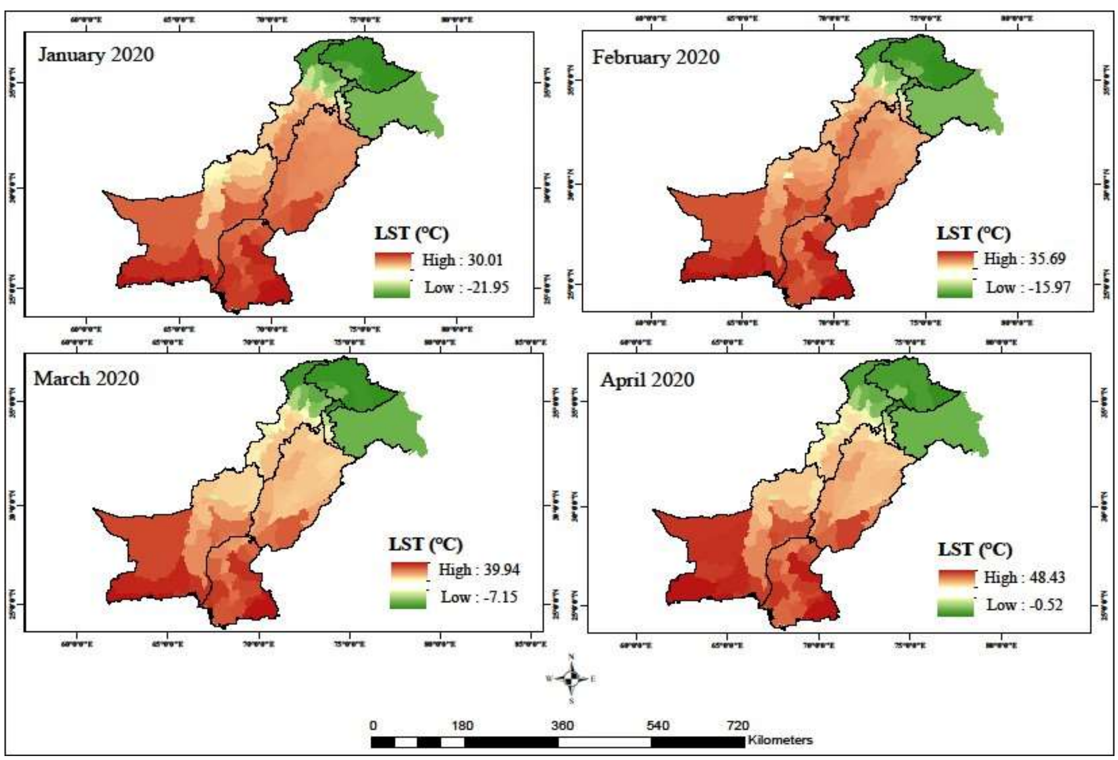

Figure 24: Spatial Distribution of LST During Covid-19 Pandemic 2020

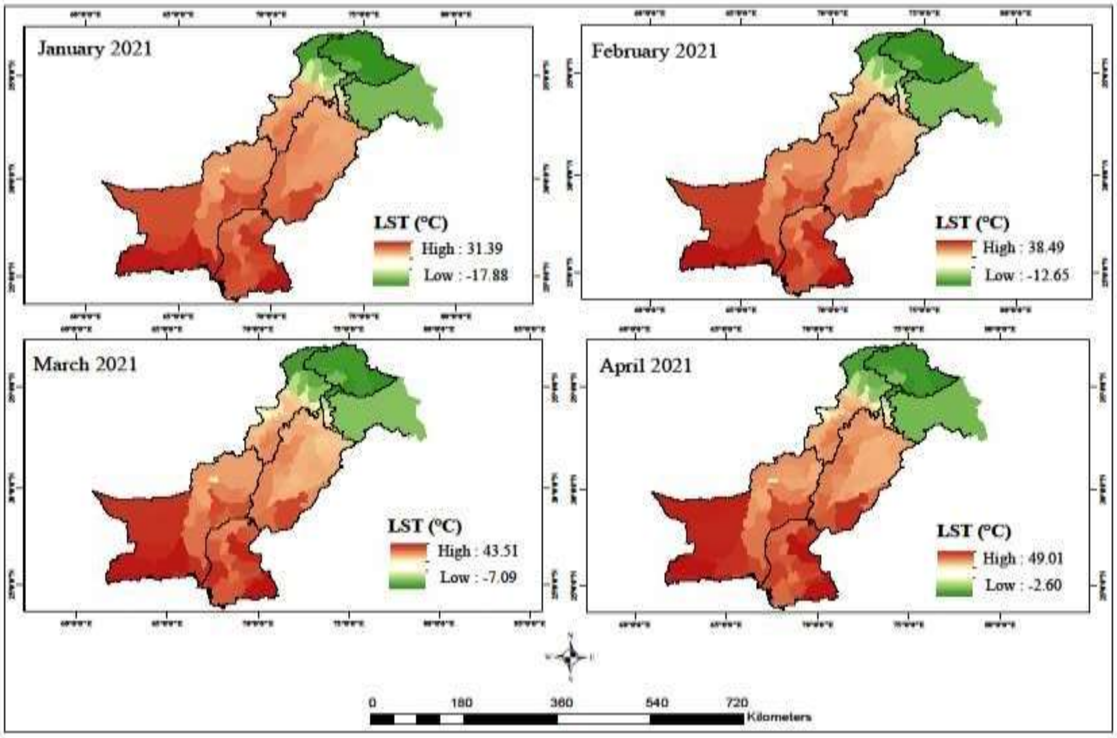

Figure 25: Spatial Distribution of LST During Covid-19 Pandemic 2021

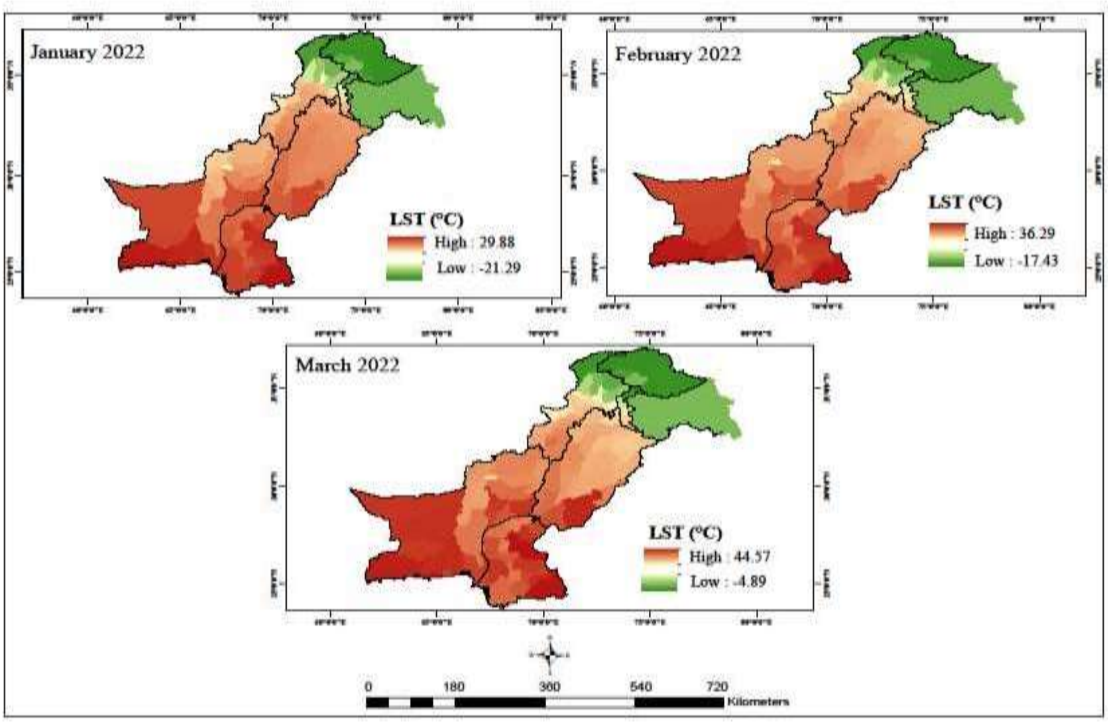

Figure 26: Spatial Distribution of LST During Covid-19 Pandemic 2022

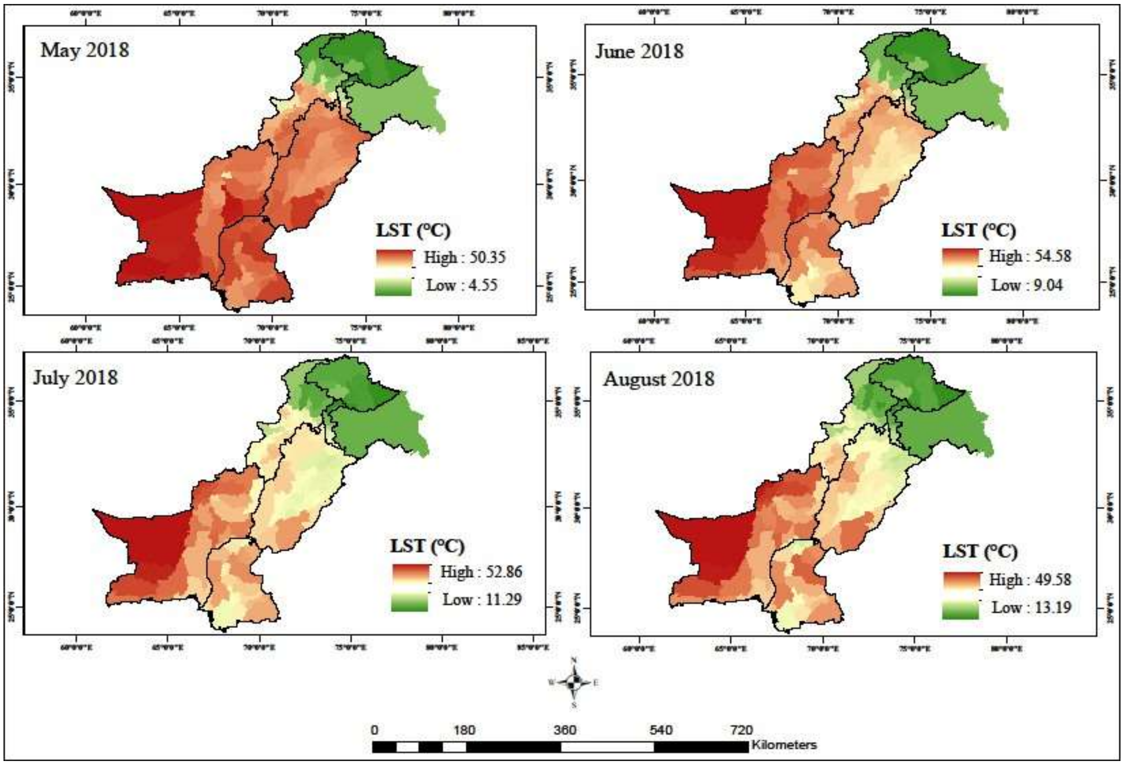

Figure 27: Spatial Distribution of LST Before Covid-19 Pandemic 2018

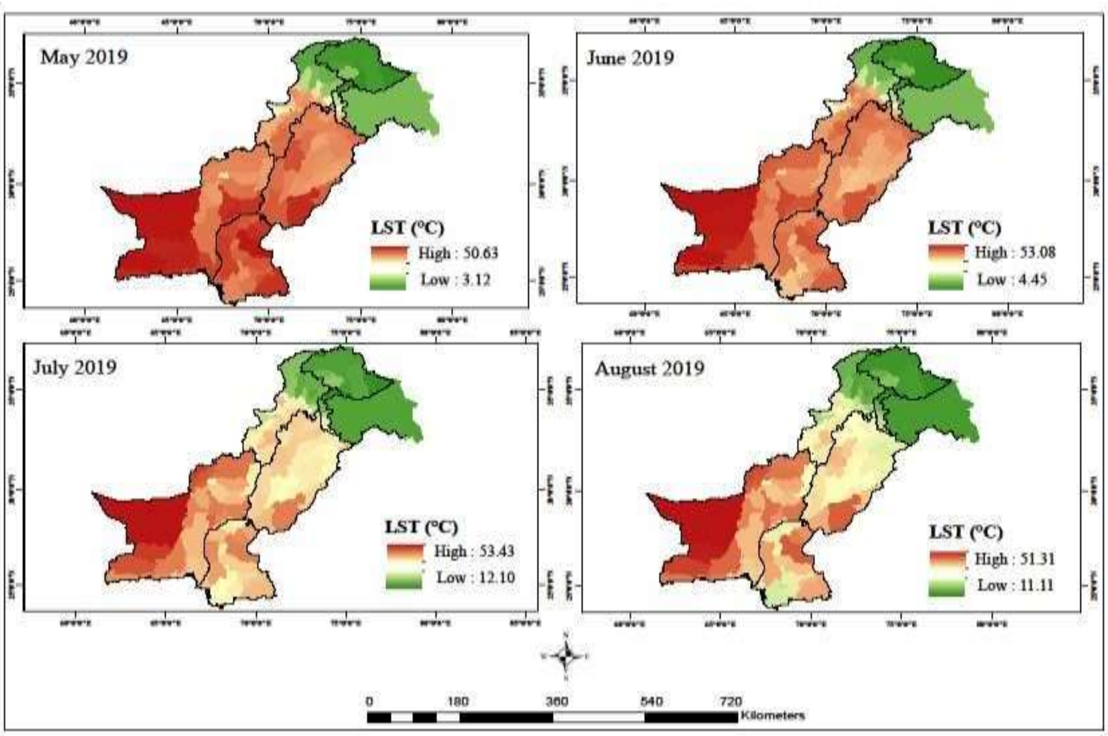

Figure 28: Spatial Distribution of LST Before Covid-19 Pandemic 2019

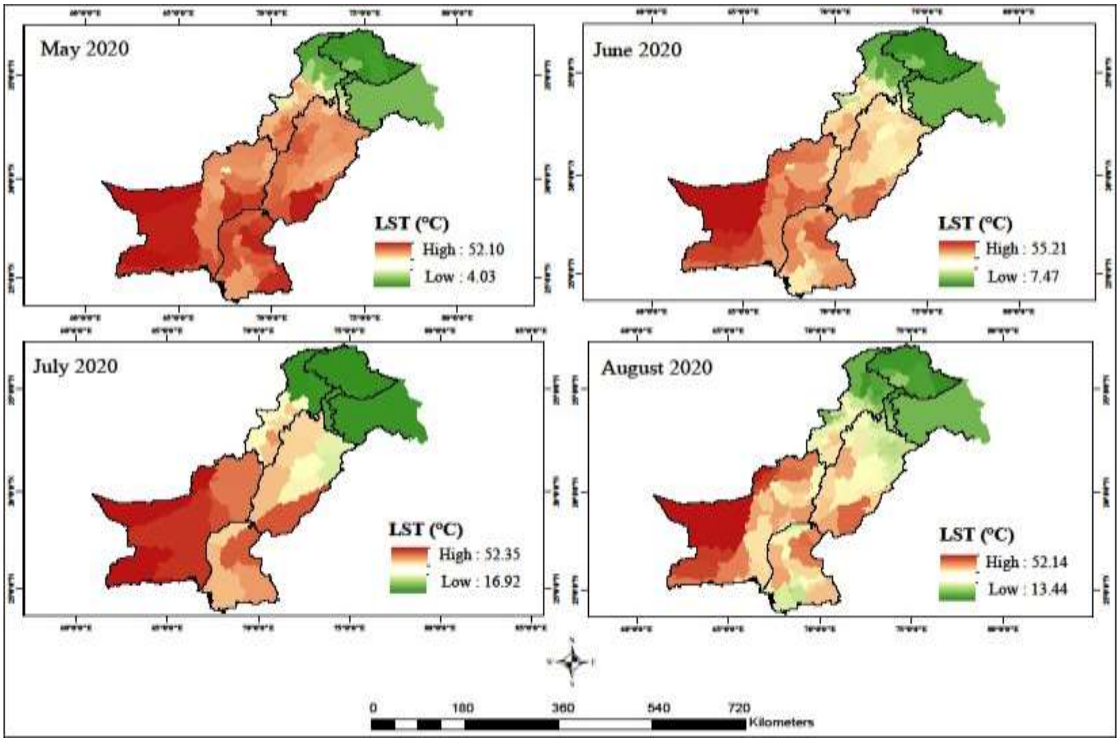

Figure 29: Spatial Distribution of LST During Covid-19 Pandemic 2020

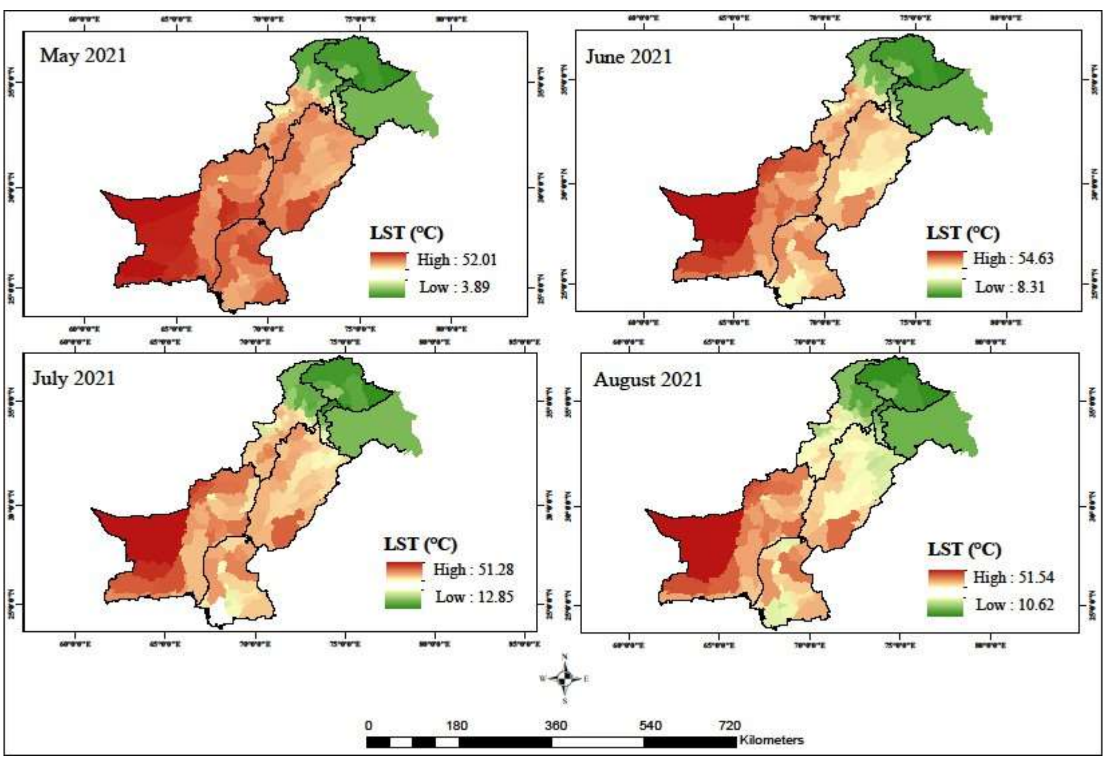

Figure 30: Spatial Distribution of LST During Covid-19 Pandemic 2021

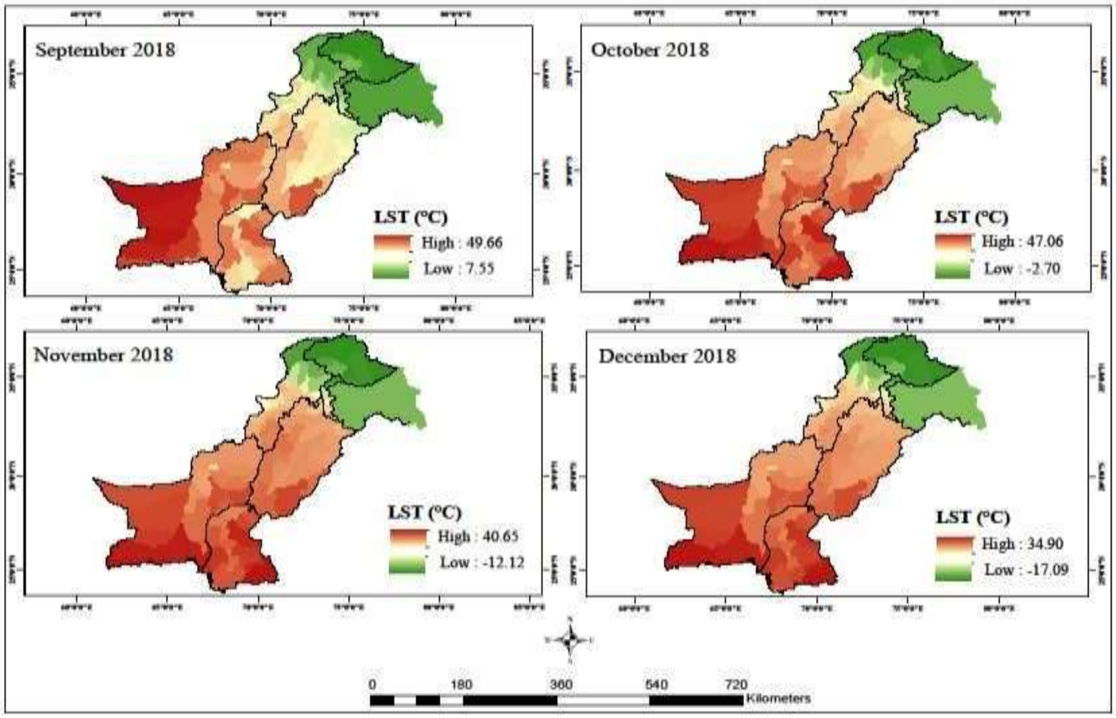

Figure 31 Spatial Distribution of LST Before Covid-19 Pandemic 2018

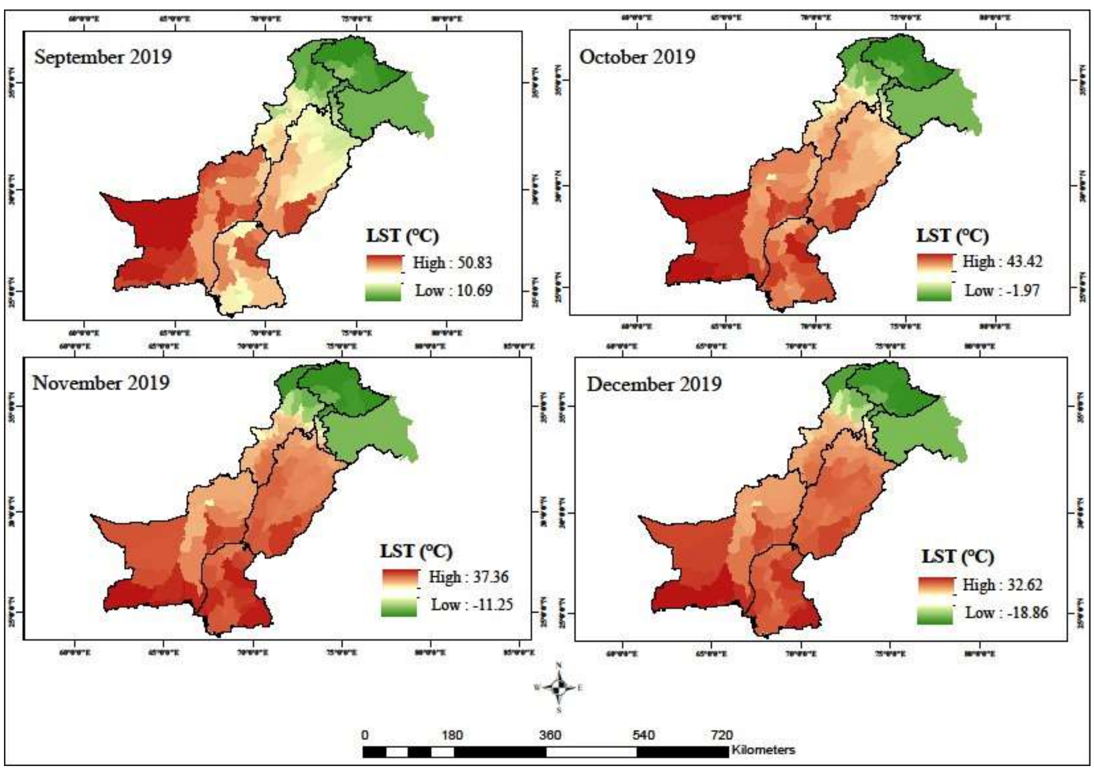

Figure 32: Spatial Distribution of LST During Covid-19 Pandemic 2019

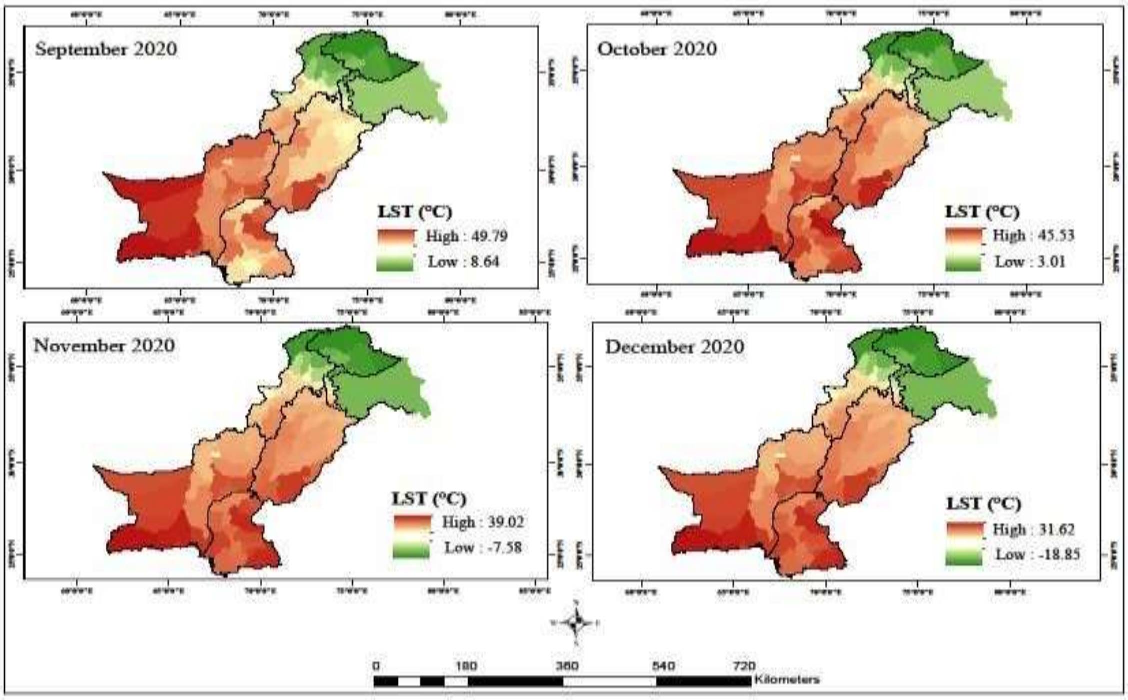

Figure 33: Spatial Distribution of LST During Covid-19 Pandemic 2020

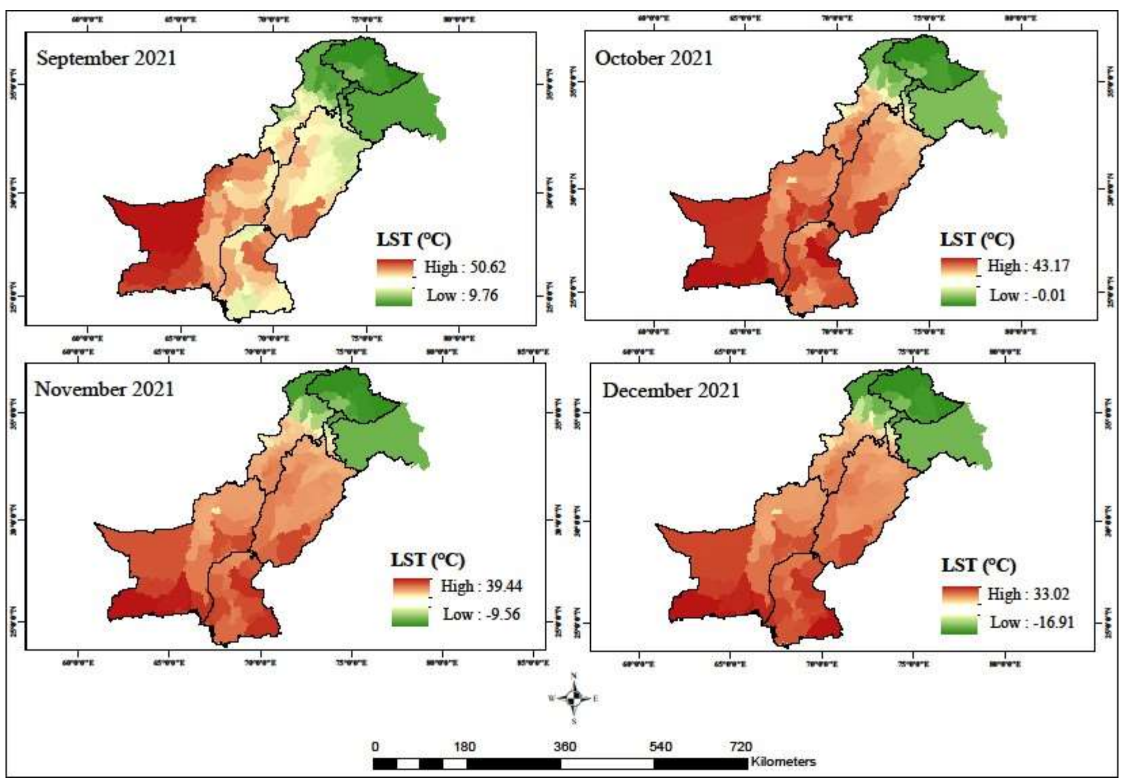

Figure 34: Spatial Distribution of LST During Covid-19 Pandemic 2021

Table 5: Statistics of LST during lockdown

LST(°C)	2018	2019	2020	2021
March	28	24	23	27
April	33	32	31	33
May	38	38	37	37
June	38	38	37	37

The main variations due to the lockdown period were observed during the 2020 pandemic year. Figure 24 and 29 and Figure 33 show the distribution of LST during the pandemic year 2020. The decrease in 2021 was basically due to a generally cooler weather pattern. Figure 25 and 30 and 34 portray spatial distribution during the COVID-19 pandemic of 2021. Figure 26 shows the distribution of LST during COVID-19 from January to March 2022. The variations in climatic conditions are very clear from the obtained results. A decreasing trend was observed during the lockdown period in wind speed and LST. Figure 35 shows the overall condition of selected environmental factors (wind speed and LST of prior years of the pandemic 2018 and 2019. Table 5 represents the district-wise average of LST during the lockdown period.

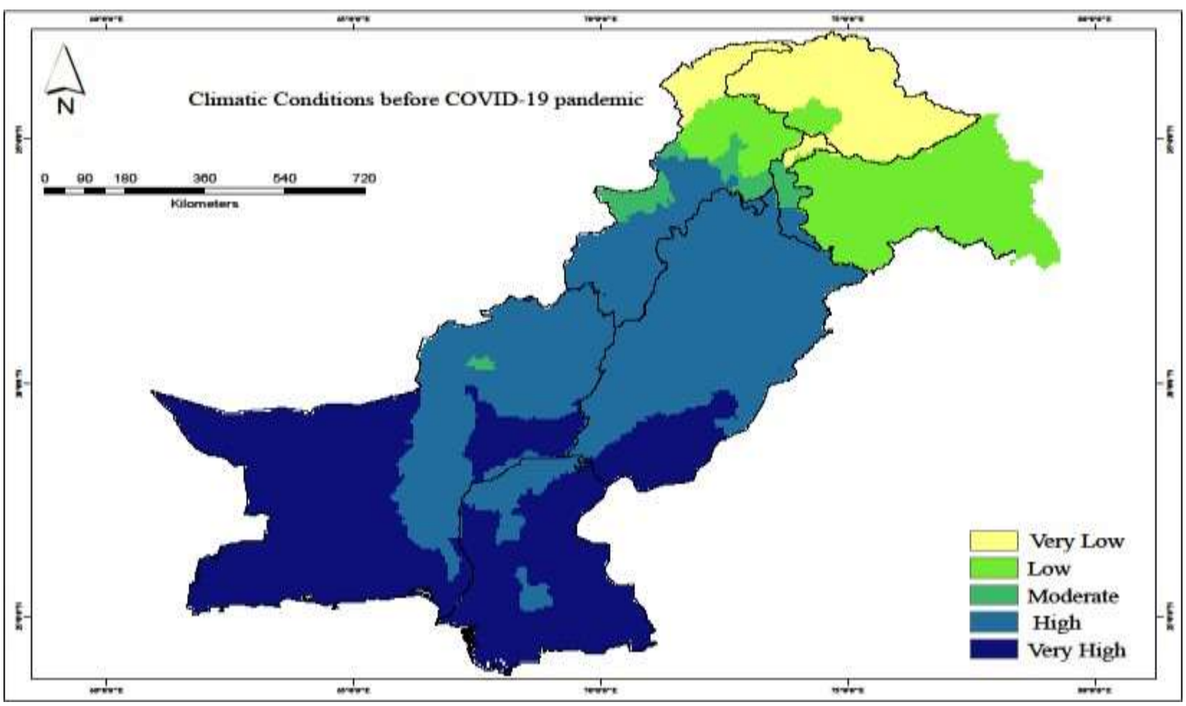

Figure 35: Spatial Distributions of Overall Environmental Conditions before Pandemic (LST, Wind Speed)

Figure 36 depicts how COVID-19 caused changes in climatic conditions during the COVID-19 pandemic in 2020, 2021 and 2022. The changes in climatic conditions were associated with lockdown period during the COVID-19 pandemic and also with a reduction in air pollutants resulting in changes in the trend of climatic conditions.

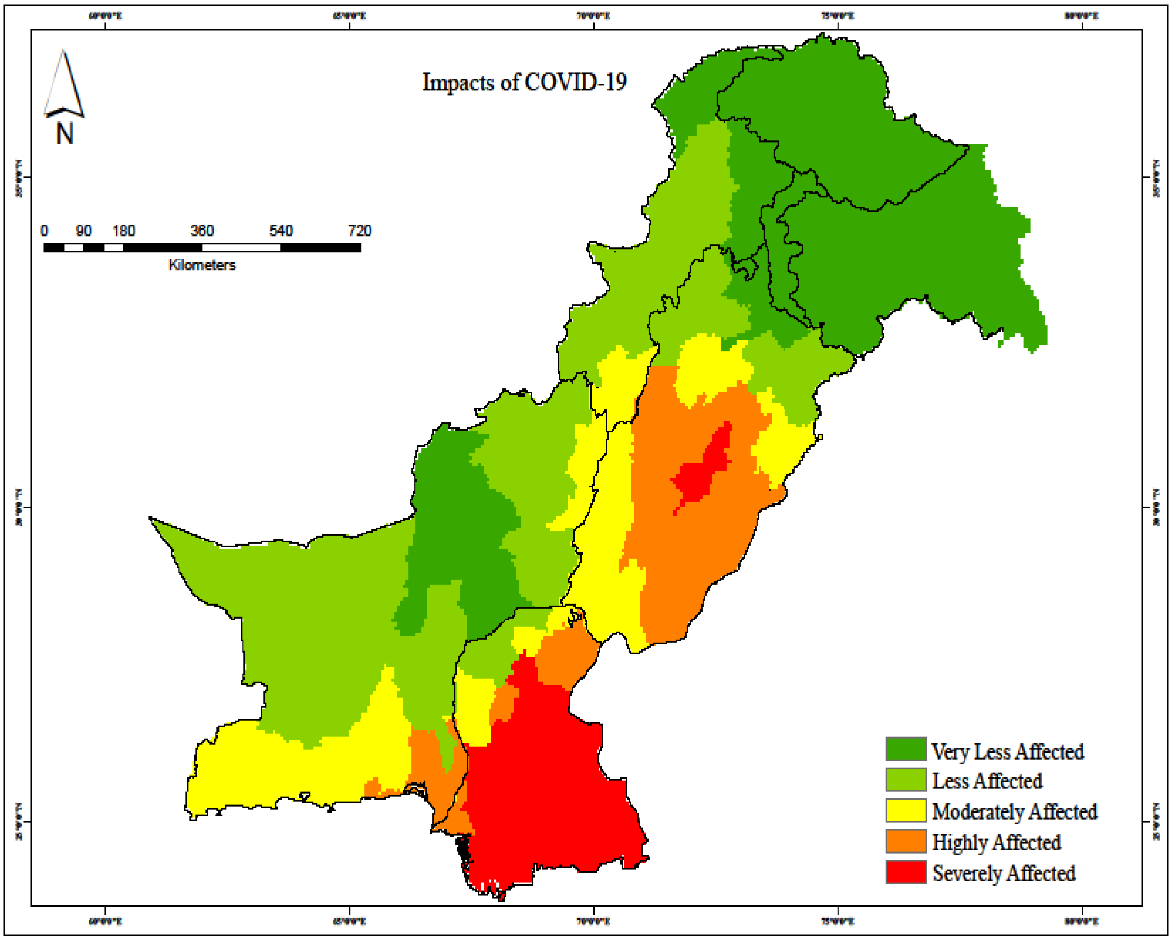

Figure 36: Impacts of Covid-19 on Climatic Conditions

Discussion

In this study the impacts of COVID-19 on environmental conditions and how preventive measures such as lockdown helped to control the spread of coronavirus and caused variations in climatic conditions were assessed over the country. From the obtained results of this research, it could be observed that the most affected province by COVID-19 was Sindh. To limit the spread of COVID-19 the government of Pakistan imposed the lockdown that not only controlled the spread of coronavirus cases but also caused variations in the climatic conditions over the country. The decreasing trend was observed in LST and wind speed in the study domain during the strict lockdown period of 2020 and 2021. These variations in climatic conditions were mainly due to a decrease in anthropogenic activities, restricted transport and closure of industries during the lockdown period of the pandemic. A similar decreasing trend in LST was also observed over different parts of Europe during the lockdown period (Parida et al., 2021). The similar decreasing trend in wind speed was also observed over the different cities of India (Navinya et al., 2020). Lockdown policies during this pandemic around the world had led a way to explain human effects on the environment. This research is of great help to understanding the variation that occurred during the COVID-19 pandemic because this study is based on long-term data analysis and discussed all lockdown periods during the COVID-19 pandemic. And in this study, only secondary data is used and only statistical analysis is performed to understand the impacts of COVID-19 on environmental conditions at district level. In the future more, advanced satellite data can improve the results and ground-based data on metrological factors can be more useful to compare variations for this kind of research paper.

Conclusion

This study provides the impacts of COVID-19 on climatic conditions in Pakistan. The COVID-19 epidemic had improved temporarily climatic conditions around the world, owing to the large-scale reduction in human activities, transport, and industrial activities which caused positive changes in environmental conditions. The results of the present study showed a generally decreasing trend in LST and wind speed around the country during the lockdown period of the pandemic was observed. The variations were mainly due to lockdowns, limited transport and reduction in industrial production. These climatic factors and anthropogenic emissions returned to their standard levels as the government removed the preventive measure such as lockdown and restrictions on transport and also resumed industrial activities. However, this study provides improvements in climatic conditions can be achieved by adopting sustainable usage of transport and industrial production. Furthermore, only secondary data of climatic factors is used in this research to understand the impacts of COVID-19 on climatic conditions over the country. By using ground-based data for comparison the obtained results could be more accurate.

Recommendations

• The officials of government should make policies such as a brief lockdown and sustainable production of industries to control the concentration of atmospheric pollutants resulting in improvements in environmental conditions.

• The officials should take preventive measures to reduce fossils fuel usage resulting reduction in aerosol concentrations. This will cause positive changes in environmental conditions.

• The most significant outcome of this study is to suggest to policymakers and officials that such purposeful actions to reduce atmospheric pollution and even population density in cities can have serious consequences for human life.

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Authors' contributions

The authors declared that this research was done by the both authors named in this manuscript and all liabilities pertaining to claim relating to the content of this article will be borne by both of them. Hazeema Mumtaz conceived the research and drafted the manuscript. Kanwal Javid revised the manuscript. Both authors performed a review of the manuscript before approving its publication in this journal.

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Geospatial Susceptibility Assessment of Landslide in Battagram, Khyber Pakhtunkhwa, Pakistan

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Abstract

A landslide is a natural disaster that can cause significant global damage and human casualties. As a flood-prone area, the Battagram district of Khyber Pakhtunkhwa, Pakistan, has seen an increase in urbanization, making it challenging to choose an appropriate location for seismic activity. This study seeks to assess the susceptibility to landslide risk through the application such as seismic activity and flooding. This analysis employs Geographic Information System (GIS) and Remote Sensing techniques. The research utilized several data sets, encompassing geological data processed with the ArcGIS 10.8 software, Shuttle Radar Topography Mission (SRTM) data, Landsat thermal images from missions 5 and 8, thematic data, meteorological data, and a seismic catalogue. SAR photos are used to map Sentinel-1A in Google Earth Engine (GEE) to determine the extent of floods. The landslide inventory was separated into training and validation sets for this investigation. Significant contributing factors, including slope aspect, elevation, land cover and use during earthquakes, normalized difference vegetation index (NDVI), road distance, fault distance, rainfall, and geology, are taken into consideration when assessing landslip susceptibility. To establish the spatial correlation between landslides and these parameters, the frequency ratio model and weighted sum analysis were utilized. The WSM analysis indicates that 1.74% of the region is classified as having very low susceptibility, with the remaining areas being classified as low (14.26%), moderate (36.01%), high (2.57%), and very high (5.41%). 44.67% of the region is classified as having very high susceptibility by the FR model, with high (40.94%), moderate (11.61%), low (1.96%), and very low (0.79%) following. The FR model demonstrated reliability in risk assessment, with an accuracy of 85.7% against known landslide events. These findings support the use of GIS-based statistical modeling in urban planning and hazard mitigation by demonstrating how well it can identify high-risk areas. For increased accuracy and scalability, future developments should concentrate on adding more localized data.

Keywords: Landslide susceptibility, weighted sum analysis, GIS, frequency ratio, remote sensing, Google earth engine

Introduction

One of the most common geological disasters, landslides are said to cause significant property loss and fatalities all over the world (Linkha, 2024). According to CRED, the landslides segment accounts for 17% of fatalities in all natural disasters worldwide (Alimonti & Mariani, 2024). Climate models project that the intensity of monsoon rainfall in southern Asia will rise in the future owed to climate change. This could feasibly enhance the winter rebound and cause more seismic events. Rainfall and flash floods can cause rockfalls and debris flow, and environmental factors like rock deterioration over time can also cause landslides. Similarly, natural disasters like earthquakes can cause a slope to become weak due to construction along its banks (Shabbir et al., 2023). Every year, during the monsoon season, landslides and floods in the Himalayan region reason fatalities and damage to property (Sana et al., 2024). The rough terrain, active seismicity, monsoon rains, and human activity on uneven slopes make northern Pakistan one of the most landslide-prone areas (Hussain et al., 2023). The deadliest and worst flood disaster in the past ten years occurred in Pakistan in 2022. Pakistan encountered a monsoon climate and extremely hot weather in mid-June 2022 (NASA, 2022), and as a result, at least two-thirds of the nation experienced the most precipitation in almost 30 years. Following the flood in 2022, some of the highland's volcanic mountains are still active. Additionally, fissures and cracks truncate the main rock types in this highland. Many landslides have occurred in the area as a result of earthquakes destroying them (Sana et al., 2024). In order to forecast future landslides, it is vital to identify the zones that are vulnerable. By using scientific analysis to identify and forecast landslide-prone areas, appropriate preventative measures can reduce landslide damage (Jena et al., 2021). Therefore, the two main causes of landslides in the region are earthquakes and rainfall (Vasil Levski & Dolchinkov, 2024). Using the data that is currently available and geospatial techniques, this study attempts to create landslide susceptibility mapping over the Battagram district that is caused by earthquake and flood activity. As a result, the study evaluates the primary causes of landslides in the Battagram district as well as the effects of land cover change over the previous 16 years on landslides in the study area. The study area has a primarily monsoonal climate, and landslides are typically caused by heavy rainfall. The risk of landslides is influenced by human activity in addition to climate and geotectonic factors.

Disasters appear on the news headlines almost every day, according to (Dietrich et al., 2024). Most of them take place in distant areas and pass by swiftly. In light of (Lu et al., 2024), there have been eighteen fatal earthquakes worldwide between 1989 and 2015, which have caused extensive landslides across a wide area. Examples of large-magnitude earthquakes in the past ten years, according to (Saima Akbar, 2024), include the 2005 earthquake in Kashmir caused thousands of landslides in northern Pakistan, resulting in a thousand deaths. Some of the most notable landslide disasters that have occurred in northern Pakistan include the 2005 Kashmir earthquake, which caused thousands of landslides over an area of more than 7,500 km³ in Kashmir and its surroundings, killing 87,350 people. (Bali et al., 2025) stated that three major mountain ranges, the Himalayas, Karakoram, and the Hindu Kush, are the dominant feature of the northern regions of Pakistan. These mountain ranges comprise the world's steepest peaks with a 45° slope

(Ahmed et al., 2019). Flash floods and landslides occurred on October 3-4 in Khyber Pakhtunkhwa Province (Northern Pakistan) due to heavy rain, leading to casualties. Across Charsadda and Lower Kohistan Districts, the Provincial Disaster Management Authority (PDMA) reports that two people have died and six have been injured. Rescue operations are taking place in Charsadda, as a few families have been relocated to relief camps. On October 6-7, there is a forecast of dry conditions over Khyber Pakhtunkhwa Province. Pakistan's history has shown numerous flood events starting from its creation, such as the floods of 1950, 1992, 1998, and 2010 (Saima Akbar, 2024)

Several revisions in this area focused on geospatial and GIS-based methods to analyze numerous spatial data types, the evolution of geostatistical models, and the predictable points of risk and vulnerability for a given area (Rehman et al., 2022) A susceptibility map that identifies areas that are likely to experience landslides in the future (Tyagi et al., 2023). An essential first step in hazard and risk assessment, landslide susceptibility assessment is a widespread practice worldwide, primarily utilized for landslide mitigation strategies. Landslide susceptibility assessment requires the use of remote sensing and Geospatial-derived outcomes, such as landslide inventory and contributing and triggering factors. Landslide susceptibility assessment methods can be divided into two categories: quantitative methods, such as statistical models, heuristics (multi-criteria analysis), and physical-based models, and qualitative methods, such as knowledge-based and geomorphological mapping (Batar & Watanabe, 2021).

According to (Dou et al., 2019) usually, rainfall or earthquakes cause landslides, though sometimes an earthquake causes a rainfall event, or vice versa. A digital elevation model (DEM) is used in large-scale physically based landslide susceptibility processes to describe the terrain constraints that fundamentally define the local elevation, slope, hydrologic, and further geomorphic processes (Schlögel et al., 2018). Land use and land cover variation can modify the geological circumstances and distress the manifestation of the landslides (Chen et al., 2019). Remote sensing data, land-based data, and numerous other data sources are used to extract the spatial information related to the aforementioned factors. Landslide susceptibility maps demonstrate the comparative possibility of future landslides based exclusively on the vital assets of a background or site (Rahim et al., 2018). Landslide susceptibility mapping (LSM) is regarded as a prime phase in the execution of instant disaster management planning and risk mitigation events (Camilo et al., 2017).

The occurrence of landslides is primarily ascribed to the combined effect of various factors, and it is never easy for researchers to assess the extent of these factors' influence (Abdı et al., 2021). Unusually, in recent years, firm changes in global climatic conditions have controlled to extreme weather events that increase the propensity of landslides (Zou et al., 2021). Even though landslides have been studied extensively, little is known about how floods and seismic activity interact to cause landslides. This is especially true in Northern Pakistan's Battagramdistrict, which is particularly vulnerable because of its complicated topography, active tectonics, and unpredictable climate. Current models frequently ignore the compounding effects of multiple hazards and only take into account landslide triggers in isolation. Additionally, little research has been done to incorporate changes in land cover over the past few decades into susceptibility assessments. By using the Frequency Ratio (FR) model and Geospatial techniques to generate an extensive Landslide Susceptibility Map (LSM), this study seeks to close these gaps.

Study Area

The geographical location of District Battagram is latitude 34.79147 and longitude 73.121641, which covers an area of 350,172 acres. The district usually has dense forests and mountains with peaks higher than 4000 meters. It is bordered to the north by Kohistan District, to the east by Mansehra District, to the south by the Kala Dhaka Tribal Area, and to the west by Shangla District.

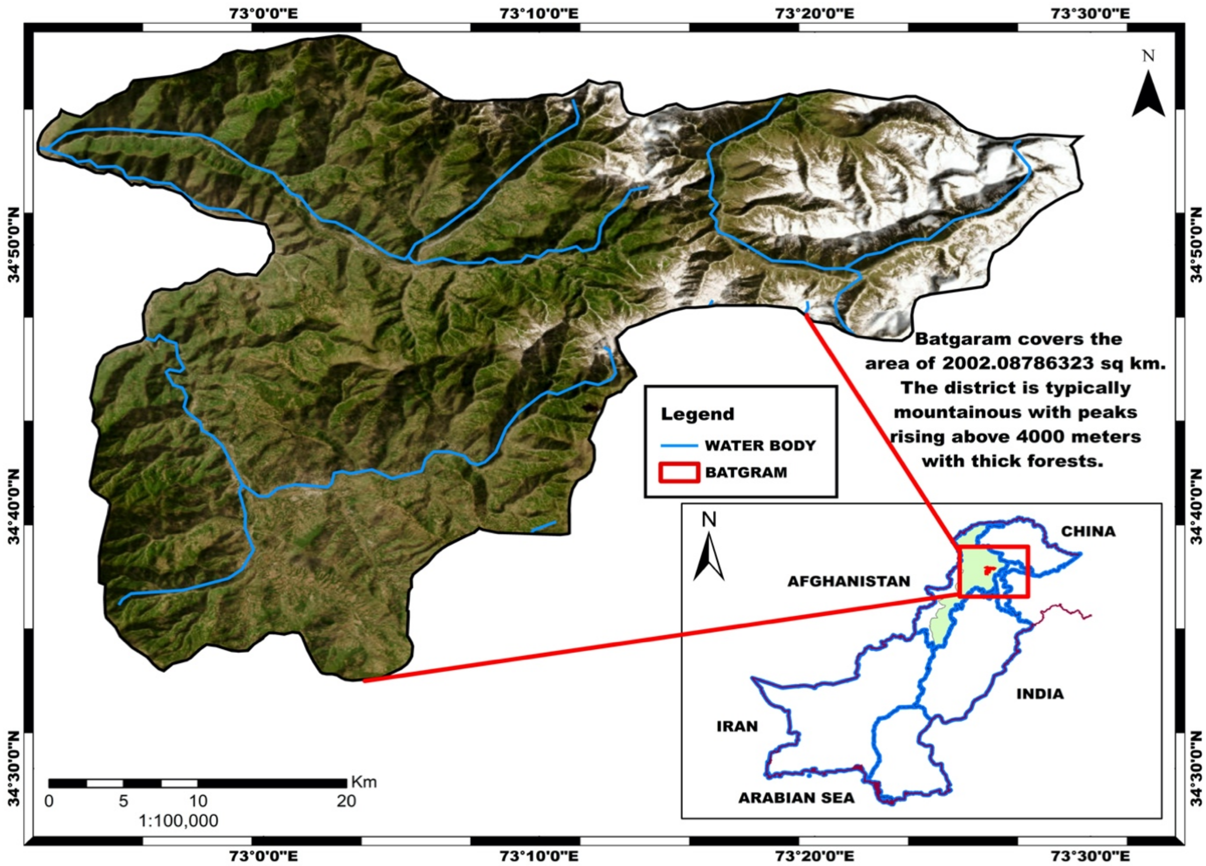


Figure 1: *Study Area Map*

The corporate headquarters is located in Battagram town, which is about 75 kilometers from Mansehra along the Silk Highway. Battagram and Allai are the two tehsils that make up the district. It features a number of stunning valleys. The Nindhyarkhawar and Allai Khawar are the two main streams, which are referred to as Khawar in the local dialect. Beginning in the "Hill" mountains, the Nindhyar Khawar flows over the main village before joining the Indus River at Thakot in the east. The Chaur Mountains are the source of the other large stream, Allai Khawar, which empties into the Indus River at Kund in the east. The maximum temperature on an average day for each month in Battagram is displayed by the "mean daily maximum" (solid red line). Similarly, the average minimum temperature is displayed by the "mean daily minimum" (solid blue line). The average of each month's hottest day and coldest night over the previous 30 years is displayed by hot days and cold nights (dashed red and blue lines).

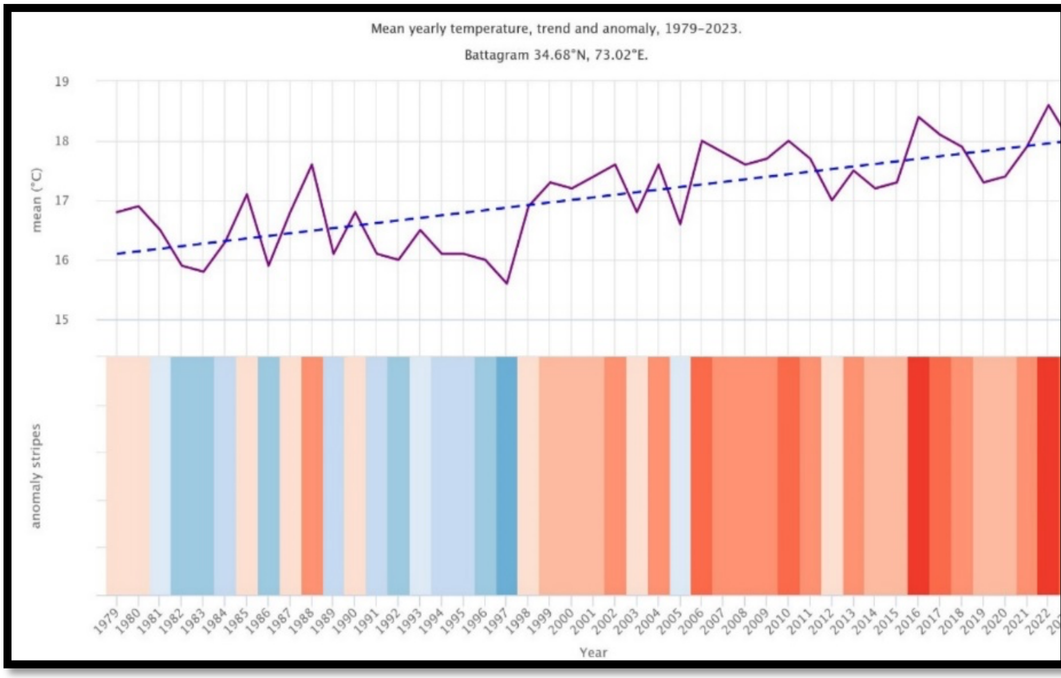


Figure 2: *Graphical representation of temperature (1979_2023)*

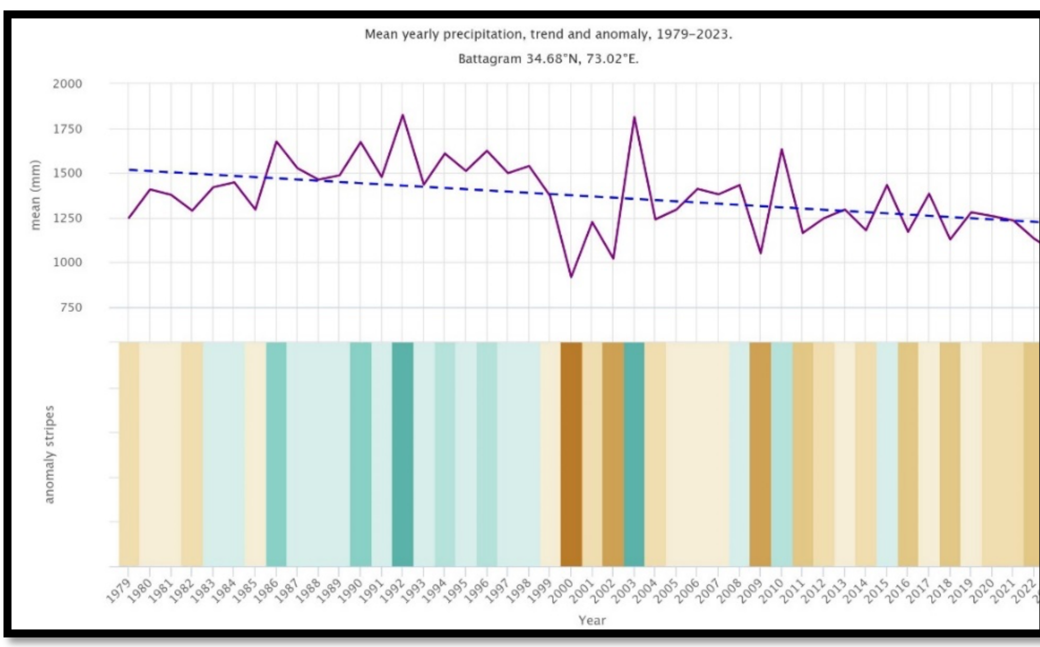


Figure 3: *Graphical representation of precipitation (1979-2023)*

The graph displays an approximation of the mean total precipitation for the greater area of Battagram. The dashed blue line is the linear climate change inclination. In the lower part, the graph demonstrates the so-called precipitation stripes. Respectively colored stripe represents the total precipitation of a year - green for wetter and brown for drier years. There is an entire 369 km road network in the valleys. The Karakoram Highway or the Silk Highway, arrives in the district at Sharkool, Mansehra, and leaves it at Thakot. The major roads in the district are Battagram-shamlai, Batagram-Oghi, Battagram-paimal Sharif and Chattar-Kuzabanda road.

It's interesting to note that geologists have long recognized a connection between seismic activity and rainfall rates. For instance, the yearly rainfall cycle of the summer monsoon season in the Himalayas affects the frequency of earthquakes (Mir et al., 2024). According to investigation, only 16% of Himalayan earthquakes happen throughout the monsoon season, with 48% occurring during the drier pre-monsoon months of March, April, and May. (Munir et al., 2021) stated that Pakistan continues to experience flooding and landslides due to the country's heavy rainfall, which also causes an increasing amount of damage and fatalities. In Khyber Pakhtunkhwa Province, flash floods and landslides caused at least 13 fatalities and 27 injuries between August 31 and September 1. According to the NDMA report, there have been 2,245 damaged homes, 189 fatalities, and 128 injuries since the start of the monsoon season. According to (Bahram & R. Paradise, 2020), nearly every element of the people's socioeconomic lives as well as the district's physical infrastructure was impacted by the earthquake. In the last ten years, 1389 earthquakes of magnitude four or higher have occurred within 300 kilometers (186 miles) of Battagram, Khyber Pakhtunkhwa. This translates to an average of 11 earthquakes per month, or 138 earthquakes annually. Near Battagram, an earthquake occurs approximately every two days on average. Battagram has experienced 19 earthquakes with magnitudes greater than 2 and up to 5.0 since 2022.

Materials and Methods

Data acquisition

Multi-source data has been used for landslide susceptibility monitoring in Battagram. This study's landslide susceptibility map was created using ten factors. The factors were entirely chosen based on their availability and efficacy. For LULC variation analysis, multi-temporal cloud-free Landsat 5 and 8 Thematic Mapper (TM) data of August 2010, 2015, and 2022 (Table 1) were obtained from USGS Earth Explorer (EarthExplorer (usgs.gov). The extraction of topographic information, including elevation, slope, aspect, hill shade hydrology, was obtained from the Shuttle Radar Topography Mission-Digital Elevation Model (SRTM-DEM) with 30 m resolution. The geological data were obtained from toposheets from the Geological Survey of Pakistan (GSP) and satellite data from the U.S. Army KMZ. The monthly rainfall data from 2010 to 2022 were collected from the Data Access Viewer-NASA POWER (https://power.larc.nasa.gov/data-access-viewer/). The historical landslide data have been collected from the NASA Landslide Viewer.

Table 1: Evidence about satellite data

Satellite	Dates of Images	Resolution	Reference system/Path/Row
Landsat 5	18/06/2010	30m	WRS/150/36
Landsat 8	15/06/2015	30m	WRS/150/36
Landsat 9	20/06/2022	30m	WRS/151/40

Data processing

The data was then imported, processed, and analysed in ArcGIS software to create various maps of the factors impacting the incidence and spreading of groundwater in the watershed. Multiple factors have been considered to regulate landslide-susceptible zones.

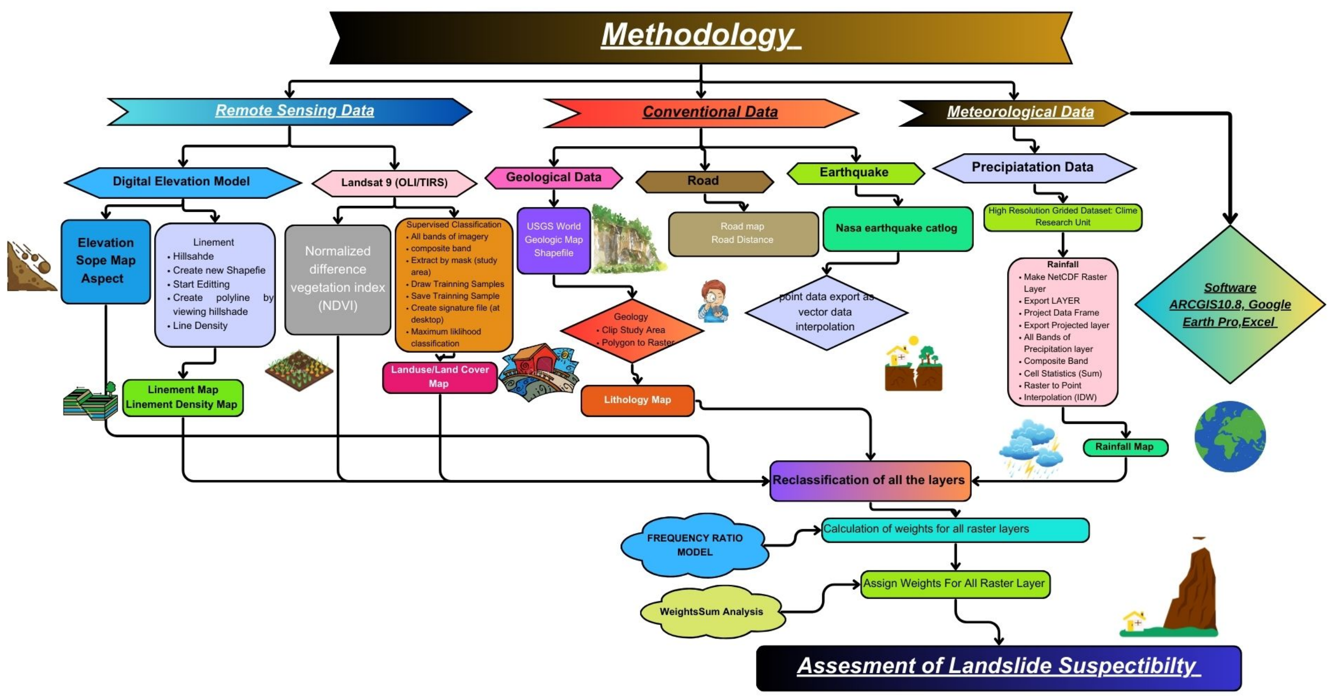


Figure 4: *The methodological framework*

Data analysis

Flood extent

Sentinel-1 SAR data were principally utilised in this study to map the flood inundation in the Battgaram District in 2022. A population dataset and land use/cover (LULC) have been used in the evaluation of flood damage. The Global Human Settlement Layers (GHSLs) and Gridded Population of the World (GPW v4) datasets were analyzed for population and density, respectively, in order to assess the effects of flooding. Using the monthly precipitation data from Terra Climate, the rainfall pattern and anomaly during the 2022 flood event have been recognized. The crop land and population density had been calculated using ArcGIS software.

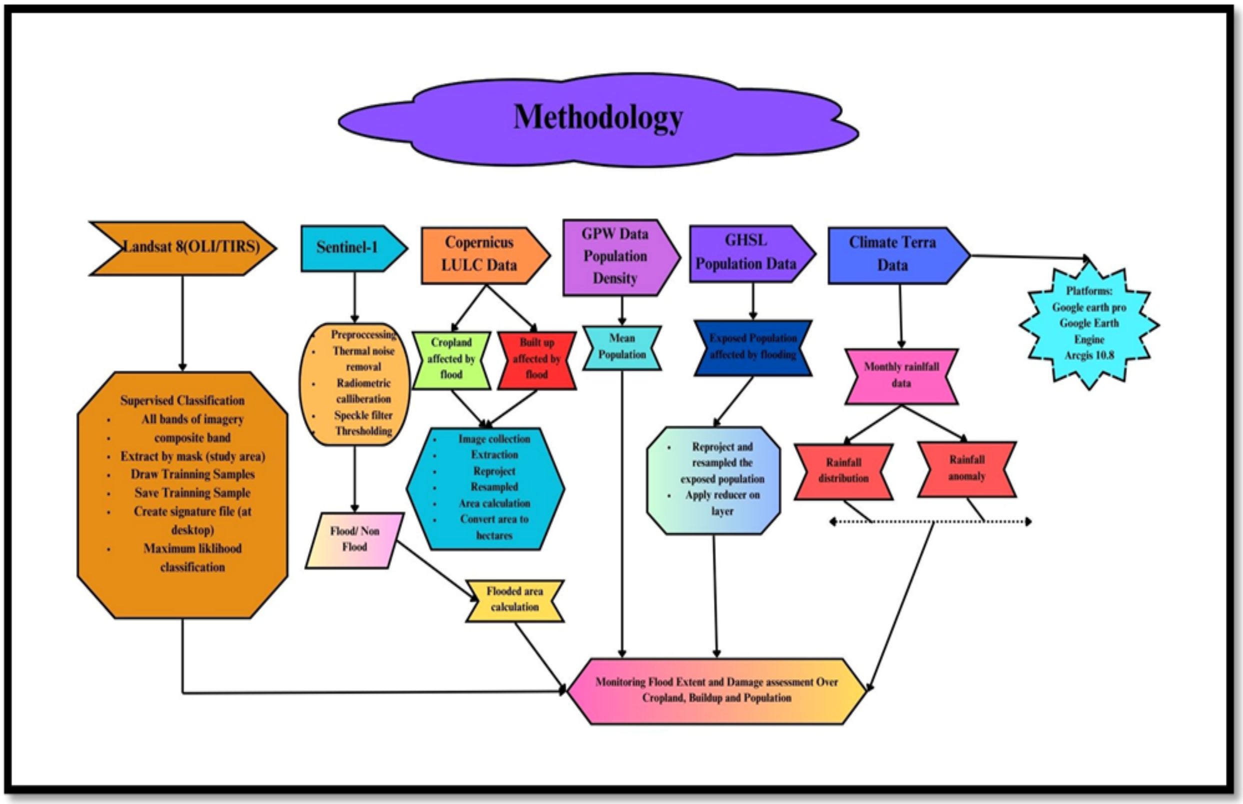


Figure 5: *The methodological framework for assessment of flood extent*

Landslide inventory map

A landslide inventory map, which illustrates the positions and contours of landslides, expresses the knowledge of landslides in a specific area. A data set that may include one or more incidents is called a landslide inventory. Forecasting the likelihood of landslides in a study area primarily relies on historical and present landslide inventory data. Sentinel-1 and Google Earth pictures were used to generate the landslide inventory map for this study.

Common factors controlling landslides

The primary determinants of seismic landslides include geological, seismic, and topographic factors. Ten common landslide-causative characteristics that are used to analyze landslides triggered by earthquakes and rainfall were examined in this study. The topography, geology, tectonic features, weather, land cover, and human activity all have a significant influence on the intensity and spatial distribution of landslides. It is crucial to assess how these causal elements affect the landslide's spatial distribution for the purpose to comprehend how they work and create a map of landslide vulnerability. The primary factor influencing the location and severity of landslides is the slope of the terrain (Jin et al., 2024).

Slope is an important causal component in landslide inquiry, according to (Mir et al., 2024), since it causes loose sediment material to migrate downslope. The current research area's slope was calculated using a DEM with a spatial resolution of 12.5 m. Next, using ArcGIS 10.8, the computed slope was divided into five classes, as Figure 8 illustrates. The research area's terrain aspect was calculated using a 3*3 moving window in ArcGIS 10.8 based on the DEM. It is usually recognized that lithological structures have a substantial influence on the physical potentials of both surface and subsurface material, counting their strength and permeability, which in turn influences the probability of landslides (Khan et al., 2019). The distribution of landslides is greatly affected by land cover; generally, landslides are less common in forested areas than in barren ones. Strong root systems of the vegetation give the mechanical and hydrological forces that frequently stabilize the slopes. The area's land cover was categorized as consisting of permanent snow, glaciers, irrigated agricultural land, barren ground, woodland and shrub land, and water bodies. The prevalence and intensity of co-seismic landslides are primarily determined by the spatial spreading and character of fault lines (Duan et al., 2023). The region's fault lines were taken from the geological map of the region. Using ArcGIS 10.8 software, the distance to the fault was split into five regions spaced 50 meters apart (Fig. 6e). Building roads and railroads as part of a communication network in hilly areas frequently causes instability in slopes and ultimately landslides (Dahiya et al., 2025). The road network was derived from the obtained Sentinel 1 pictures and then verified in the field to evaluate the influence of the road network on the landslides in the research area. Then, using ArcGIS software, distance from the road was measured at 50-meter intervals. Streams can cause undercutting from toe erosion and saturation of the slide toe from increased water penetration, both of which can negatively impact a slope's steadiness (Hussen et al., 2024). Using Arc Hydro tools, the stream network for the study area was computed using the ASTER DEM to evaluate the influence of the streams on the distribution of landslides. The streams that accumulated more than 20 square kilometers were extracted.

Weighted Sum Analysis

There are ten elements - Roads, Streams, Vegetation, and Slope - and three criteria established for each element to regulate habitat correctness for the black bears. Feature to Raster, Euclidean Distance, Slope, Reclassify and Weighted sum are cast-off for the analysis. First, layers are converted and analysed to formulate for reclassification. Next, converted and evaluated layers are reclassified giving to the criteria provided in the study. Reclassification for additional specifics concerning reclassification. Finally, all the reclassified layers are draped. A map representing appropriate areas for the black bears, representing three levels of habitat suitability, is fashioned.

Frequency Ratio model

According to (Khan et al., 2019) to assess the likelihood of landslides, it is crucial to comprehend the physical features unique to the place and the mechanisms that cause them. A quantitative method for assessing landslide susceptibility that makes use of geographic data and GIS technology is the frequency ratio. For mapping landslide susceptibility, the frequency ratio (FR) technique is widely and successfully employed. It depends on the measured correlation between the causal variables for landslides and the landslide inventory. We compute the FR for each factor using Eq. 5.

FR = (Ni P x/N)/N i l Q/Nl

Where N is the total number of pixels in the study area, N i lP is the number of landslide pixels in each landslide conditioning factor, Nl is the total number of landslide pixels in the study area, FR is the frequency ratio, and Ni Px is the number of pixels in each landslide conditioning factor class.

Landslide susceptibility mapping

It is crucial to make the assumptions that future landslides will occur within the same conditions as prior landslides and that the geographical distribution of landslides is inclined by the elements that trigger landslides while doing landslide susceptibility mapping. Frequency Ratio (FR) has been utilized throughout this research to map the vulnerability to landslides.

Results and Discussion

Although landslide growth is influenced by a variety of natural and man-made elements, it is a complex process. (Khan et al., 2019). The most significant criteria for precipitation and the detachment to the fault lines were determined to be those created by consulting experts in the landslide susceptibility study (Konurhan et al., 2023). In order to lessen the effects of present and future hazards, LSM was created in this work using geospatial approaches that consider landslide events and risk influences (elevation, slope, aspect, curvature, precipitation, LULC, distance to fault, lithology, distance to road, and distance to streams).

Landslide inventory map

First, we used data from satellites and ground stations to create an inventory map. The determining characteristics for landslides can be observed in the topographic aspects of aspect, curvature, slope, and altitude. As seen in Figure 1, 324 past and present landslide occurrences in the research area were found using ground-based data and satellite imagery.

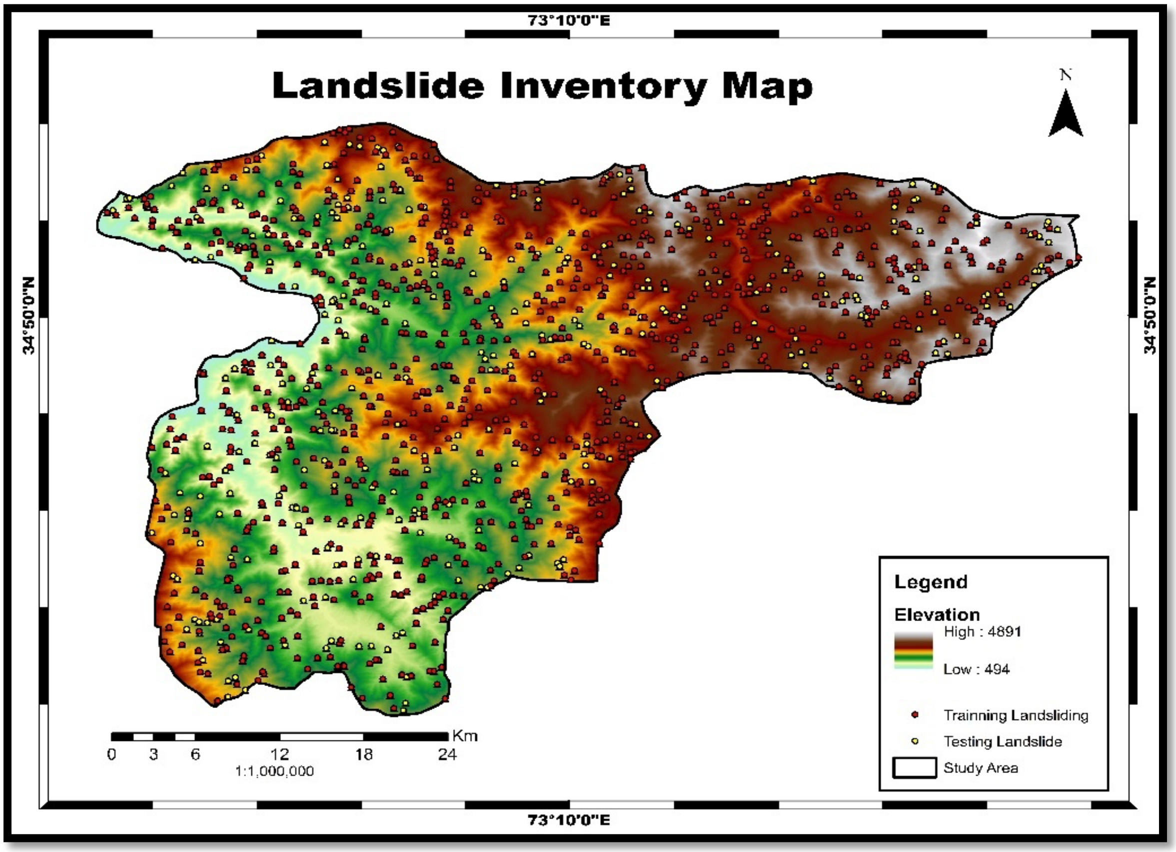


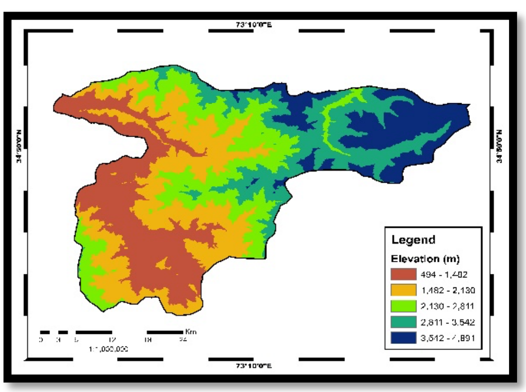
Figure 6: *The landslide inventory map of Battgaram*

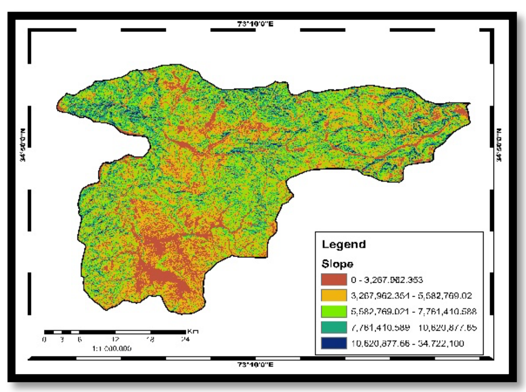
To generate a non-landslide area, we first abstract the landslide polygon after the research area polygon. Next, we created random spots in the study zone which has been designated as a non-landslide area using ArcGIS tools(Jin et al., 2024). The various forms of landslides that occur during these occurrences include mudflows, debris flows, rockfalls, and rockslides, topples, and creeps. Three bivariate models are used in this study to generate the study area's LSM. Table 2 displays particular details of each model's outcomes.

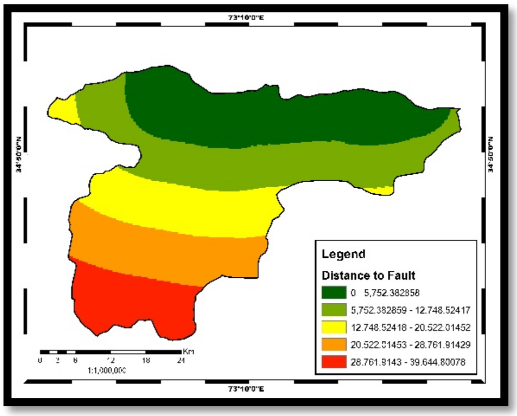
Causative Factors of Land sliding

According to (Khan et al., 2019), elevation is a significant requirement for landslide incidence. The current study's elevation characteristics show a substantial correlation with landslide occurrences. >4,500 m is the most significant elevation class, followed by 494 – 4,891 m. The slope, which is the independent variable in this study, is seen to be the most important component. According to Table 2, the slope component has an impact up to 30° because landslides occur more frequently at higher slopes. Above that point, however, landslide activity declines as the slope increases. The results showed that the most prone class of slope is 15-30 °, while the most resistant class to landslides is >30 °, followed by the 10°–15 ° class. According to Table 2, the most important class of aspects is SE, which E, S, and SW. As shown in Table 2, the tabulated findings clarified that the critical class of landslides is concave structure. As Table 2 illustrates, the current study's findings suggest that faults have no direct bearing on the likelihood of landslides. The findings show that a relatively limited number of landslide pixel values of 0−39,644 for WOE and FR, respectively, occurred in a zone <50 m equidistance from the fault. To measure the relationship between rainfall parameters and landslide incidents, a rainfall map derived from CHIRPS data was created in the current study, verified using data collected from the ground, and classed into five classes. The precipitation data in Table 2 indicate that rainfall plays a substantial part in the occurrence of landslides.

The precipitation period is the censorious class for landslides, according to the results, followed by 301.87–391.30 mm/year. The vegetation cover is crucial for stabilizing slopes because roots anchor and strengthen soil layers. The NDVI values of plant formations are mainly positive and fall between 0.571 to 0.086. The results demonstrate that lithology plays a major causal role in the analysis of landslides. The furthermost prone geological creation for landslides is pC, tracked by Mi, PzpC, and S, as Figure 9 illustrates. It is believed that road construction is a direct effect of human activity, which leads to slope instability. The road network map is a polyline vector generated from the data, as seen in Figure 9. As a result, varying land use plays a vital role in determining landslide susceptibility in numerous studies (Abdı et al., 2021). Different land uses have varying effects on landslides. Table 1 results indicate that the current study area's flooded vegetation and forest land make it particularly vulnerable to landslides.



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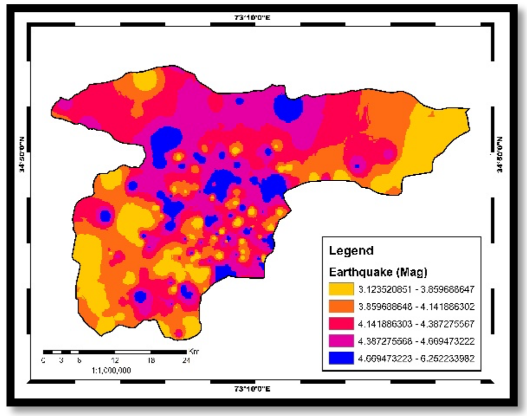
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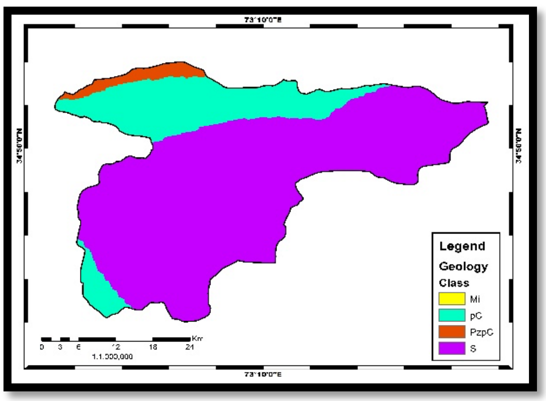
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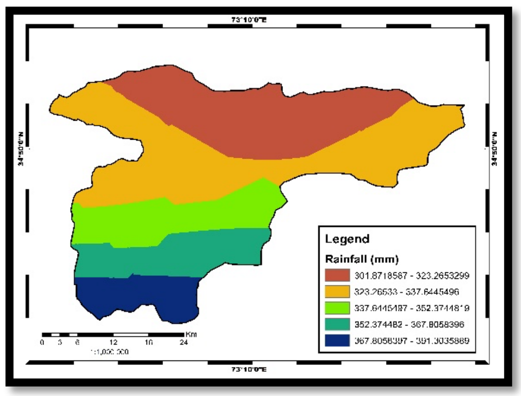
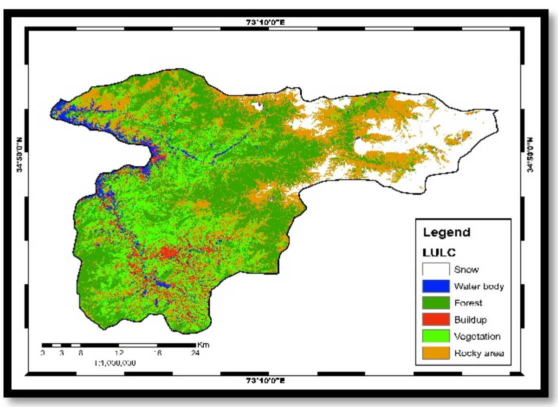
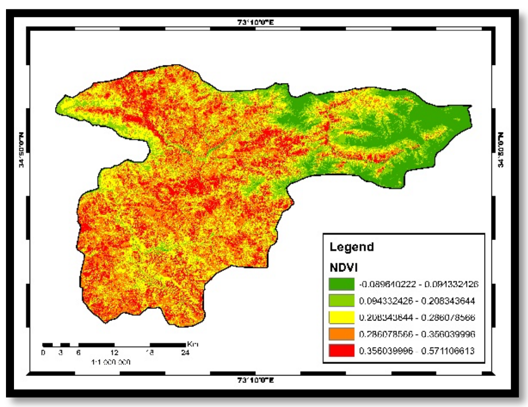
34°50'0"N
Legend
Geology Class
Mi
pC
PzpC
S
Km
1:1,000,000


73°10'0"E
34°50'0"N
Legend
Rainfall (mm)
301.8718587 - 323.2653299
323.26533 - 337.6445496
337.6445497 - 352.3744819
352.374482 - 367.8058396
367.8058397 - 391.3035889
Km
1:1,000,000


73°10'0"E
34°50'0"N
Legend
LULC
Snow
Water body
Forest
Buildup
Vegetation
Rocky area
Km
1:1,000,000


73°10'0"E
34°50'0"N
Legend
NDVI
-0.089640222 - 0.094332426
0.094332426 - 0.208343644
0.208343644 - 0.286078566
0.286078566 - 0.356039996
0.356039996 - 0.571106613
Km
1:1,000,000

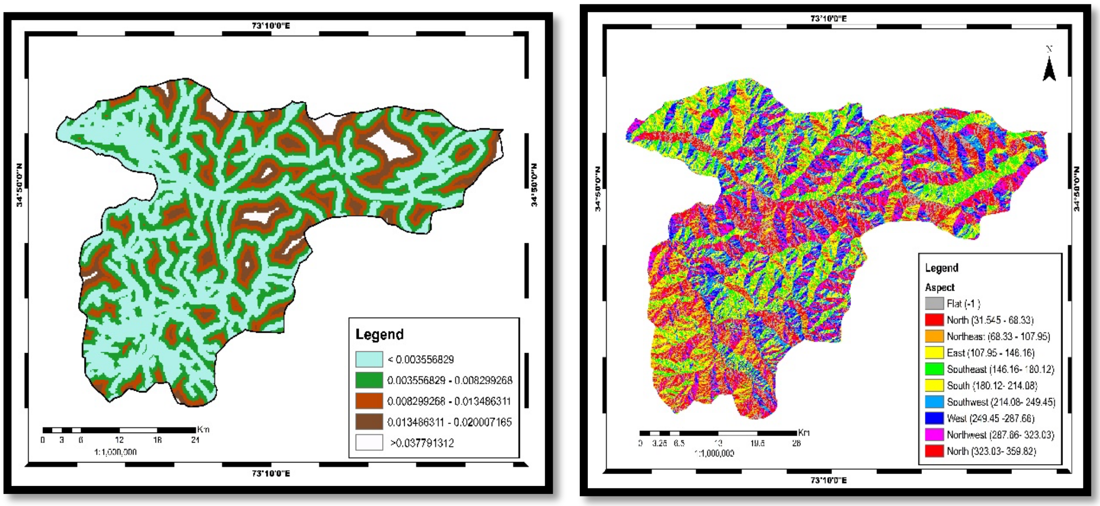


Figure 7: *The resultant maps included land use and cover, geology, rainfall, lineament density, slope, and soil.*

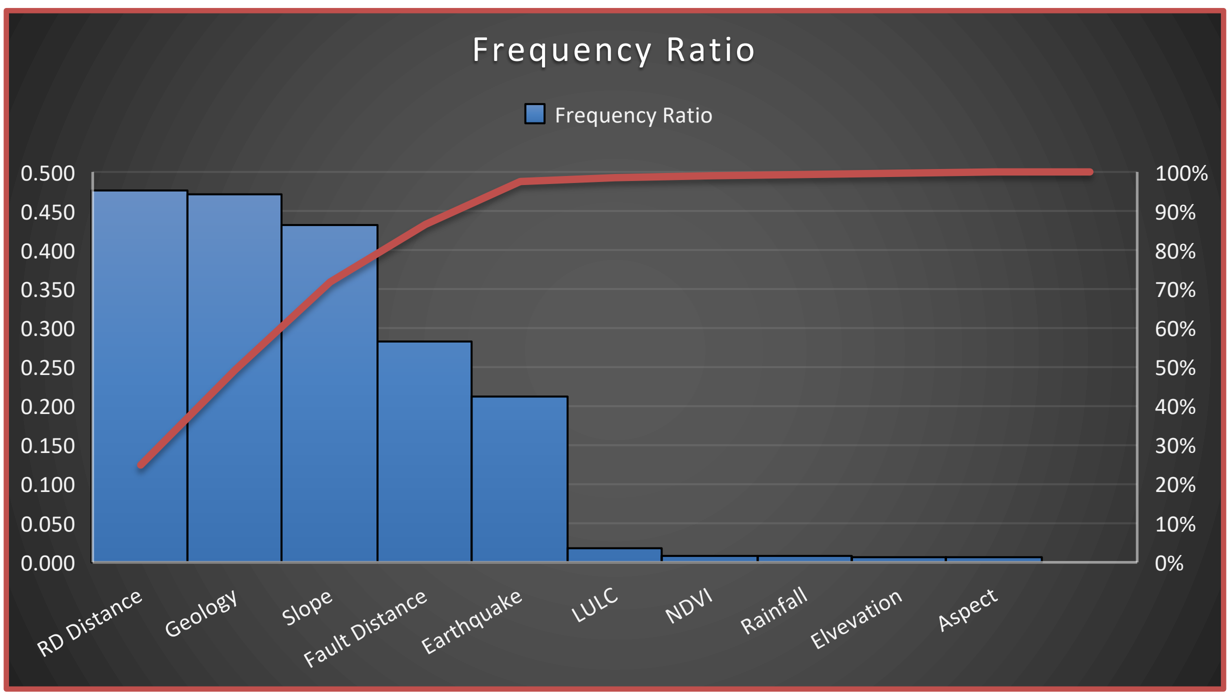


Figure 8: *The frequency ratios of different landslide-related factors*

Flood Extent in 2022 as Derived from SAR

A continuous rise in flooding was pragmatic in the inundation area from the Sentinel-1A data within 3 months since 13 March 2022 to 31 August 2022. In March, a significant percentage of the region was flooded under water owing to a particularly impacted exposure in Figure 10. Nevertheless, in later months, such as August of 2022, the extent of the flood inundation increased. The comparison between these months has been shown in the display figure that has been generated in the software ArcGIS 10.5 after applying the analysis of the normalized difference water index (NDWI). The difference in water bodies has been shown very clearly through magnificent results. The Indus River touches the borderline of Battagram, and some stream coverage in which the flood extends seems to be through image processing.

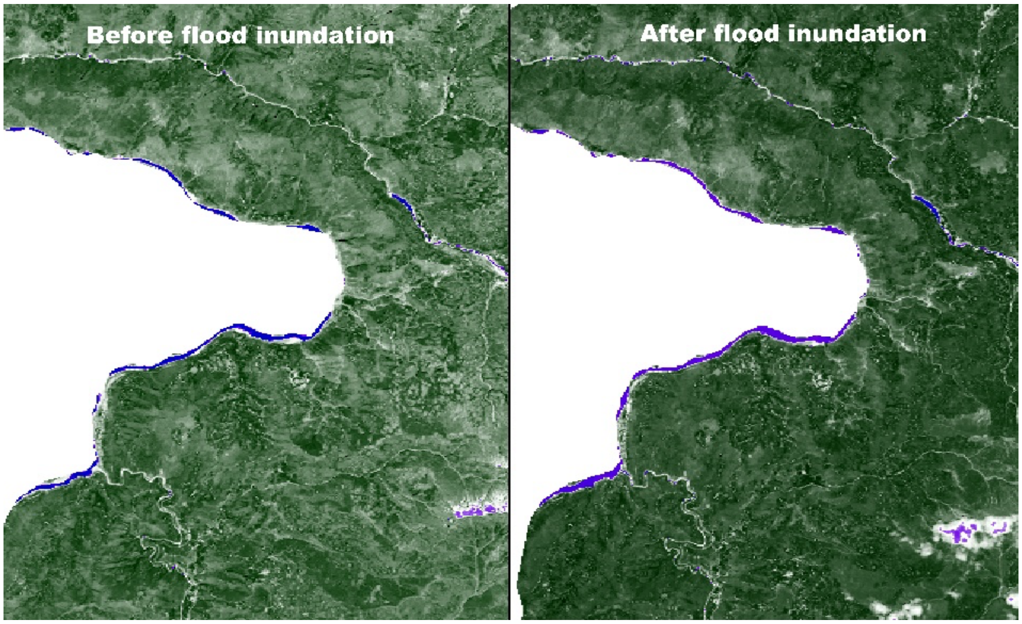


Figure 9: *Comparison between before and after flood simulation*

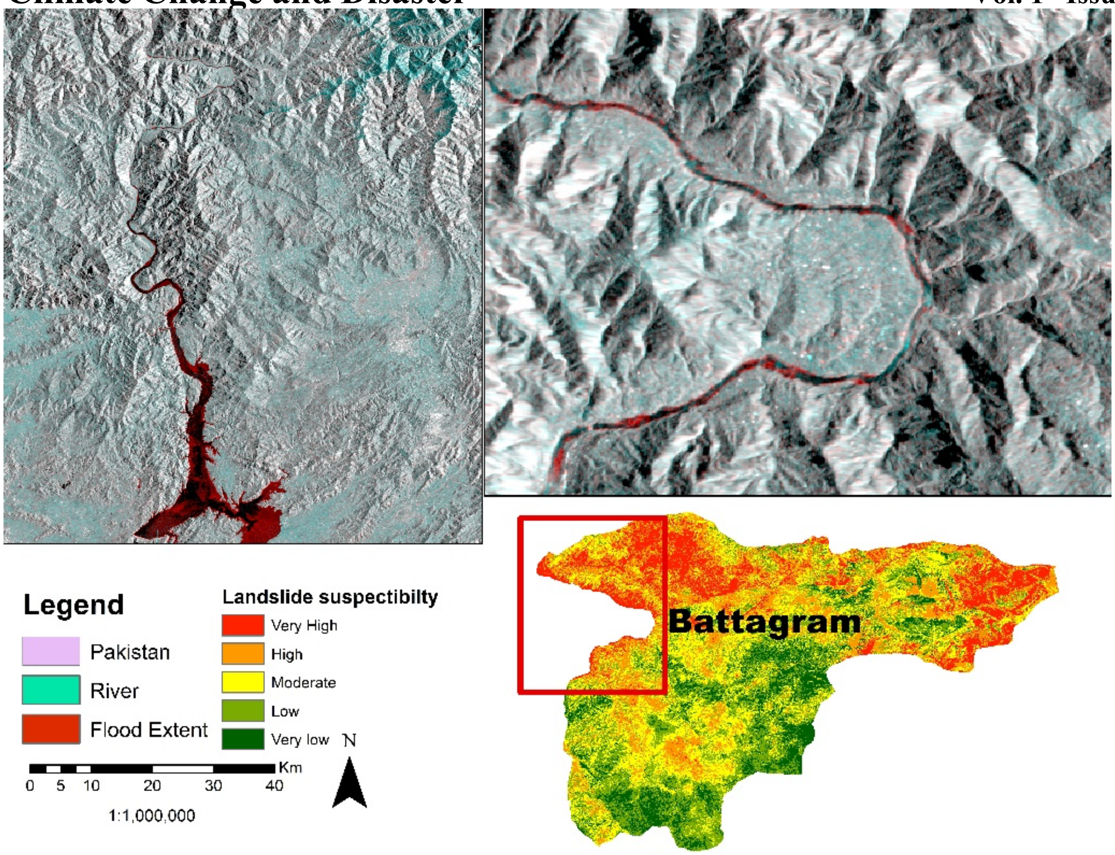


Figure 10: *The flood extend map*

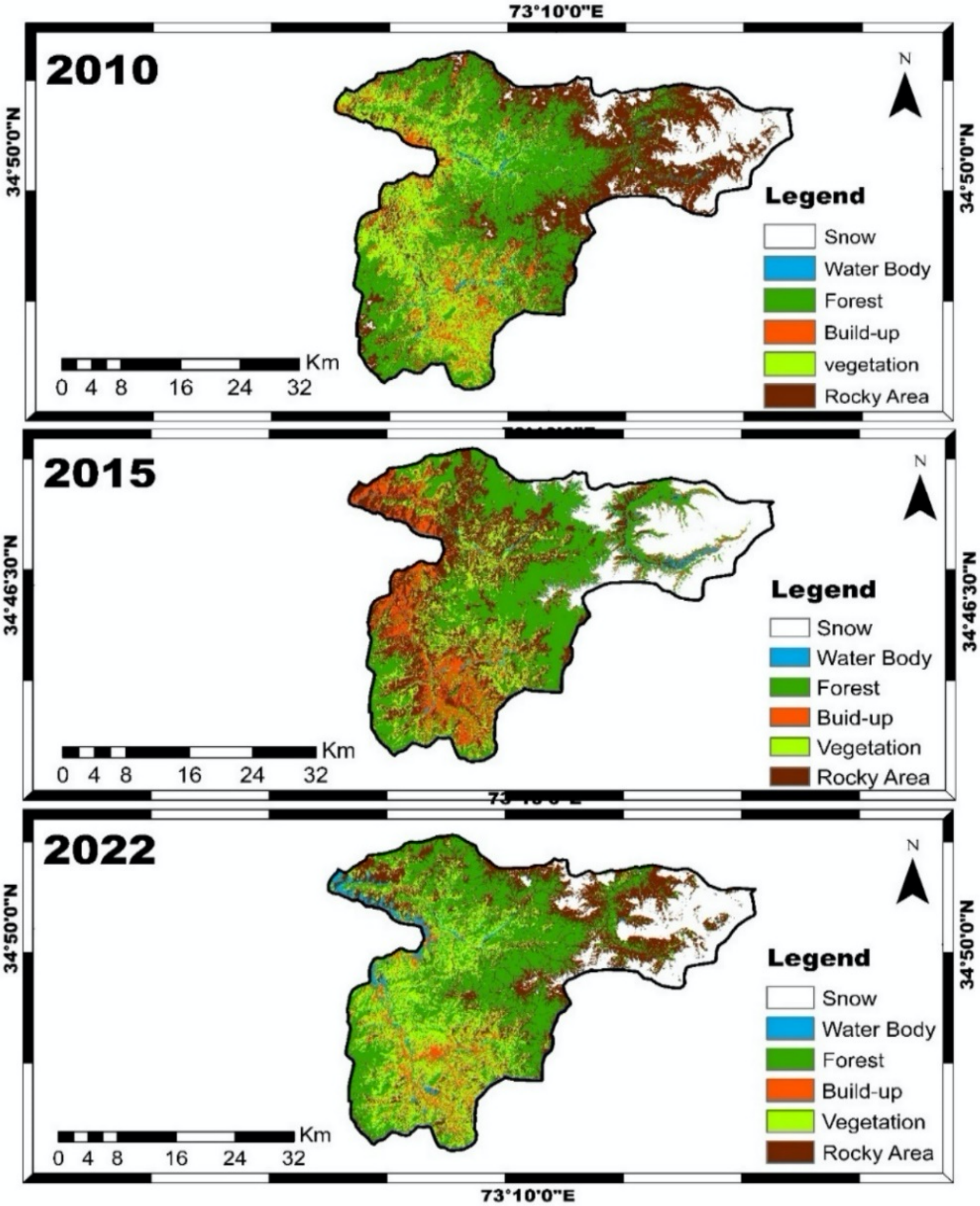


Figure 11: *Temporal map of land use and land cover (2010-2022)*

Figure 11. Presents the LULC changes by comparing categorized Landsat photos from 2010 and 2022. Significant increases were observed in the case of the water body, while major losses were observed in

the forest. Although there was a minor increase in snow, the overall amount of built-up contributing increased in 2015 to 11.85 then decreased due to flood, so the migration may be the reason of the declining rate of built-up. By using randomly selected samples that were spatially well-distributed, the total accuracy of the classification process was found to be 82.37%. Since our goal was to investigate agricultural land, the results were ultimately compared with LULC to mask out the permanent characteristics like forests and glaciers.

Table 2: The area calculation of LU/LC throughout 2010-2022

LULC results of the study area and comparison of both the years (2010–2022).						
Years	2010		2015		2022	
Classes	Area(sq km)	Percentage (%)	Area(sq km)	Percentage (%)	Area(sq km)	Percentage (%)
Snow	1687.06	11.27	2542.01	16.98	2051.09	13.7
Water Body	254.97	1.7	431.74	2.88	544.24	3.63
Forest	4784.61	31.96	4731.33	31.61	4818.3	31.19
Build-up	847.91	5.66	1774.36	11.85	809.89	5.41
Vegetation	3062.92	20.46	1731.58	11.56	3324	22.2
Rocky area	4328.97	28.92	3755.42	25.09	3418.92	22.84

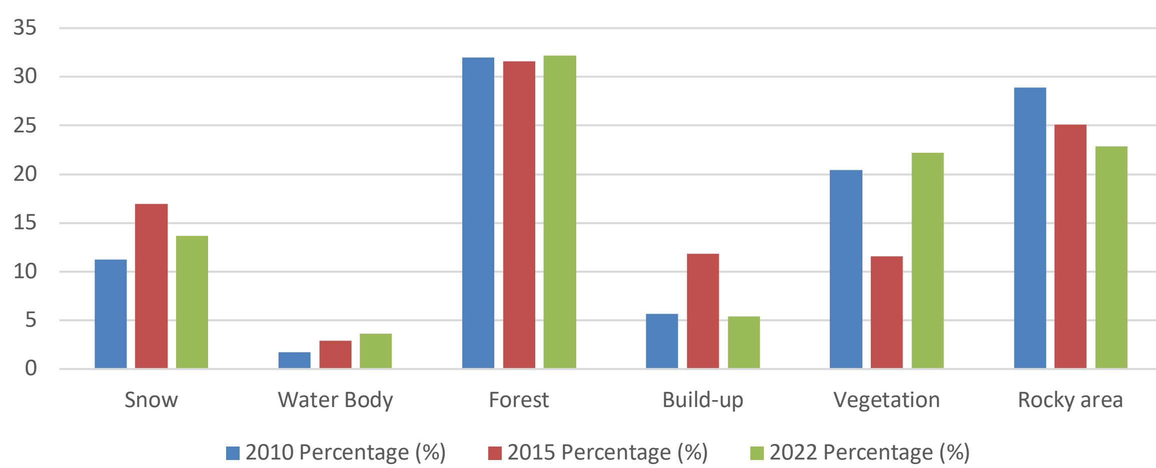


Figure 12: *Graphical representation of landcover*

Weighted Sum Analysis

These final weights are integrated into the GIS environment and used in ArcGIS software to generate the resulting map using the Weighted Sum method. Five classes have been generated from the results as shown in the map Very high (5.41%), high (42.5714%), moderate (36.0127%), low (14.2585%), and very low (1.74178%).

Table 3: The weights assigned to all factors

Data layer	Weight
Aspect	3
Slope (degree)	30
Elevation(m)	11
Rainfall	10
Rd distance	5
Fault distance	8
Land use/land cover	8
Geology	10
Earthquake	10
NDVI	5

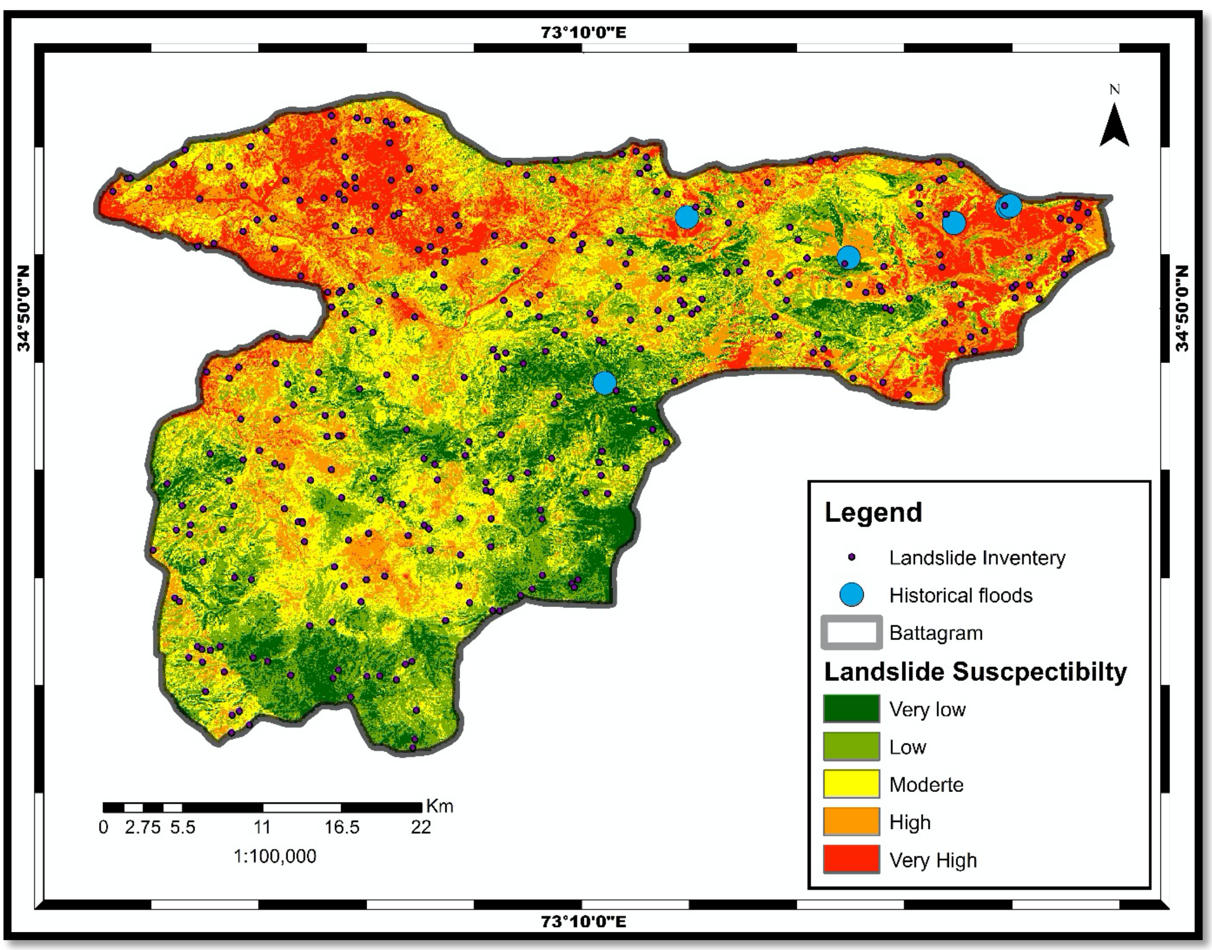


Figure 13: *The landslide susceptibility map by using weighted sum analysis*

Frequency ratio model

From the association between the landslide-causing factors and the places where landslides had not happened, one might infer the relationship between the landslide occurrence area and the landslide causal factors. A straightforward statistical method known as the frequency ratio approach has been used to determine the landslide susceptibility. To advance an LSM map, the frequency ratio for the designated contributing influence classes was mutual in geospatial (Figure 13).

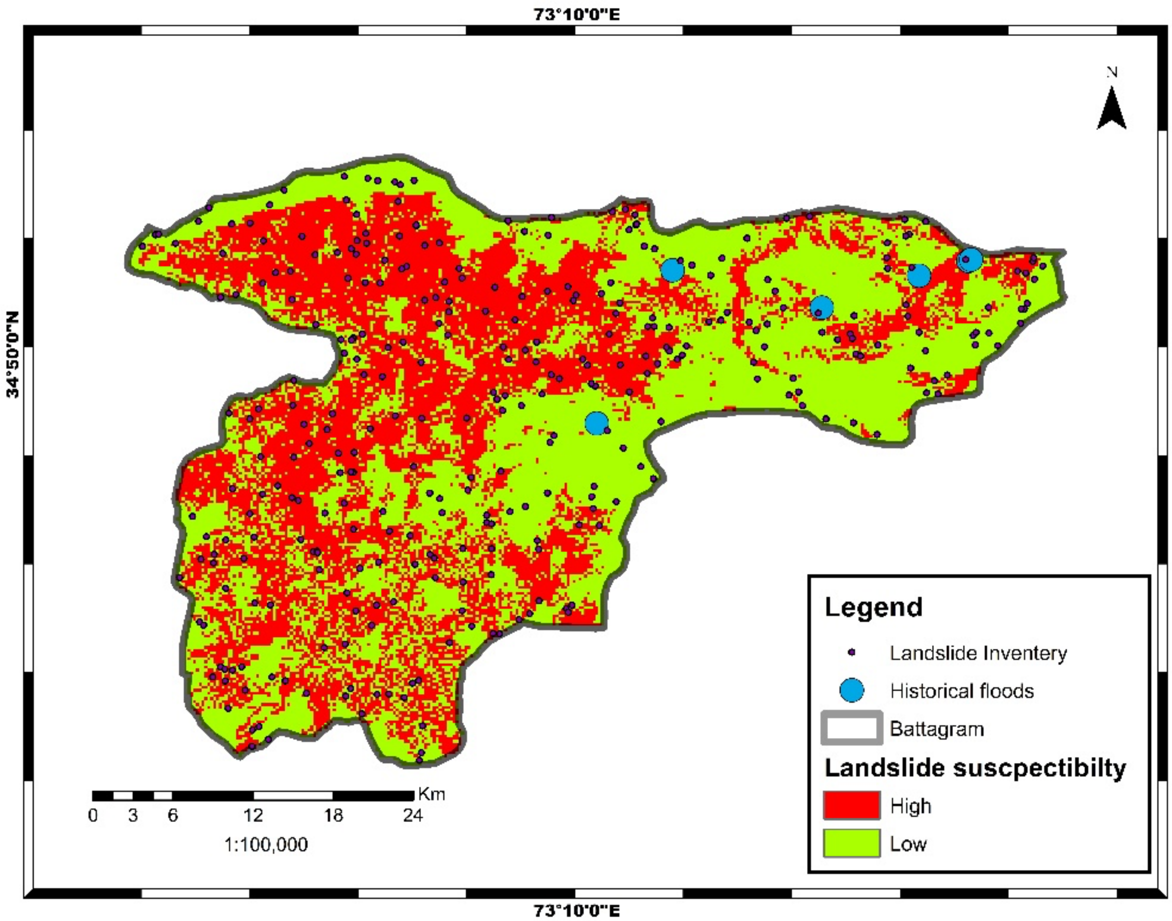


***Figure 14:** The landslide susceptibility map by using Frequency Ratio*

Towards advance a landslide susceptibility map for learning zone, the LSM map is classed into two classes: very low and extremely high susceptibility (Fig. 15).

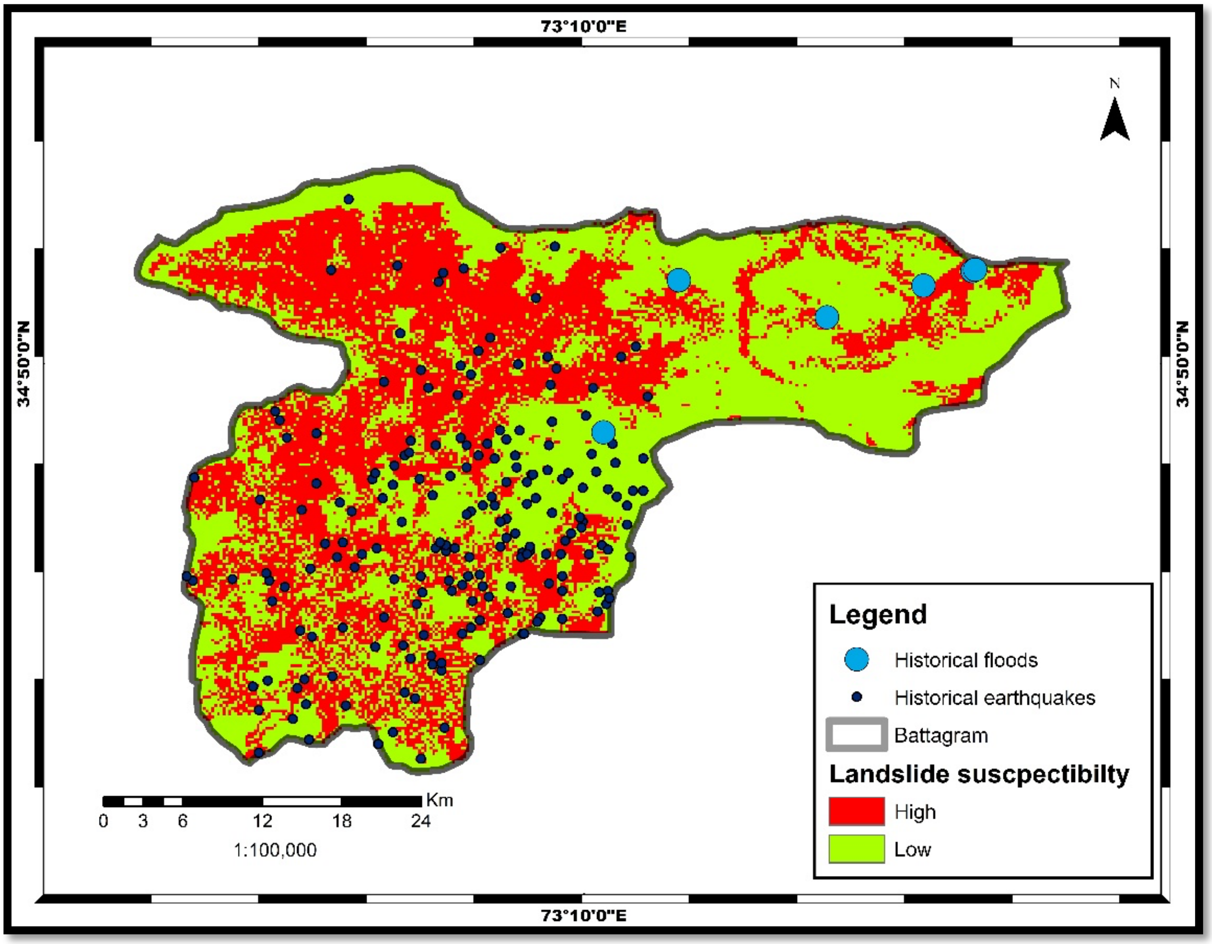


Figure 15: *Landslide susceptibility map induced from earthquake and flood*

According to the results, 44.67% of the range is in the very high class, followed by the high susceptibility class (40.94%), moderate class (11.61%), low susceptibility class (1.96%), and very low susceptibility class (0.79%). The LSM map (Fig. 15) gives rise to the success rate curve. The LSM map's index values for every pixel stayed as expected overall. The 1% cumulative intervals were used to reclassify these values into 100 classes. The landslide susceptibility map and the classified map used to overlap. According to the justification results, 70% of the pixels are correctly categorized as landslide pixels.

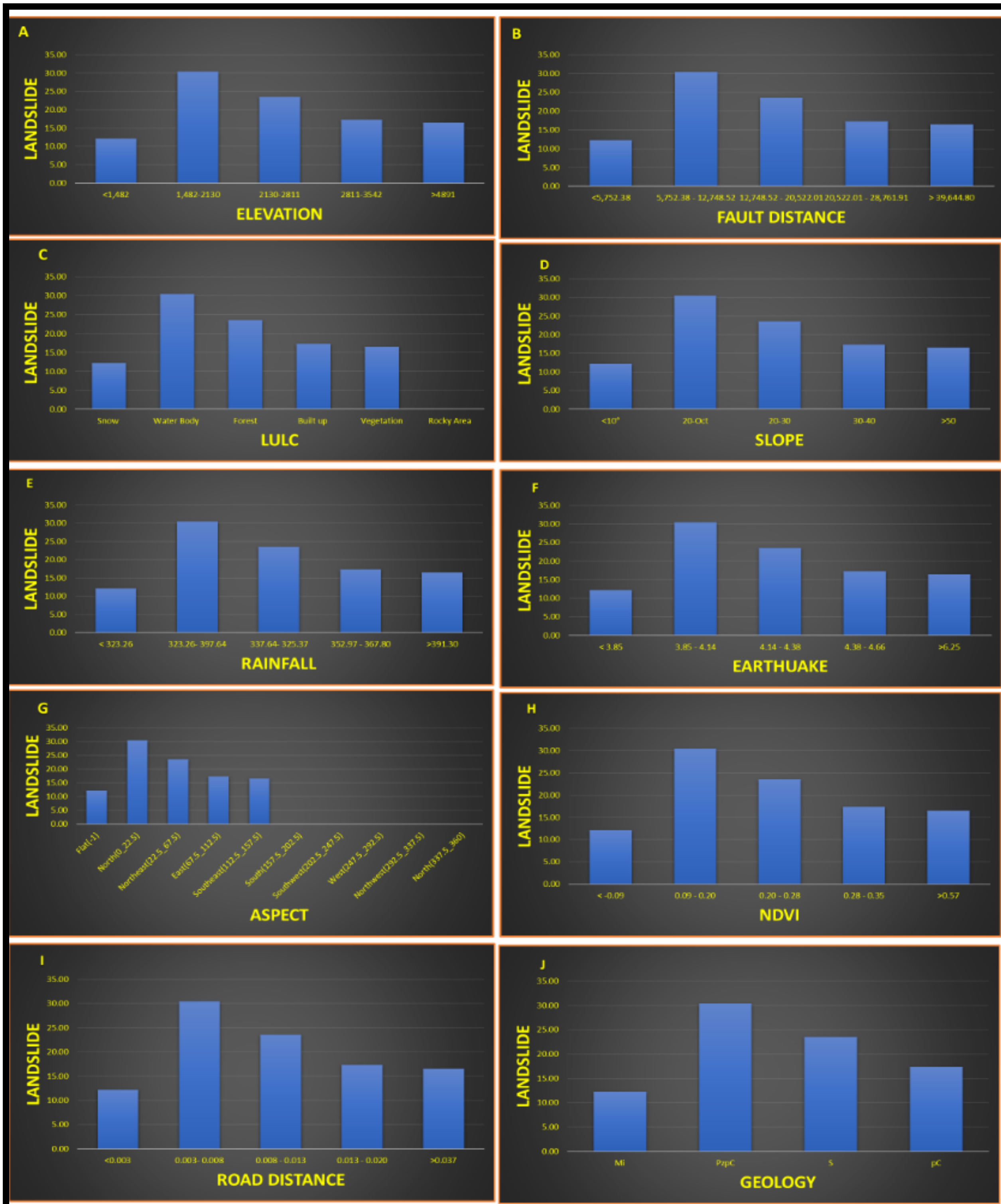


Figure 16: *The Relationship between landslide and all parameters*

Table 4: The calculation of frequency ratio for landslide susceptibility

Parameters	Class	Value	Class Pixcel	% Pixcel	Landslide Pixel	Landsliidng Pix	FR
Elvevation	<1,482	1	381830	22.21	231	12.19	0.001
	1,482-2130	2	440629	25.63	577	30.45	0.001
	2130-2811	3	348330	20.26	446	23.54	0.001
	2811-3542	4	311525	18.12	328	17.31	0.001
	>4891	5	237177	13.79	313	16.52	0.001
			1719491		1895		0.006
NDVI	<- 0.09	1	175123	11.70	231	12.19	0.001
	0.09 - 0.20	2	180965	12.09	577	30.45	0.003
	0.20 - 0.28	3	399932	26.72	446	23.54	0.001
	0.28 - 0.35	4	486289	32.49	328	17.31	0.001
	>0.57	5	254335	16.99	313	16.52	0.001
			1496644		1895		0.008
Aspect	< 73.99603642	1	314573	18.29	231	12.19	0.001
	73.99 - 148.99	2	278285	16.18	577	30.45	0.002
	148.99- 216.91	3	376541	21.90	446	23.54	0.001
	216.91 - 287.66	4	352692	20.51	328	17.31	0.001
	> 359.82	5	397400	23.11	313	16.52	0.001
			1719491		1895		0.006
Earthquake	<3.85	1	6919	14.05	231	12.19	0.033
	3.85 - 4.14	2	10190	20.69	577	30.45	0.057
	4.14 - 4.38	3	13978	28.39	446	23.54	0.032
	4.38 - 4.66	4	13424	27.26	328	17.31	0.024
	> 6.25	5	4732	9.61	313	16.52	0.066
			49243		1895		0.212
Fault Distance	<5,752.38	1	10707	29.17	231	12.19	0.022
	5,752.38 - 12,748.52	2	9668	26.34	577	30.45	0.060
	12,748.52 - 20,522.01	3	6059	16.51	446	23.54	0.074
	20,522.01 - 28,761.91	4	6031	16.43	328	17.31	0.054
	> 39,644.80	5	4236	11.54	313	16.52	0.074
			36701		1895		0.283
LULC	Snow	1	205109	13.70	231	12.19	0.001
	Water Body	2	54424	3.64	577	30.45	0.011
	Forest	3	481830	32.19	446	23.54	0.001
	Built up	4	80989	5.41	328	17.31	0.004
	Vegetation	5	332400	22.21	313	16.52	0.001
	Rocky Area	6	341892	22.84	1895		0.000
			1496644				0.018
Rainfall	< 3.85	1	415847	27.71	231	12.19	0.001
	3.85 - 4.14	2	556394	37.07	577	30.45	0.001
	4.14 - 4.38	3	216290	14.41	446	23.54	0.002
	4.38 - 4.66	4	186865	12.45	328	17.31	0.002
	>6.25	5	125352	8.35	313	16.52	0.002
			1500748		1895		0.008
RD Distance	<0.003	1	24328	49.40	231	12.19	0.009
	0.003- 0.008	2	13073	26.55	577	30.45	0.044
	0.008 - 0.013	3	7080	14.38	446	23.54	0.063
	0.013 - 0.020	4	3596	7.30	328	17.31	0.091
	>0.037	5	1166	2.37	313	16.52	0.268
			49243		1895		0.476
Slope	<10°	1	494599	65.46	231	12.19	0.000
	20-Oct	2	251548	33.29	577	30.45	0.002
	20-30	3	5765	0.76	446	23.54	0.077
	30-40	4	1994	0.26	328	17.31	0.164
	>50	5	1666	0.22	313	16.52	0.188
			755572		1895		0.432
Geology	Mi	1	11381	21.95	231	12.19	0.020
	PzpC	2	1408	2.72	577	30.45	0.410
	S	3	17065	32.92	446	23.54	0.026
	pC	4	21990	42.42	328	17.31	0.015
			51844		1582		0.471

The landslide susceptibility map comprises of the predicted landslide area hence it can be used to decrease the potential hazard associated with the landslides in this study area. It means this model is 88.9% accurate to predict the probability of landslide and the model is 92.3% success to generate the prediction in the study area.

Table 5: The prediction ratio for all the factors

Slope (degree)	2.357866	235.79
Elevation(m)	2.17186737	217.19
Rainfall	1.03679384	103.68
Rd distance	2.95838643	295.84
Fault distance	1	100.00
nduse/land cov	3.24558626	324.56
Geology	4.56060049	456.06
Earthquake	1.06810309	106.81
NDVI	1.8171733	181.72

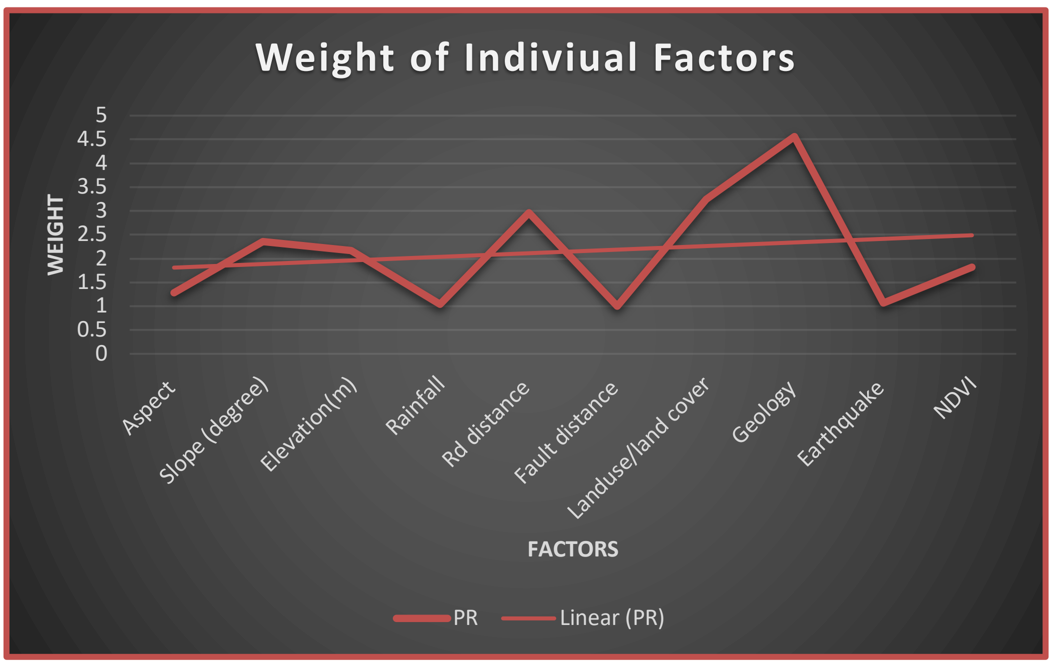


Figure 17: *Graphical representation of Prediction ratio*

Conclusion

The purpose of this work was to create a complete database of landslides caused by the Battgaram earthquake and rainfall by interpreting multitemporal images and correlating them with environmental, seismic, and rainfall parameters. These landslides resulted from a mix of rainfall- and earthquake-induced occurrences. It is difficult to assess how the climate affects landslides because the two phenomena only partially overlap in space and time. While rainfall is likely the most frequent cause of landslides, this study has identified earthquakes and floods as additional triggers for landslide risk. The northern portion of Battgaram is closely watching the extent of the flood and the activation of the earthquake in 2022, which increases the susceptibility of landslides. Examining the landslide inventory map made especially for the study area, it is evident that the majority of the region's active landslide locations are located in its higher-elevation sections. The findings lead to the following conclusions, which are proposed: The purpose of this study was to use geographic methods to create an LSM of the research region in order to lessen the effects of potential dangers. The weighted sum analysis of the study showed that 1.74178% of the area had very low susceptibility. The area of Muzaffarabad is divided into four susceptibility zones: high (2.5714%), moderate (36.0127%), low (14.2585%), and very high (5.41%). Specifically, 44.67% of the range falls into the very high class, followed by the high susceptibility class (40.94%), the moderate class (11.61%), the low susceptibility class (1.96%), and the very low susceptibility class (0.79%) in the frequency ratio model. In the current study, the GIS-based statistical models WSM and FR were utilized to calculate the correlation between dependent variables (the elements that cause landslides) and dependent variables (the events or inventories of landslides).

The purpose of this study was to assess the relationship between the occurrence of landslides and causal factors. The topography, geology, hydrology, climate, and geomorphology of these factors were listed. After applying the Weight Sum analysis method and transferring the weight data to the GIS environment, a landslide susceptibility map was produced. The results of the validation showed that the FR model is a reliable approach for the LSM. The susceptibility map was validated by comparing its positions with those of known landslides. 85.7% of the predictions were shown to be accurate. We conclude that the most authentic, adaptable, and dependable way to generate LSM is through statistical modeling based on GIS. The maps of landslide susceptibility that this study produced are crucial for local governance and sustainable urban development. Initial decision-making and policy planning may benefit from the data obtained from the created map. Furthermore, in order to be widely applied in more regional areas, more relative data must be obtained.

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Drought Risk Assessment of Muzaffargarh District by Using Geospatial Techniques

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Abstract

Drought is a major natural hazard characterized by extended periods of insufficient precipitation, posing serious threats to both ecosystems and human livelihoods. This study evaluates drought risk in Muzaffargarh District, Pakistan, by combining geospatial techniques such as remote sensing (RS) and geographical information systems (GIS). Landsat ETM+ and OLI imagery from 2002, 2008, 2013, and 2018 were used to compute the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). The study found that LST increased from 38.77 °C in 2002 to 42.54 °C in 2018, while NDVI values decreased from 0.989 to 0.576. This inverse trend confirms declining vegetation cover and rising surface temperatures, which are important indicators of increasing meteorological and agricultural drought risk. Regression analysis confirms a negative correlation between LST and NDVI ($R^2 = 0.4167$), indicating the region's vulnerability to climatic stress. The supervised classification of LU/LC data reveals significant urban expansion and vegetation loss between 2002 and 2018. The resulting drought risk maps identify increasingly dry zones, providing critical spatial insights for policymakers and stakeholders as they develop targeted and proactive drought mitigation plans.

***Keywords**:* Drought, GIS, LST, meteorological drought, NDVI, remote sensing.

Introduction

Drought is one of the most complex and devastating natural hazards, affecting millions of people worldwide, particularly in arid and semi-arid areas. It is characterized by a prolonged deficiency in precipitation, resulting in water scarcity, crop failure, and socioeconomic distress.
(WHO 2021). Climate change has increased the frequency, severity, and duration of droughts, posing significant challenges for water resource management and food security (IPCC et al. 2023). Pakistan, as a predominantly agrarian economy, is especially vulnerable to droughts. Southern Punjab's Muzaffargarh District is not an exception; it has experienced ongoing dry spells that have negatively impacted livelihoods and agricultural productivity (Ahmad et al. 2020).

Traditional drought monitoring approaches frequently deficiency spatial resolution and fail to deliver timely warnings at the local level. The integration of geospatial techniques, with remote sensing (RS) and geographic information systems (GIS), has been established as a reliable and cost-effective technique for drought risk assessment (Nepal et al., 2021). These technologies permit unceasing monitoring of vegetation health, land surface temperature, soil moisture, and rainfall anomalies, all of which are key gauges of drought. The Normalized Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), and the Standardized Precipitation Index (SPI) are broadly used indicators to measure drought vulnerability and spatial degree (Amarasingam et al. 2022). In Muzaffargarh, a comprehensive drought risk assessment is vital for making knowledgeable decisions and planning. The district's varied agro-climatic zones, reliance on seasonal rainfall, and growing demand for water resources necessitate the usage of advanced geospatial tools for real drought monitoring and mitigation. This study purposes to assess drought risk in Muzaffargarh District by investigating multitemporal satellite data and climatic variables through geospatial techniques. The consequences are anticipated to provision local authorities and stakeholders in developing targeted drought preparedness and resilience strategies.

Research objectives

This study aims to:

- To evaluate the underlying factors contributing to drought risk in the study area through geospatial analysis.
- To track changes in vegetation health and surface temperature over time.
- To investigate how land use and land cover changes contribute to drought risk.

Study area

Muzaffargarh District is located in south-central Punjab province, Pakistan, at latitude 30°4′10″N and longitude 71°11′39″E. The district covers 8,249 km² and borders the Chenab River to the east and the Indus River to the west. The region is divided into four tehsils: Muzaffargarh, Jatoi, Alipur, and Kot Addu, with 111 union councils in total.

- The districts of Khanewal and Multan are located on the eastern side of District Muzaffargarh, across the Chenab; the district of Layyah borders the district on the north; and the districts of Bahawalpur and Rahimyar Khan Border to the south. The districts of Dera Ghazi Khan and Rajanpur are located on the western bank of the Indus River, while District Jhang is located in the northeast.

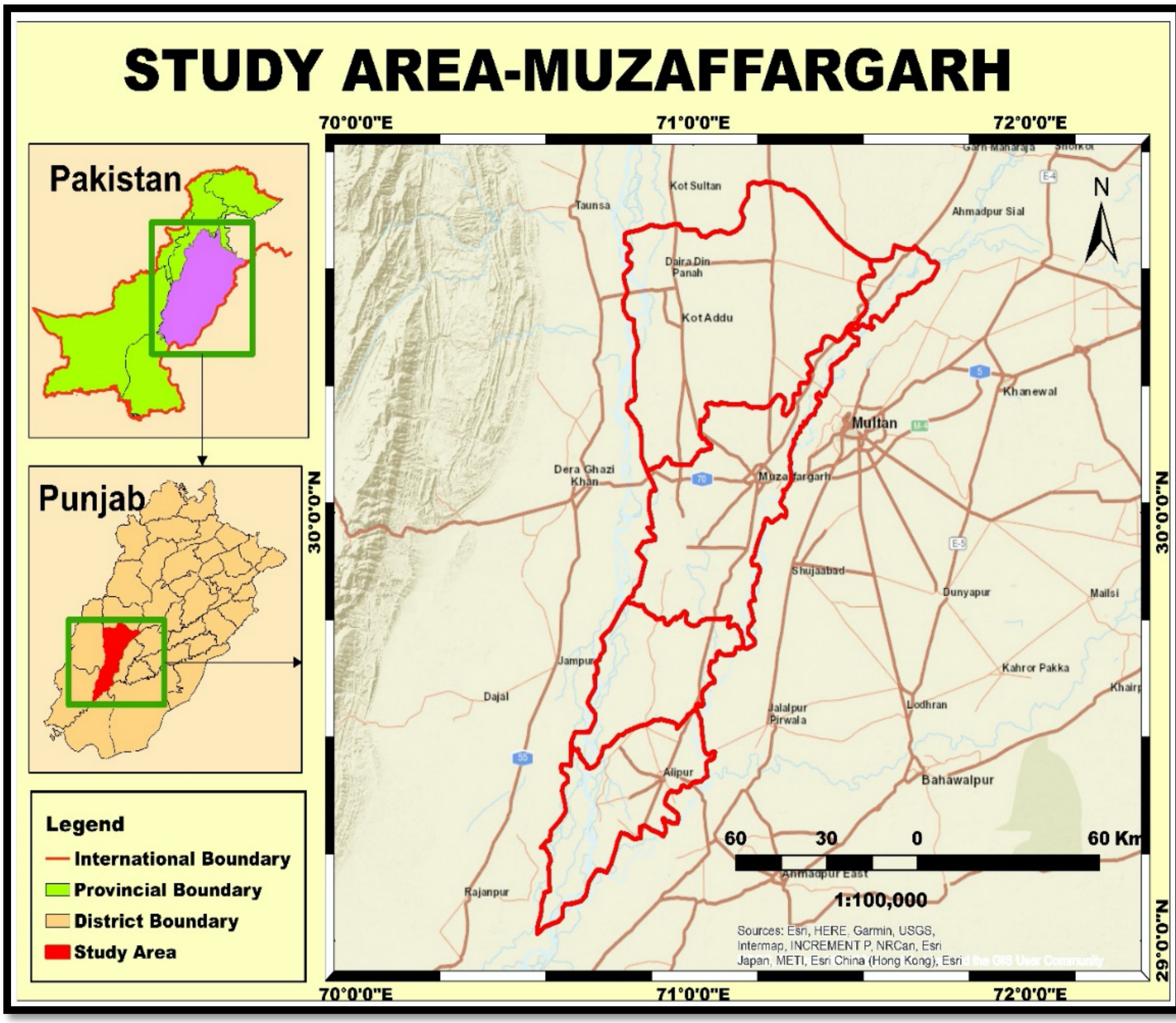

Figure 1: *Study Area Map*

(Source: USGS Earth Explorer)

Climate

Mostly the area of Muzaffargarh is dry and also consists of the barren lands and sand dunes known as the thal area, but the other portion of the area, whether flooded from the river or irrigated by inundation canals, is less dry.

- The climate of Muzaffargarh is arid, with scorching summers and moderate winters. The city has seen among Pakistan's most severe weather. The months of May through September are hot, but between mid-August and mid-September, a cool breeze might begin to blow, which would lower the temperature. In December and January, there are cold nights with heavy frost, which seriously damages vegetables, cotton, ma ngoes, and sugarcane.

- The temperature that was recorded was roughly 1°C at the lowest point and 54°C at the maximum.
- The maximum temperature graph displays how many days per month reach certain temperatures. Figure 2 shows that the maximum temperature that is of 40^{o}C the Muzaffargarh is in June to July, the whole month in 2018.

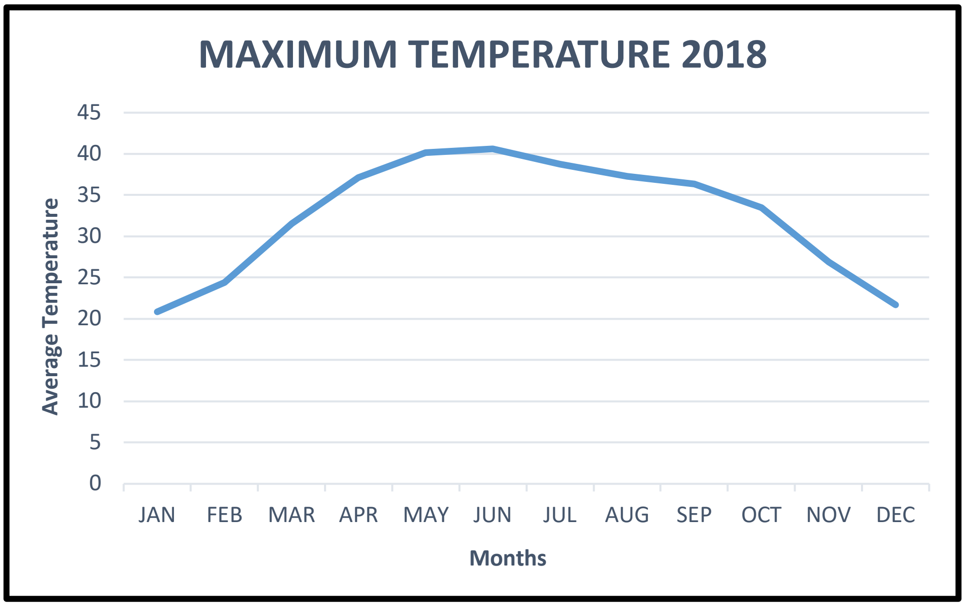

Figure 2: *Graphical representation of the maximum temperature in Muzaffargarh (2018)*

Material and Methods

The overview of used methodology used to work out the proposed research. Reliable indices to distinguish the spatial and temporal dimensions of drought existence and its concentration are necessary to evaluate the impact, and also for decision-making and crop research priorities for improvement. The methodological framework is illustrated in Figure 2.

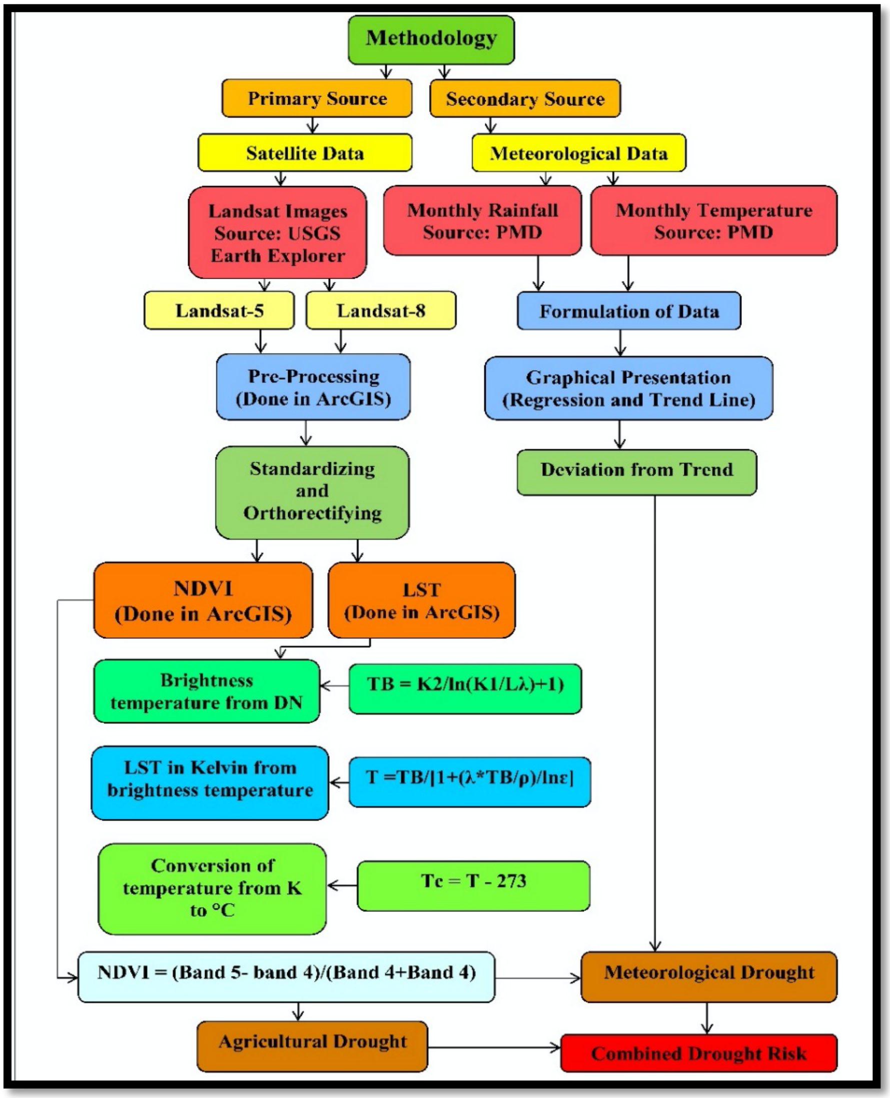

Figure 3: *Methodological Framework*

Dataset used

The satellite data, that has been taken from the United States Geological Survey (USGS) (http://earthexplorer.usgs.gov), Landsat 5 and 8 Enhanced Thermal Mapper (ETM+) and Operational Land Imager (OLI), images (path 150 rows 39, path 151 rows 39 and path 151 row 40) with the 30 m resolution, of July, for the years 2002, 2008, 2013 and 2018 as mentioned in Table 1 used for applying the analysis by using the Remote Sensing and Geographical Information System techniques. In this study, the secondary data source, as Pakistan Meteorological Department (PMD), brings meteorological data on monthly rainfall and monthly temperature, which has been collected for the period 16 years, ranging from 2002-2018.

Table 1. Detailed Information about satellite imagery. (Source: USGS Earth Explorer)

Satellite	Dates of Images	Resolution	Reference system/Path/Row
Landsat 5	14/07/2002	30m	WRS/150/39

Landsat 5	21/07/2002	30m	WRS/151/39
Landsat 5	21/07/2002	30m	WRS/151/40
Landsat 5	14/07/2008	30m	WRS/150/39
Landsat 5	05/07/2008	30m	WRS/151/39
Landsat 5	21/07/2008	30m	WRS/151/40
Landsat 8	12/07/2013	30m	WRS/150/39
Landsat 8	19/07/2013	30m	WRS/151/39
Landsat 8	19/01/2013	30m	WRS/151/40
Landsat 8	10/07/2018	30m	WRS/150/39
Landsat 8	01/07/2018	30m	WRS/151/39
Landsat 8	01/07/2018	30m	WRS/151/40

Data analysis

Satellite imagery was analyzed using key drought indices such as the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and supervised classification for Land Use and Land Cover (LU/LC). The Pakistan Meteorological Department (PMD) provided secondary climatic data in addition to satellite data. Microsoft Excel was used to establish and examine the mean temperature and precipitation averages for the year. The line graphs were formed by applying regression analysis to these variables, which assisted in influential and identifying the study area's drought risk. A vigorous measure of the Earth's surface energy balance, land surface temperature (LST) is extensively recognised as a vital variable in the investigation of land-surface processes at both regional and global scales (Yadav et al. 2024). In this study, LST was performed by means of satellite thermal bands—Band 6 for Landsat 5, and Bands 10 and 11 for Landsat 8. The satellite imagery for Muzaffargarh, Pakistan, experienced knowledgeable preprocessing, which comprised mosaic generation and geometric correction.

Satellite data was transformed into real-world spatial coordinates during image processing by applying the WGS 1984 datum and the Universal Transverse Mercator (UTM) projection system. Table 2 shows the full sequence of image processing and analytical procedures used in this LST:

Step no. 1: Conversion of DN values to the spectral radiance by using the equation

$$\mathbf{L\lambda = ML*Qcal + Al}$$

$L\lambda$ is the cell value as radiance (Ebaid 2016). ML is the radiance multi-band value, Al is the radiance add band value, and Qcal is the thermal band used in it.

Step no.2: Radiance values from the TM 5 / L8 thermal band were then changed to radiant surface temperature, that is, top-of-atmosphere brightness temperature, using thermal calibration constants (Ebaid 2016) by the given equation:

$$\mathbf{TB = K2/ln(K1/L\lambda)+1)}$$

Step no.3: In the very last step in we got the outcomes that are the temperature, which was in kelvin, converted into Celsius (C^{o}) through this equation:

$$\mathbf{T= T(K)-273.15}$$

Table 2. Processing steps, as well as the conversion of DN numbers to LST

Processing Steps	Formulas	Explanation
Conversion of DN (Digital Number) to At-Satellite Brightness Temperature.	$TB = K2/\ln(K1/L\lambda)+1)$	• K1 Band specific thermal conversion constant (in watts/meter squared *ster*μm) • K2 = Band-specific thermal conversion constant (i n kelvin) • $L\lambda$ =spectral radiance at sensor aperture measures (in watts/ meter squared *star*μm) • λ =wavelength of emitted radiance • $\rho = h*c/\sigma$ (1.438*10^-²m-K) • h=Plank's Constant (6.62*10^-34 j-s)
Calculation of Land Surface Temperature in Kelvin	$T=TB/[1+(\lambda*TB/\rho)/\ln\varepsilon]$	• σ = Boltzmann Constant (1.38*10^-23 j/K) • c =velocity of light (2.998*10^8 m/s) • ε =emissivity, which is given at: $\varepsilon = 1.009+0.047 \ln(NDVI)$
Conversion from Kelvin to Celsius	$Tc = T - 273$	• T = land surface temperature in Kelvin • Tc = land surface temperature in Celsius.

The Normalized Difference Vegetation Index (NDVI) is one of the most extensively used and reliable vegetation indices for monitoring plant health and assessing drought conditions (Whig et al. 2024). Tucker and Choudhury applied it to drought monitoring for the first time in 1987. In this study, vegetation-related features were extracted from the Muzaffargarh district 3-band satellite imagery using the NDVI technique.

NDVI = (NIR- RED)/(NIR+RED)

Or

NDVI = (Band 5 – Band 4)/(Band 4 + Band 5)

NIR signifies near-infrared reflectance, and RED characterizes red reflectance. This ratio demonstrates the difference between healthy vegetation, which strongly reflects NIR and absorbs RED, and stressed or non-vegetated surfaces, which do not exhibit this spectral behavior. Using this index on Landsat satellite imagery, variations in vegetation cover across space and time were successfully identified, allowing for a detailed assessment of vegetative stress and potential drought conditions in the region.

Variations in land use and land cover (LU/LC) pose a threat to our comprehension of environmental change on a global scale. In this study, supervised classification of LU/LC dynamics in the Muzaffargarh district was carried out using ArcGIS 10.5.

- The process began with the satellite images being organized. For each tile, multispectral images were formed by combining Landsat 5 bands 1–6 and Landsat 8 bands 1–11. After extracting the study area from the larger dataset, a mosaic process was carried out using a reliable spatial reference system.
- To confirm the land features in the study area, ground truthing was carried out by superimposing a base map in ArcGIS. Initiating the pertinent tool and generating training samples in polygonal form over the removed image tiles was the first step in supervised classification. Water, vegetation, and built-up areas were the three main LU/LC categories into which these samples were detached. After that, a GCS (Geographic Coordinate System) signature file encompassing the training data was saved.
- Importing the GCS signature file into the ArcGIS workspace was the last step by step. Applying the symbology of the layer, each land cover class was given a distinct color: brown for built-up areas, green

for vegetation, and blue for water bodies. The inclusive distribution of land cover and its variations over time were accurately and clearly represented by this classification.

Results

Abundant geospatial analyses, such as the Index of Normalized Difference Vegetation (NDVI), Land Surface Temperature (LST), and supervised classification for Land Use/Land Cover (LU/LC) mapping, were performed using the Landsat satellite sequence. To confirm outstanding spatial resolution, all maps were made at a scale of 1:10,000. Agricultural and meteorological drought risks have been mixed to generate a composite risk map, which demonstrates that the study area is likely to knowledge compounded hazards due to the convergence of these drought categories.

Land cover change

In this study, LU/LC variations were analyzed using a supervised classification method, chiefly applying the Maximum Likelihood Classification (MLC) technique. The land cover was classified into three major groups: water, vegetation, and built-up areas, by normal remote sensing classification practices. The investigation of the Muzaffargarh district over 16 years (2002-2018) exposes a significant change in land use patterns.

The most notable change is rapid urbanization, which has resulted in a significant increase in built-up areas. This trend coincides with both population growth and the arrival of refugees in the region. As urbanization has increased, vegetative cover has decreased, indicating a significant shift in land use. These spatial changes are displayed by LU/LC maps created with ArcGIS 10.5. Although the built-up area has grown, vegetation still occupies a larger portion of the district. However, the consistent decline in vegetation suggests a possible change in local climatic conditions, particularly an increase in land surface temperature. This pattern demonstrates a direct relationship between land use changes and the risk of meteorological drought, which can lead to agricultural drought. The temporal LU/LC maps for 2002 and 2018 show in Figure 4 visual evidence of these changes, emphasizing the importance of sustainable land management in mitigating environmental risks.

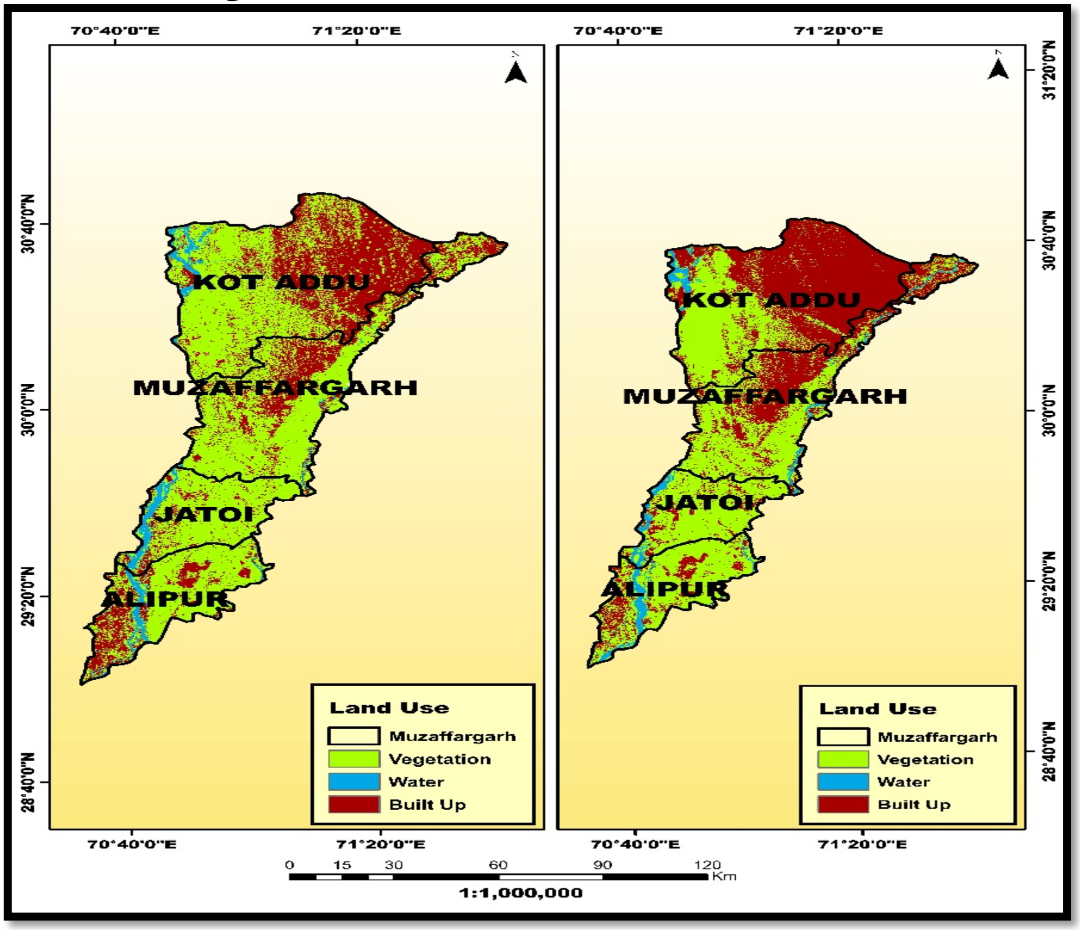

Figure 4: *Temporal Variation in Land Use Mapping (2002-2018)*

Land surface temperature (LST)

Globally, urban temperatures have been steadily increasing (Patel and Patel 2024). Several studies have used satellite-based measurements to accurately calculate Land Surface Temperature (LST) (Mustaquim 2024). The present analysis shows in Figure 5 a significant increase in maximum temperature from 38.77 °C in 2002 to 42.54 °C in 2018. The line Graph 1 and 2 depicts the trend in average maximum and minimum land surface temperature (MMaxT and mminT) for the years 2002, 2008, 2013, and 2018. This consistent temperature rise indicates an increasing risk of meteorological drought. Furthermore, the rise in LST has had a direct impact on vegetation health and coverage, accelerating the onset of agricultural drought. Over the 18-year study period, the maximum Normalized Difference Vegetation Index (NDVI) value decreased significantly, from 0.989 in 2002 to 0.576 in 2018. This decrease reflects the declining vigor and extent of vegetative cover, particularly cropland, which is extremely vulnerable to climatic stress. A comparison of NDVI and LST maps reveals that the study area experienced increasingly dry conditions in 2018. The spatial correlation between rising surface temperatures and declining vegetation highlights throughout Table 3 the region's increased vulnerability to drought, emphasizing the importance of proactive mitigation strategies and sustainable land management practices.

Table 3. Summary of Land Surface Temperature (LST)

Year	**LST Value (C°)**	
	Maximum	**Minimum**
2002	38.77419	21.012
2008	38.7097	21.324
2013	39.4871	21.42

2018	42.5432	21.54

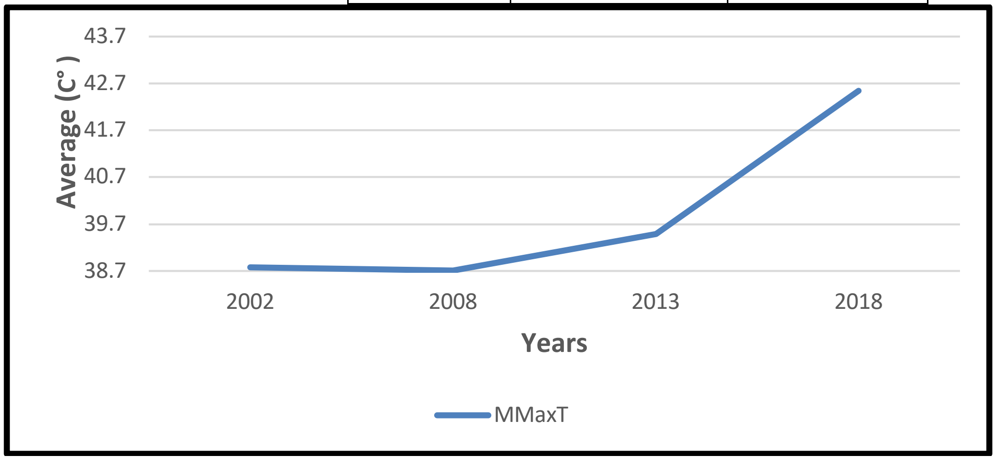

Figure 5: Temporal variation in maximum temperature of Muzaffargarh in the month of July (2002-2018). (Source: PMD)

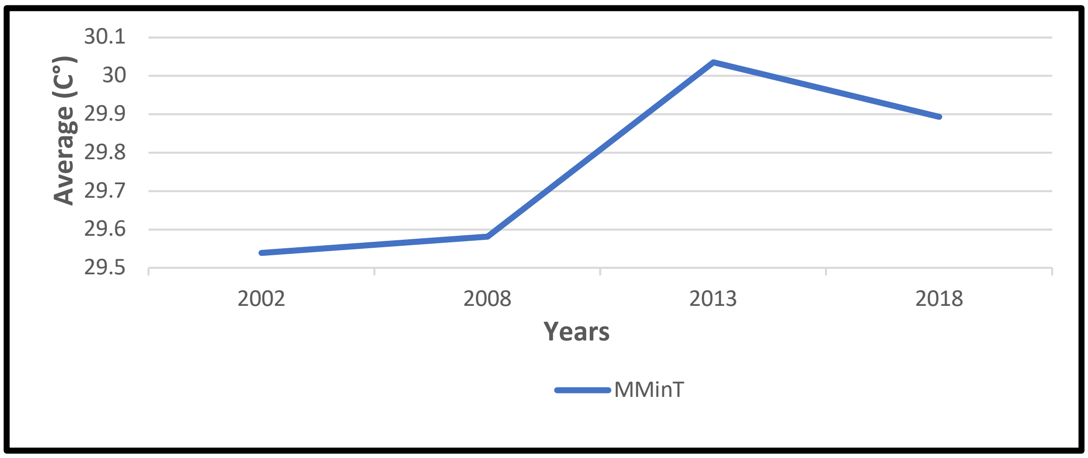

Figure 6: Temporal variation in minimum temperature of Muzaffargarh in the month of July (2002-2018). (Source: PMD)

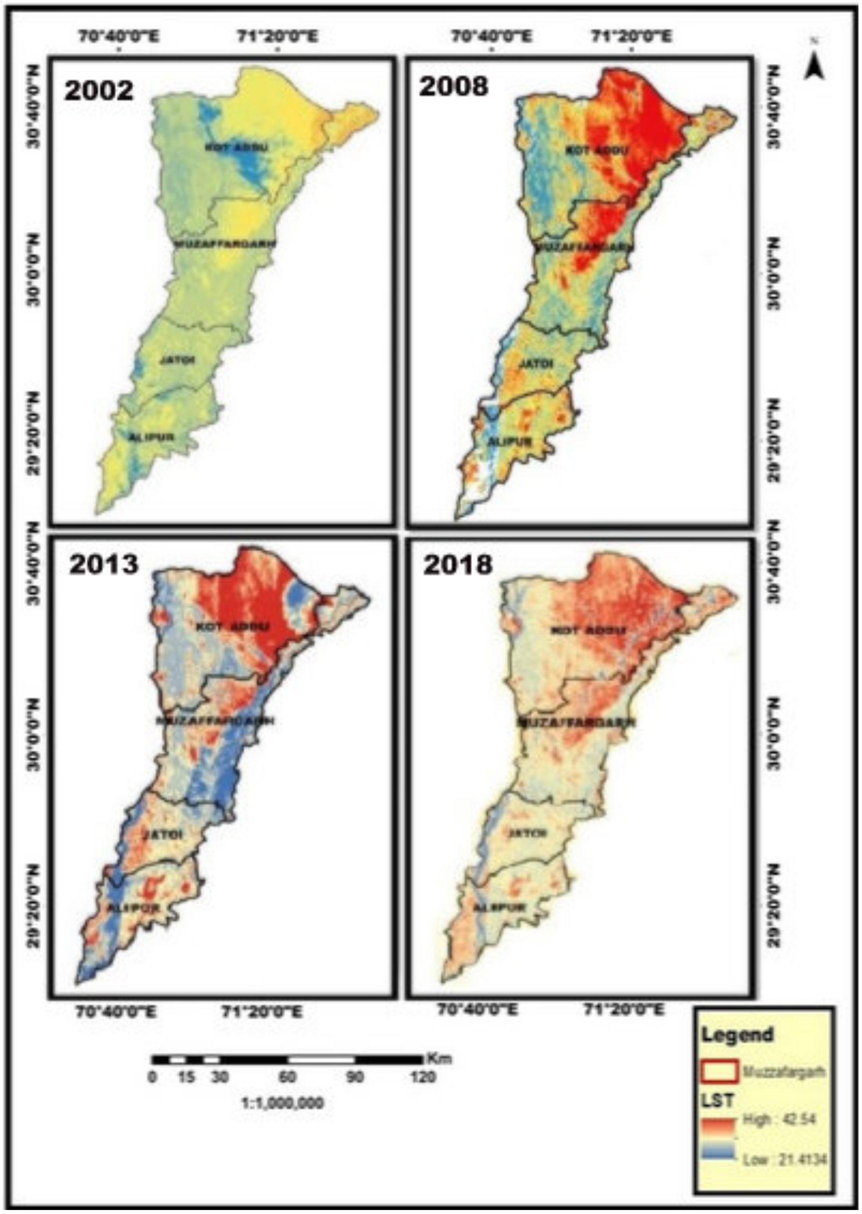

Figure *7: Temporal Map of Land Surface Temperature (LST) (2002-2018*)

Normalized difference vegetation index (NDVI)

NDVI was used to derive vegetation cover classes, allowing for the identification of spatial and temporal variations between 2002 and 2018. NDVI values fell dramatically during this time, from a high of 0.989 in 2002 to 0.576 in 2018, indicating, through Figure 6, a significant decline in vegetation health and density. This decline is primarily due to climate change, specifically rising atmospheric and land surface temperatures. According to international classification standards, much of the study area has shifted from moderate vegetation to increasingly dry conditions, as shown in Table 4. This shift indicates an increased risk of agricultural drought, which could harm crop productivity and local livelihoods. The observed trend emphasizes the critical need for climate-resilient agricultural practices and sustainable land use planning.

Table 4. Classification of NDVI

NDVI Ranges	Drought
<0	Extreme Drought
0-0.2	Dry

0.2-0.4	Moderate
0.4-0.6	Wet
>0.6	Extreme Wet

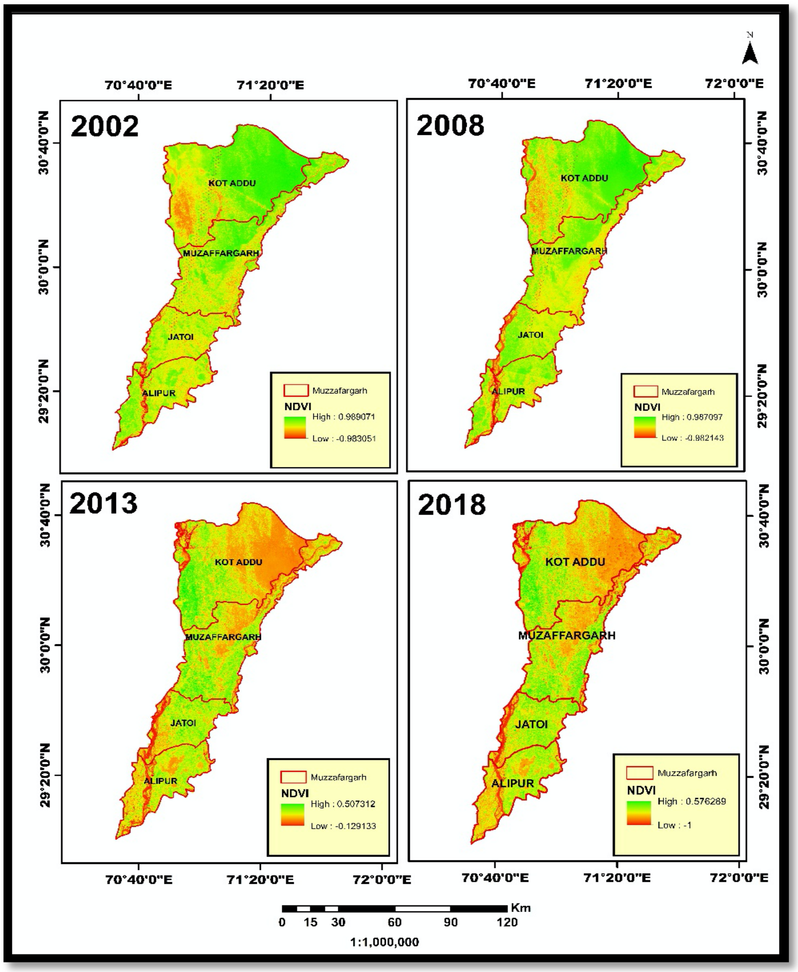

Figure 8: *Temporal Variation in Normalized Difference Vegetation Index (NDVI)*

The NDVI values in Muzaffargarh District indicate as well in Table 8, a clear decline in vegetation health over time. The maximum NDVI values for 2002 and 2008 were relatively high (0.989 and 0.987, respectively), indicating dense and healthy vegetation cover. However, by 2013, the maximum value had fallen significantly to 0.507, with only a slight recovery to 0.576 in 2018. Similarly, minimum NDVI values indicate increased vegetation stress, with the lowest value recorded in 2018 (-1.0). These trends indicate a consistent degradation of vegetation cover, most likely due to rising temperatures, urban expansion, and climatic stress, implying an increased risk of agricultural droughts.

Table 5. Summary of Normalized Difference Vegetation Index (NDVI)

Year	**NDVI**	
	High	**Low**
2002	0.989071	-0.98305
2008	0.987097	-0.98214
2013	0.507312	-0.12913
2018	0.576289	-1

Correlation and linear regression analysis were performed between NDVI and LST anomaly. Graph 3 displays a clear view that there is an inverse correlation between land surface temperature (LST) and normalized vegetation index (NDVI). This directly indicates the risk of drought in this research target area. The graph demonstrates a negative linear relationship between temperature and NDVI, represented by the regression equation:

$$y=-0.0924x+4.4492$$

This means that for every 1°C increase in temperature, the NDVI drops by about 0.0924 units, indicating a decline in vegetation health.

- The coefficient of determination ($R^2 = 0.4167$) indicates a moderate negative correlation. Temperature changes account for approximately 41.67% of the variation in NDVI.
- The NDVI values decrease as the temperature rises from 38.77°C (2002) to 42.54°C (2018), indicating that vegetation cover and surface temperature are inversely correlated.
- This tendency supports the theory of increased drought risk, which holds that vegetation stress, a decline of greenness, and possible agricultural drought are caused by increasing temperatures.

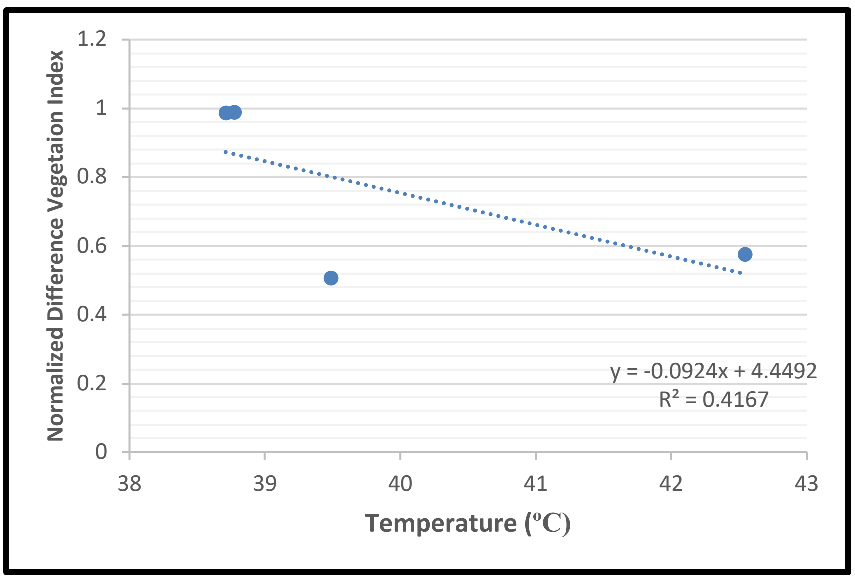

Figure 9: *Correlation between Land Surface Temperature and Normalized Difference Vegetation Index* (Source: PMD)

Discussion

This study's objective was to measure the Muzaffargarh district's risk of agricultural and meteorological drought using geospatial methods. A mutual occurrence worldwide, droughts have distressing belongings on agriculture, ecosystems, and socioeconomic systems (WHO 2021). The absence of long-term, high-resolution rainfall data for the target area was a component of the study's restrictions. Nevertheless, this limit was addressed by using satellite-derived indices like the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and Land Use/Land Cover (LULC) classification. To professionally map and track situations of drought, a amount of studies have employed NDVI and LULC analysis (Mahajan and Dodamani 2015). Forest and shrubland areas have progressively decreased over time, according to historical trends in land cover shifts, while agricultural land, built-up areas, and water bodies have improved (Gandhi et al. 2015). In this study, a alike trend was detected, with supervised classification of LULC data and NDVI analysis revealing a gradual decline in vegetation cover from 2002 to 2018, representing increased agricultural drought vulnerability.

LST has been widely used in prior studies as a proxy for surface moisture circumstances and drought risk (Latha 2021). Our analysis reveals a rising trend in surface temperatures across the district, typically in recent years, which further supports the presence of meteorological drought. The inverse relationship between NDVI and LST, also engrained in earlier studies (Mahajan and Dodamani 2015; Sun and Kafatos 2007), was validated settled regression analysis in this research. The negative correlation experiential through the summer season strengthens the notion that improved surface temperatures contribute to vegetation stress and decline. Overall, the integration of NDVI, LST, and LULC data brings a comprehensive thoughtful of drought dynamics in Muzaffargarh. This approach not only enables spatial identification of drought-prone areas but also offers a scientific basis for developing risk mitigation strategies. Such multi-source geospatial analyses are energetic for effective drought monitoring, early warning systems, and adaptive land management planning under changing climatic circumstances (IPCC, 2023).

Conclusion

Prolonged precipitation deficiencies, or drought, pose thoughtful problems for agriculture and the situation. By pursuing agricultural and meteorological droughts using geospatial tools like the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), this study measures the risk of drought in the Muzaffargarh District. It has been demonstrated that declining rainfall lowers NDVI values, suggesting the beginning of drought and vegetation stress. From 2002 to 2018, research was led in Muzaffargarh, which is situated between the Chenab and Indus rivers. In accumulation to notable land use moves from vegetation to built-up areas, the results validate a steady rise in surface temperatures and a consistent decline in vegetation cover. This trend designates which drought vulnerability is increasing. Regression analysis demonstrates that LST and NDVI have an inverse relationship, highlighting surface temperature rise as a key factor influencing the risk of agricultural and meteorological drought.

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Flood Risk Reduction **Using Integrated Community-Based Disaster Risk Management and Geo-Spatial Approaches in** Gin River Basin, Sri Lanka

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Abstract

Floods present considerable risks to the sustenance of livelihoods, infrastructure, and social fairness within the Gin River Basin, Sri Lanka, necessitating an integrated methodology for efficient risk mitigation. This article investigates the implementation of Community-Based Disaster Risk Management (CBDRM) combined with geospatial techniques to reinforce community resilience and involvement in reducing flood hazards. Encompassing an area of 932 square kilometers, the research site displays various climatic conditions impacted by monsoons and diverse topography spanning from mountainous forested inclines to agricultural floodplains. The methodology involved the selection of 100 households and stakeholders for data collection through quantitative surveys and qualitative interviews, focusing on demographic characteristics, livelihood trends, flood impacts, and coping strategies. Data was acquired from both primary and secondary resources, encompassing governmental publications and hydrological observation stations. The Delphi method was employed to enhance the CBDRM model customized for the area. The investigation pinpointed crucial socio-economic variables influencing community engagement in flood risk governance. The outcomes of the study underscored the recurrent flood occurrences intensified by climate variations, underscoring the necessity for a multifaceted strategy encompassing both physical and non-physical interventions. The strategy for lessening flood risks integrates traditional local knowledge, participatory risk evaluations, and sophisticated geospatial technologies like OpenStreetMap for instantaneous flood delineation. Proposed physical interventions involve the establishment of new sluices, refurbishment of pump houses, and the erection of flood embankments, while non-structural actions emphasize prompt warning systems, land utilization supervision, and community enlightenment. This holistic approach accentuates the significance of community responsibility, regional proficiency, and sustainable developmental techniques in augmenting flood resilience. The findings aim to enhance the wider conversation on disaster risk reduction and provide practical solutions for managing flood hazards in the Gin River Basin.

***Keywords**:* CBDRM, demographic, DELPHI, flood hazards, flood resilience

Introduction

The Millennium Development Goals (MDGs), adopted globally in 2000, highlight the importance of addressing vulnerability, disaster management, and risk assessment in development (WMO, 2017). Disasters, both large and small, can undo years of progress, severely impact livelihoods, and increase the risk of extreme poverty, disease, and poor health. Floods, in particular, are frequent hydrological disasters causing significant economic damage, threatening human lives, and disrupting infrastructure. Their impacts on businesses, public services, and the environment exacerbate social and economic inequalities, affecting community resilience and participation in flood-risk management. Effective community involvement in disaster risk reduction (DRR) requires understanding the socio-economic factors influencing participation, such as poverty, education, and access to services (Ashvin et al., 2021).

This paper attempts to address the importance of enhancing community resilience is underscored by Sri Lanka's experience in DRR over the past two decades. Despite traditionally high resilience, government and civil society efforts have primarily focused on preparedness and recovery, affecting attitudes and knowledge about disaster risk (David, 2021). Community-based institutions play a crucial role in managing flood risks, with indigenous knowledge providing valuable coping strategies. For instance, in Bangladesh, communities adapt by raising houses and storing emergency provisions. Sri Lanka, frequently affected by floods, experiences significant disruptions and damage during monsoon seasons (Pakneshan et al., 2023). Understanding the magnitude and frequency of floods is essential for effective planning and management. Models like the disaster-resistant and disaster-resilient communities emphasize minimizing vulnerability and enhancing community participation in DRR efforts (Chamal et al., 2023).

Research objectives

The main objective of this study is to determine Flood Risk Reduction **using integrated Community-Based Disaster Risk Management and Geo-spatial Approaches in** GIN River Basin, Sri Lanka. The sub-objectives of the study are to analyze the flood risk reduction in the Gin River area, prepare a flood risk reduction plan using integrated community-based disaster risk management (CBDRM) and geospatial approaches, and to align the CBDRM with a suitable existing model of flood risk reduction.

Study area

The study area, as delineated by latitudes 6°18'-6°24'N and longitudes 80°19'-80°35'E, encompasses the Gin catchment, situated between longitudes 80°08'E to 80°40'E and latitudes 6°04'N to 6°30'N, covering an estimated area of 932 square kilometers. The climatic conditions in this region are shaped by the influence of the southwest monsoon (May to September) and the northeast monsoon (November to February), interspersed with inter-monsoon showers during the remaining months. Precipitation levels exhibit variation in accordance with elevation, ranging from more than 3500 mm annually in the upper regions to below 2500 mm in the lower areas. (Salajegheh, 2013) The catchment area, entirely situated within the wet zone, showcases mountainous forested slopes in the higher elevations, while the middle and lower parts feature human habitation, agricultural activities, and forested areas. Thawalama, positioned in the mid-section of the catchment, primarily comprises human settlements and cultivated lands within the expansive floodplain of the Gin River (Wickramaarachchi, 2016). This zone borders the Sinharaja Rain Forest, a designated natural world heritage site, and incorporates anthropogenic practices like tea and rubber cultivation, domestic gardens, and regenerated forests.

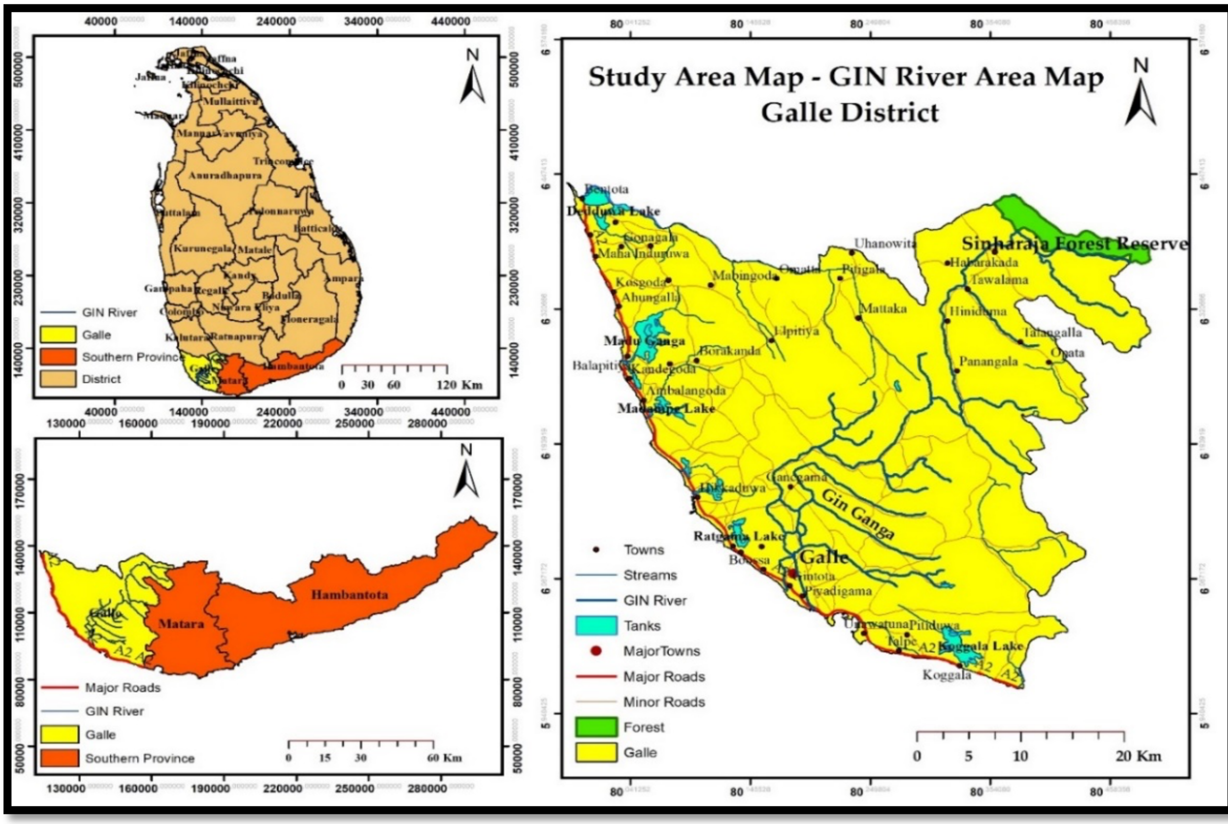

Figure 5: Study Area Map

Topography

The geographical features of the locality are defined by steep-sided, northwest-oriented strike ridges and valleys, characterized by basement rocks comprising highly resistant Precambrian metamorphic formations. The flow patterns of tributary streams are influenced by geological formations, where smaller streams rely on seasonal precipitation, whereas larger streams exhibit perennial flow. The Gin River basin, classified as a fifth-order stream, spans an area of 947 square kilometers with a river length of 112 kilometers, originating from elevated terrains exceeding 1300 meters (Kumari et al., 2018).The data for this research endeavor was obtained from the hydrological monitoring station at Thawalama (6°20'33"N, 80°19'50"E), covering an upstream catchment area of 470 square kilometers. (Dennis et al., 2019). The average annual precipitation within the catchment region is around 3,200 mm.

Material and Methods

The methodology involved purposively selecting 100 households, institutions, community leaders, and practitioners at household, district, and community levels due to time and financial constraints. Both quantitative and qualitative approaches were used to study community-based disaster risk management (CBDRM), focusing on disaster preparedness and recovery. Data collection methods included narrative literature review, secondary data (e.g., government reports), and primary data (e.g., interviews, focus group discussions, key informant interviews, and field observation). The Delphi technique was employed in three stages to refine the final CBDRM model for the Gin River basin (Hua et al., 2020).Quantitative data was gathered through household questionnaires covering demographics, livelihood patterns, flood impacts, vulnerable groups, and coping strategies. Qualitative data was collected via key informant interviews with district-level stakeholders, NGOs, religious institutions, and community representatives, discussing topics such as livelihood patterns, income sources, flood impacts, vulnerability causes, coping strategies, and development options (Ekeu-Wei, (2018).

Data Analysis

The disaster risk reduction method consists of six consecutive steps that can be used either in advance of or during a disaster to lower risks in the future. Each stage develops from the one before it and leads to additional action. The stages in the disaster risk reduction process are given in the figure below:

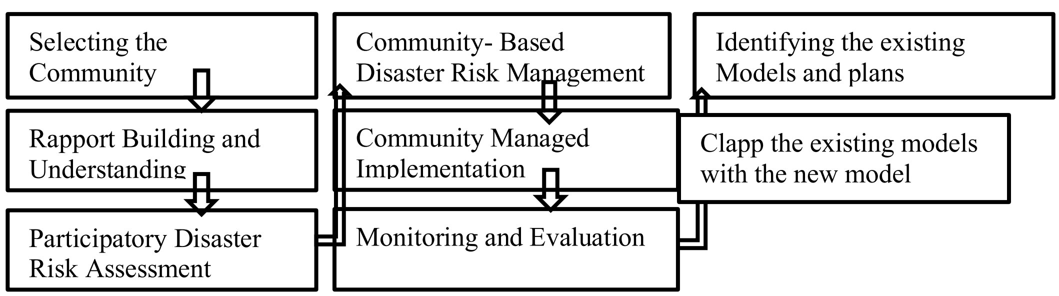

Figure 6: Disaster Risk Reduction Process (Adpc 2006)

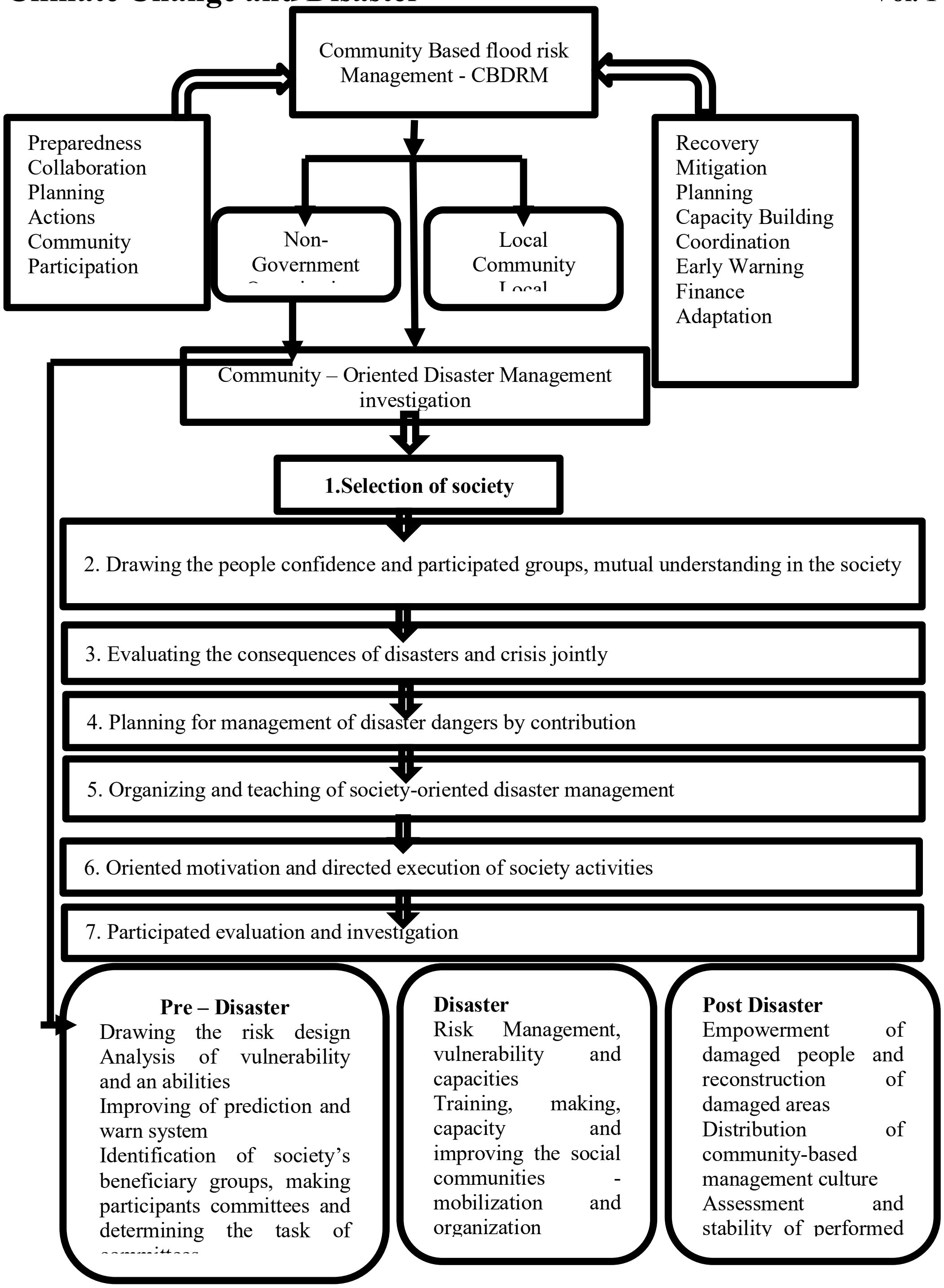

Figure 7: Methodological Framework

Results

However, the area is prone to recurring flood events, posing significant challenges to both the local communities and infrastructure. As climate change exacerbates weather patterns, the vulnerability of this region to flooding has become more pronounced, necessitating comprehensive studies and interventions to mitigate these risks (JMMU et al., 2020).

Several research endeavors have underscored the multifaceted aspects of flood risk within the GIN River basin. These studies often investigate the complex interplay of environmental factors, land use practices, hydrological patterns, and anthropogenic influences contributing to the heightened flood vulnerability. They explore diverse methodologies encompassing hydrological modeling, spatial analysis, and socio-economic assessments to understand the dynamics of flood occurrences and their impacts on the region. Furthermore, the GIN River basin has witnessed various efforts aimed at flood risk reduction and management. These initiatives span a spectrum from structural interventions such as embankments and reservoirs to non-structural measures like community-based preparedness and early warning systems. The effectiveness of these strategies, their sustainability, and their alignment with local socio-economic contexts form pivotal focal points in the ongoing discourse on flood risk reduction in this region (Kanchana et al., 2020).

This paper aims to synthesize and critically analyze existing research on flood risk reduction in the GIN River area of Sri Lanka. By examining the current state of knowledge, identifying gaps, and evaluating the efficacy of mitigation strategies, this study seeks to contribute to the ongoing dialogue on enhancing resilience against flooding in this ecologically rich and socially vibrant region.

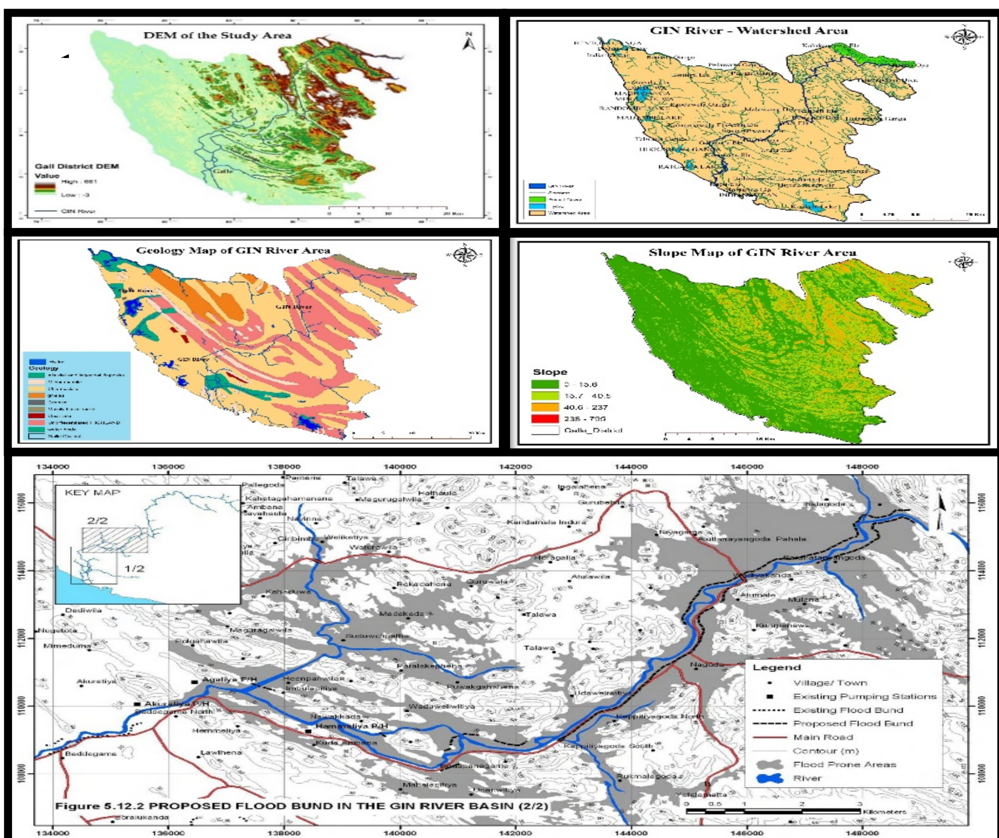

Figure 8: Gin River Area Dem, Gin River Watershed Area, Gin River Slope Map, Gin River Area Geology Map, Flood Prone Areas In Gin River Map

Society Participation

As per the definition provided by the World Health Organization (WHO) in 2002, community participation is characterized by individuals actively engaging in decision-making processes, identifying pertinent issues, and executing development policies and services (WMO. 2017). This approach enables individuals to exert influence on the design of development initiatives, decision-making processes, and the allocation of resources. Participation involves collaborative decision-making and societal supervision, covering all essential activities required to address present needs. It capitalizes on the inherent capacities of individuals, granting them the ability to effectively oversee their health and manage their lives through the acquisition of knowledge, skills, and self-assurance (Sadegh Nejad, 2009). To participate people in society, the different roles are determined for people which are as fallow:

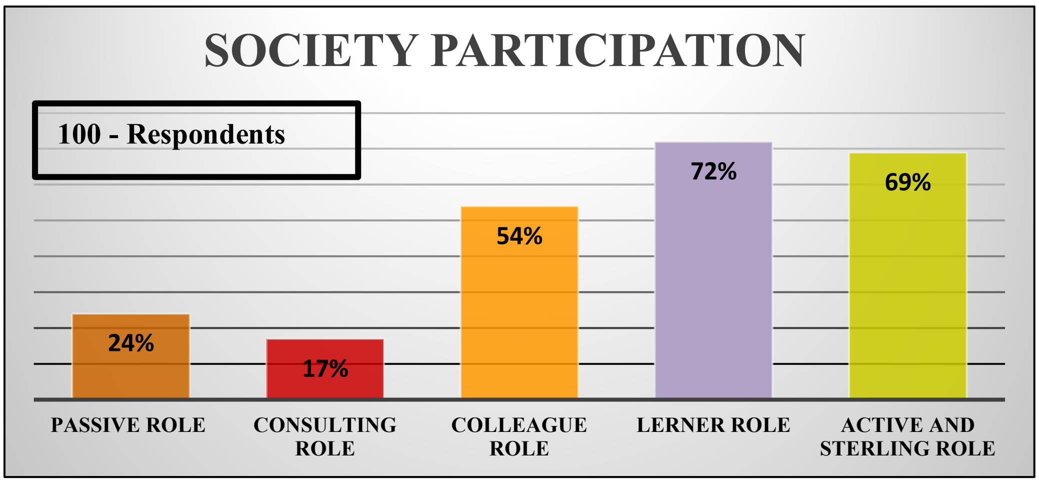

Figure 9: Society Participation (Source- Compiled by Author, 2022)

- **Passive role:** fallowing and obeying of rules and plans of decision makers and lawmakers
- **Consulting role:** using of people views
- **Colleague role:** people cooperation in management processes
- **Lerner role:** learning knowledge and necessary skills for people interventions
- **Active and sterling role:** people cooperation as a partnership (Jahangiri, 2010)

In flood analysis within the GIN River area, various socio-economic factors significantly impact both the vulnerability of communities to floods and the subsequent recovery and resilience-building efforts (Rojanamon et al., 2009).

Community-based flood disaster risk management is crucial in Sri Lanka to enhance resilience and preparedness against the frequent flood hazards that pose a threat to the nation. The damage inflicted on structures and infrastructure by floods underscores the necessity for integrating disaster risk reduction (DRR) mechanisms within the current systems. Despite the advocacy for sustainability by the Green Building Council of Sri Lanka, the complete integration of DRR into its framework remains incomplete. Consequently, Community Disaster Management Committees

(CDMC) are being formed in at-risk areas such as the Gin River region. (Perera, B, H, N., Wickramaarachchi, N, C., 2022) These committees offer DRR information, carry out vulnerability assessments, and provide training for effective disaster preparedness and response. Furthermore, there is a development of multi-stakeholder networks to facilitate the exchange of knowledge between government bodies and flood-prone communities.

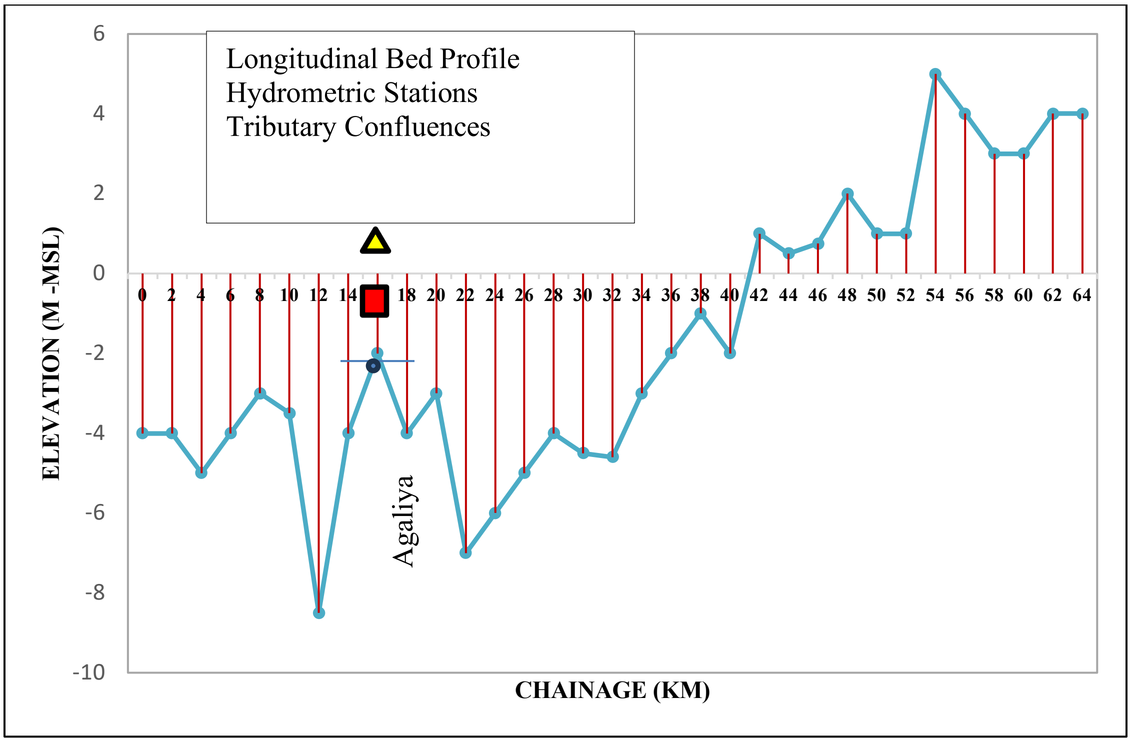

Figure 10: Longitudinal Profile of Gin River (Source: LHI, 2021)

Diverse methodologies are being utilized to effectively involve communities in flood disaster risk management. These methodologies encompass Participatory Risk Assessment (PRA), Vulnerability and Capacity Assessment (VCA), community hazard mapping, and the establishment of community-based early warning systems. Additional strategies include simulation drills, workshops for capacity enhancement, formulation of community-based disaster management plans, and mobilization of local resources. Attention is also given to gender and social inclusivity, the reinforcement of local institutions, nurturing partnerships, promoting sustainable livelihoods, and engaging communities in recovery and rehabilitation endeavors. These strategies underscore the significance of community ownership and empowerment, utilizing local expertise to bolster flood disaster resilience in Sri Lanka.

Existing flood management Master Plan Gin River Basin

Structural Measures

Table 1: Proposed Major Structures in Master Plan (Gin River)

	Kind of structure	Major dimensions
Short Term Plan	1. New sluices	9 nos.
	2. Rehabilitation of existing pumps	10 pump houses
	3. Mound dike	A=51,000 m^2 (3 sites)
	4. Flood bund	Left bank (L=8,360 m, H=5.4m) Right bank (L=7,620m, H=5.3m)
Long Term Plan	5. Flood bund (heightening)	Left bank (L=8,360 m, H=6.6m), Right bank (L=7,620m, H=6.3m)
	6. New pump house	8 nos.

Non-structural Measures (To proceed in parallel with the short-term plan)

Table 2: Non-Structural Measures to be promoted (Gin River) (Source: JICA Study Team)

Measures	Major Items
1. Early warning and monitoring system	- 8 rain gauge stations - 5 hydrometric stations
2. Restriction of further development in urban area	- Management and monitoring of land use - Prohibiting housing development in flood prone area - Flood zoning with hazard mapping,
3. Promotion of water-resistant architecture	- Heightening of building foundation - Construction of column-supported - Housing, change to multi-storied housing - Water proofing of wall/housing materials, etc.
4. Promotion of flood fighting activities	- Information dissemination in the communities - Evacuation to safer area, - Removal of properties in house/building, etc.
5. Resettlement	- Mound dike
6. Institutional strengthening of implementing agency	- Consensus building for project implementation - Integration with urban development and land use

	development plans

Flood Risk Reduction Plan Using the Cbdrm and Geospatial Approaches

A plan for reducing the risk of floods has been examined in Sri Lanka using the Community-Based Disaster Risk Management (CBDRM) and geospatial methods. The focus of the research was to identify areas that are vulnerable to flooding and develop models to evaluate the levels of flood risk. The studies integrated different criteria, such as the built environment, physical environment, and socio-economic environment, to categorize vulnerability and assess the levels of risk (Reaves, 2013). Open-Source applications, like OpenStreetMap (OSM), were employed to gather on-site information and identify areas that are inundated by floods. (Dr.Sanjar Salajegheh, 2013) Advanced models were utilized to assess the advantages of local infrastructure adaptation measures and determine the costs of not responding to changing flood risks (Gireesan, 2013). The spatial variations of drought and flood hazards were also analyzed in the Northern Region of Sri Lanka. These studies offer valuable insights and tools for the development of effective plans to reduce flood risks using CBDRM and geospatial approaches in Sri Lanka.

Creating a flood risk reduction plan for the Galle District in Sri Lanka using integrated Community-Based Disaster Risk Management (CBDRM) and geospatial approaches involves a comprehensive and collaborative process. Here's a general outline of the steps Researcher identified by the outputs (Pacific et al., 2008).

Step 1: Understand the Context

Risk Assessment: Conduct a detailed risk assessment of flood-prone areas in the Galle District. This includes identifying vulnerable communities, assets, infrastructure, and natural features that are at risk.

Step 2: Engage Stakeholders

Stakeholder Mapping: Identify and engage key stakeholders, including local communities, government agencies, NGOs, academic institutions, and private sector entities.

Step 3: Data Collection and Analysis

Geospatial Data Collection: Gather geospatial data such as elevation, land use, drainage systems, and flood history. This data will be essential for creating flood hazard and vulnerability maps.

Step 4: Community Participation

Participatory Mapping: Involve local communities in mapping flood-prone areas, safe shelters, evacuation routes, and critical infrastructure. Their knowledge is crucial for accurate planning.

Step 5: Risk Mapping

- Flood Hazard Mapping: Use geospatial data to create flood hazard maps indicating areas at risk of flooding based on elevation and historical flood patterns.
- Vulnerability Mapping: Combine socio-economic data (population density, poverty rates, etc.) with flood hazard maps to identify vulnerable communities and assets.

Step 6: Risk Assessment

Integrated Risk Assessment: Combine hazard and vulnerability information to assess the overall flood risk in different areas of the district.

Step 7: Strategy Development

- Community-Based Strategies: Collaborate with local communities to develop strategies tailored to their needs. This could include early warning systems, community training, evacuation plans, and resource mobilization.
- Infrastructure Improvement: Identify critical infrastructure in flood-prone areas and develop plans for upgrading or relocating them.

Step 8: Early Warning Systems

Community Early Warning Systems: Design and implement community-based early warning systems that utilize both modern technology and local knowledge.

Step 9: Capacity Building

Training and Workshops: Conduct capacity-building workshops to enhance community members' skills in disaster preparedness, response, and first aid.

Step 10: Monitoring and Evaluation

Implementation Monitoring: Continuously monitor the implementation of the flood risk reduction plan

Step 12: Public Awareness and Education
Community Outreach: Conduct public awareness campaigns to educate the community about flood risks, safety measures, and the importance of their participation.

Step 13: Documentation and Reporting

Figure 7: Identified Flood risk reduction plan for the GIN River Area

Communities and institutions involved in disaster management were forced to take proactive measures to lessen the impact of disasters due to the rising trend of disasters. The Sri Lankan government and other DM actors have begun to recognize the Community Based Disaster Risk Management (CBDRM) method as a fundamental tactic for increasing community capacity and resilience. The Government Road Map and the National Disaster Management Plan have designated Sri Lankan Red Cross Society as one of the primary actors in delivering CBDRM measures (Mohamed et al., 2023).

In accordance with the framework established by the government, SLRCS CBDRM interventions concentrated on conducting participatory risk profiling through evaluations of hazard, vulnerability, and capability, followed by the creation of community risk reduction plans, forming community groups to serve as village disaster management committees, training and outfitting local reaction teams, Identifying and implementing small-scale, community-managed mitigation activities, conducting simulation exercises and drills, installing signboards to indicate safe evacuation routes, executing DM awareness campaigns, and distributing information, education, and communication materials are just a few examples (Miyami et al., 2022).

The CBDRM program includes a school programming that is put in place to foster a culture of readiness within the school community. This entails the creation of a school-based disaster management unit, the creation and training of safety teams, the creation of plans and maps for the reduction of disaster risk at the school level, the execution of disaster mitigation and preparedness operations at the school level, and the conducting of practice drills.

Combining the Gin River Cbdrm Process with Existing Cbdrm Approach Model

The harmonization of the GIN River Community-Based Disaster Risk Management (CBDRM) approach with the participatory methodologies of the Participatory Learning and Action (PLA) model presents a compelling opportunity to fortify community resilience, instigate sustainable solutions, and cultivate an all-encompassing flood risk reduction strategy within the GIN River basin of Sri Lanka. (Wickramaarachchi, 2016) The GIN River CBDRM approach, tailored to the region's specifics, lays the foundation by engaging local stakeholders, leveraging community insights, and pinpointing flood vulnerabilities unique to the basin. (Kodikara et al., 2019). This initiative champions community involvement and context-sensitive strategies to mitigate risks.

Conclusion

In conclusion, the objectives set forth to analyze flood risk reduction in the GIN River area have paved the way for a holistic approach towards managing and mitigating potential flood hazards. By employing integrated Community-Based Disaster Risk Management (CBDRM) techniques alongside geospatial methodologies, a comprehensive flood risk reduction plan has been crafted. This plan considers the unique vulnerabilities of the GIN River area and harnesses suitable existing models of flood risk reduction, thereby fostering a proactive and adaptive strategy aimed at enhancing resilience and ensuring the safety of the communities within this region against the threat of floods.

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Assessment of Risk Factors, Disease Control, and Health-Seeking Behavior of Diabetes Mellitus among Urban Slum Populations

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Abstract

This cross-sectional descriptive study aims to specify the trend, major risk factors, and control of Diabetes mellitus (DM) patients in urban slum areas. A significant progression in adult populations globally has made it a major public health issue and a disaster of recent times. Lack of awareness, social constraints, and absence of community participation to address this public health issue contributed to a socio-economic burden on society. The study concluded the trends, major risk factors, and behavior regarding Diabetes Mellitus. A total of 164 males and 211 females were included in the study with a median age of 53.03 years. Following demographic information, the risk factors, duration of DM presence, practice regarding control, type of treatment taken, and the medical advice to manage the disease were observed as variables of the study. Risk factors such as hypertension 65%, dyslipidemia 41%, obesity 29%, and ischemic heart disease 33% were observed significantly. A high ratio of 62% among the study population did not control the disease properly. Only 35% of people knew the presence of the disease for 6-15 years. Only 26% of participants visited a general physician for medical advice regarding DM. Diabetes mellitus needs to be addressed due to lack of awareness, poor perception, and behavior among the diabetic community of urban slum areas. Further study on a large scale, considering a larger sample size and expanding the community area, may be helpful to establish guidelines to fight against this public health disaster.

Keywords. Diabetes mellitus, prevalence of diabetes, diabetic complications, diabetic awareness, urban slums communities

Introduction

Diabetes Mellitus (DM) is a non-communicable chronic disease also termed hyperglycemia, which is a raised blood glucose level in the body. This is because of the condition referred to as insulin resistance, in which insulin is not produced or does not work properly to convert glucose into energy. The main types of DM are listed as type 1, type 2, and gestational diabetes (Khali & Azar 2024; Solomen & Chew, 2017)**.** This is estimated at present that about 537 million (3 in 4) of the adult world population are living with DM, and this number is specifically rising so predicted that 643 million in 2030 and 783 million by 2045, as stated by IDF Diabetes Atlas. This scenario is more alarming in low and middle-income countries than in high-income countries. Another big challenge to global health is that DM is more prevalent globally due to the fact to remain the condition is uncontrolled or untreated (Mishra & Pandey, 2024)**.** According to IDF, the prevalence of DM in the adult population in Pakistan, by 2021 is about 12-13 million (12.3%, 1 in 8 adults) and expected to rise to around 18-19 million (15.4%, 1 in 6 adults) by 2045.

This alarming condition made Pakistan a more targeted point regarding DM progression among the general adult population (Basit & Fawad, 2018). The adult diabetic population nearly 44.7% are living as undiagnosed and this is a cause of a global burden of socioeconomic scenario and needs to be addressed regarding effective prevention, early detection, and proper management of diabetes (Wali, Rafique, 2020; Tokhirovna, 2024). There are several risk factors of DM, are known as non-modifiable risk factors including family history, age, and ethnic background, but modifiable risk factors are a sedentary lifestyle, smoking dietary behavior, cardiovascular issues, hyperlipidemia, excessive alcohol consumption, and mental stress (Wang & Li,2021). Complications of DM include serious conditions such as microvascular conditions such including diabetic retinopathy, diabetic nephropathy, and diabetic neuropathy, as well as macrovascular conditions, such as cardiovascular issues, stroke, and peripheral arterial diseases. Additionally, the population suffering from DM is expected to get infections and slower wound healing (Casqueiro & Casqueiro, 2012).

In a community-based study conducted in Nepal, hypertension was recorded as the leading risk factor for DM, in the list of global disease burdens of a public health issue of underdeveloped countries found as 29.4%, in this study, while 25% of individuals suffered from hypertension and < 50% were known about their disease[i]. In the Chinese population, the rate of hypertensive conditions evolved to 26-29% among the adult population (Swedish Council on Health Technology Assessment, 2008). As a genetic and environmental factor of diabetes, obesity has been found a considerable increase in ratio worldwide (Ruze & Liu, 2023). Obesity and DM have a significant ratio of 29% among our study population mentioned already in the study. DM was also established as a strong risk factor for cardiovascular diseases and available research data explained the high prevalence of CVD as a result of both Type 1 and Type 2 DM and a cause of atherosclerosis as well as heart attack (Heather & Hafstad, 2022). Arterial fibrillation was also established as increasing in prevalence all over the world and a significant risk factor of sudden death in the Type 2 DM population of the older age group > 75 years of age Mozaffarian, Kamineni, 2009; Volgman, & Nair, 2022). The study conducted by the American Diabetic Association settled a standard protocol to address the behavior, treatment, and comorbid conditions, and in older patients over the age of 65 years, this was established that in kidney diseases, the patient must be evaluated regarding kidney functions, also (Pecoits-Filho & Abensur, 2016).

Longer duration of uncontrolled and untreated DM represents the evidence of more complications resulting from DM (Park, & Cho, 2024). Better diet control established good glycemic control as a result of the best strategy to control Type 2 DM among the adult population, and in the middle age group including the overweight and obese population were best-treated population of higher body mass index which was moderately control of the DM scenario (Chiavaroli & Lee, 2021). The diabetic population has little knowledge about the disease, and 94% of people know about the disease, but only 17% know about the risk factors and preventive measures of DM. The knowledge about the disease was recorded higher among the diabetic population those have diabetes in their relatives and families (Tellawy & Alfallaj, 2021).

Hypertension is a condition with DM type 2 and interlinked with each other, so the prevalence is increasing worldwide due to arteriosclerosis so be considered as an emerging cardiovascular disease (Balakumar & Maung, 2016). Moreover, data expressed that the association between high blood pressure and DM more significant cause of many other cardiovascular complications, so needs to be conscious for the treatment and control of hypertension and diabetes both together (Przezak, Bielka, & Pawlik, 2022). Dyslipidemia is another comorbid condition to be considered in patients with DM, due to the raised value of triglycerides and low high-density lipoprotein cholesterol (HDL-C), which is more prevalent and evident. The finding showed that cardiovascular diseases are also associated and have a high prevalence in the diabetic population (Kaze, & Santhanam, 2021) Ischemic heart diseases like cardiomyopathy, myocardial infarction, and heart attack have high mortality rates with DM type 2, and adopting a standard protocol to monitor diabetes and heart issues on regular basis (Shrivastava & Ramasamy, 2013), (Heather, & Hafstad, 2022). Duration of occurrence of DM is a more prevalent factor about 25% among the population of older age group as a main health burden, so has a higher risk of increasing in frequency in the next decades. This is now established from the data that normally the older age group of population has the more complications because in this group the duration of DM is directly associated with the growing age, eventually greater the age longer the duration of diabetes if present (Huang & Laiteerapong, 2014; Izzo, Massimino, & Riccardi, 2021). The control of DM is directly associated with the lack of awareness of the disease, and lifestyle also has an impact on the control of DM. An active lifestyle may be very helpful in coping with the effects and complications of diabetes. Research showed that about 23% population takes care of and shows good response to the medication for the treatment of DM (Shrivastava & Shrivastava, 2013). The adherence rate also has a direct impact on treating diabetes among the population with pharmacological ways such as oral medication or insulin, so clinical depends upon the uptake of the machines as medical advice enhances good clinical outcomes (Alharbi & Alaamri, 2023).

The biology of type 2 DM is one of the risk factors, and the absence of enough production of insulin or insulin produced by the pancreas not being able to work properly. Accumulation of fat in the liver due to static lifestyle resulting in physical inactive behavior. Poor hygienic environment, social isolation, sleep disturbance, air, and noise pollution are the strong risk factors of DM. Smoke, green area elimination, burden of traffic cause severe stress, enhancing the disease condition. (Dendup & Feng, 2018). Strong associations of rapid population growth, unhealthy air quality index, urbanization, and thickly populated areas, specifically urban slums, are at high risk of developing worse condition of DM .among adult and especially in old age group in general population (Hankey & Marshall, 2017).

Materials and Methods

This cross-sectional study was conducted among the general population involving 375 individuals with a simple random sampling technique and calculated by the formula,

$n = Z^2 (p\ q) / d^2$

$= Z^2\ p\ (1-p)/d^2$

$= (1.96)^{2\times} 70.4\ (100-70.4)/5^2$

$= 30.96 \times 70.4\ (29.6) / 25$

$= 8252 / 25$

$= 330$

With a 10% attrition rate, 330 +33 = 363

For convenience, 375 individuals were included in the study.

All new and follow-up patients residing in urban slums of Lahore visiting Gulab Devi Teaching Hospital Lahore, with known patients of DM type 2, were included in the study for a dilated retinal examination in the eye department. A self-structured questionnaire was used to collect the data, and all patients for the study were interviewed with informed consent. After data collection, data were analyzed on SPSS version 26. Categorical variables were computed and presented in tables, charts, and graphs. In the descriptive analysis, frequency tables were generated. Cross tabulation and association of variables were done by chi-square test, P – P-value < 0.05 was considered as significant. ANOVA was used to analyze the difference between the mean of groups, and an independent sample t-test was used to analyze the difference between the means of two unrelated groups.

Results and Analysis

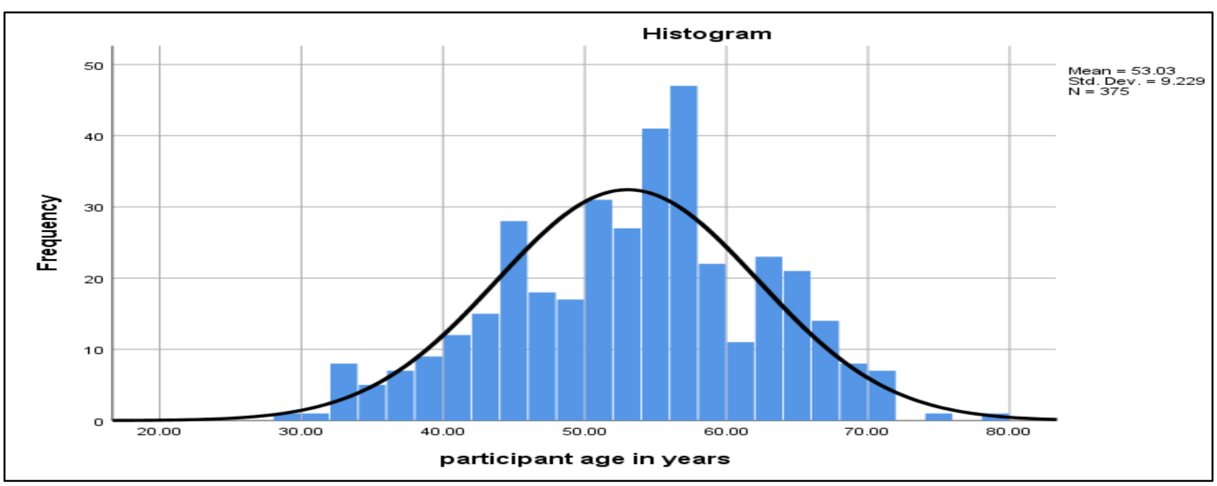

Figure 1: Age Distribution of the Participants

Figure 1 shows the age and gender of the study population and explains that the median age was 53.03 years, with a standard deviation of 9.23. The total number of participants included in the study was 375.

Table. 1 Demographic Presentation of the Participants

	Category	*f*	%
Gender	Males	164	43.73
	Females	211	56.26
Educational Status	Illiterate	132	35.2
	Primary9o78	72	19.2
	Secondary	113	30.13
	Graduate	58	15.46
Profession	Govt. Job	31	8.26
	Private job	35	9.33
	Labor	34	9.06
	Retired	39	10.4
	Housewife	176	46.93
	Unemployed	60	16

Out of 375 participants in the study, 164 (43.73%) were males, and 211(56.26%) were females. The ratio of females was higher than that of males. The educational status of the participants was as follows: 132 (35.2%) illiterate, 72 (19.2%) primary level, 113 (30.13%) secondary level, and 58 (15.46%) were graduate.

The professional status of participants was recorded as Govt. Job 31 (8.3%), Private Job 35 (9.3%), Labor 34 (9.1%), Housewives 176 (56.9%), Retired 39 (10.4%), and Unemployed 60 (16.0%) (Table 1).

Table 2 Major Risk Factors of Diabetes Mellitus

Risk Factors	*f*	%
Hypertension	244	65.06
Dyslipidemia	155	41.33
Obesity	109	29.06
Ischemic Heart Disease	123	32.8

This table explains the co-morbidities of DM, as hypertension was evident in 244 (65.1%), dyslipidemia in 155 (41.3%), obesity in 109 (29.1%), and ischemic heart diseases in 123 (32.8%) (Table 2).

Table 3 Duration of Diabetes Mellitus

Duration in years	*f*	%
3-5	81	21.6
6-10	129	34.4
11-15	128	34.13
16-20	30	8.0
>20	7	1.86

Table 3 shows the duration of the diabetes best known by the individual was observed in the category of 3-5 years 81 (21.6%), 5-10 years 129 (34.4%), 11-15 years 128 (34.1%), 16-20 years 30 (8.0%), and more than 20 years 7 (71.9%).

Table 4 Control of Diabetes mellitus

Control	*f*	%
Very Strict	16	4.26
Strict	126	33.6
Not Strict	230	61.33

Table 4 explains the behavior towards the control of the DM, and data was recorded as individuals who control the disease very strictly were 16 (4.26%), strictly 129 (34.4%), and not strictly 230(61.33%).

Table 5 Type of Treatment Adopted by Individual

Treatment taken	*f*	%
Pills	244	65.06
Insulin	71	18.93
No medication	60	16

The table 5 shows the practice regarding taking any treatment to control the disease as 244 (65.06%) were on oral medication, 71 (18.93%) were insulin-dependent, and 60 (16.0%) were not taking any treatment to control the disease.

Table 6 Visit to General Physician

Visit to Physician	*f*	%
Regular	97	25.86
Not Regular	267	73.6
Never	11	2.93

The table 6 shows that participants 97 (25.86%) visited regularly, 267 (73.6%) not regularly, and 11 (2.9%) never visited to physician to take advice for the disease.

Discussion

Awareness and socio-economic status are both directly influencing factors of increasing diabetes in the adult population. (Saeed & Saleem, 2018). In our study, we concluded that the individuals involved in the study were of a median age of 53.03 years with a standard deviation of 9.23, which predicts the condition that the prevalence was significant in the old age group. It was also observed that the ratio of female patients was high at 53% as compared to female participants were 43%. Our data established a higher ratio of 35.2% in the illiterate category, the category of the primary level was 19.2%, and secondary level was 30.1%, the graduate level was recorded as 15.5%. Socio-economic and literacy status were considerable factors in this study. The profession also affects the behavior and practice to control and prevent non-communicable diseases as the busy schedule in many professions, awareness and self-care strategies are the main factors established in studies. (Agha & Usman, 2014) The professional status of participants was recorded in our research, as Govt. Job 31 (8.3%), Private Job 35 (9.3%), Labor 34 (9.1%), Housewives 176 (56.9%), Retired 39 (10.4%), and Unemployed 60 (16.0%). In this study, the highest ratio was recorded among housewives (56.9%), and the second largest group was recorded among the unemployed population. The larger group of housewives was the dominant group of participants in the study.

The comorbidities were experienced in this study, including hypertension 244 (65.1%), dyslipidemia 155 (41.3%), obesity cases 109 (29.1%), and ischemic heart diseases 123 (32.8%). In a study done on Madrid's general population, the comorbid conditions were found to be hypertension 70%, dyslipidemia 67%, and obesity 32%, in the study. (Barrio-Cortes & Mateos-Carchenilla, 2024). This study showed the equal proportions of results as suggested by other researchers. The results found that the duration of DM was also a significant factor in the emergence of many complications. The data has been recorded in this research regarding the duration and presence of the disease as among the categories of 3-5 years 81 (21.6%), 5-10 years 129 (34.4%), 11-15 years (128 (34.1%), 16-20 years 30 (8.0%), and more than 20 years 07 (1.9%). The highest ratio among the group 11-15 years was 34% among the population under observation during the study conducted in this study. Meta-analysis established in a survey declared that the duration of DM is evident due to glycemic conditions among the diabetic population (Stolar, 2010; Hemmelgarn, 2011).

The data regarding behavior among the study population has been recorded to control the diabetic condition as very strict control 4.26%, strict control 129 (34.4%), and not strict control 230 (61.3%), and as in the low-income population, the control of DM type 2 is behavior dependent, so knowledge and practices to overcome diabetes and its complications are significant among diabetic population (Papatheodorou, Banach, 2018). A study established that general health awareness, lifestyle changes, and following the right treatment plan remained good to control diabetes (Gruss & Nhim, 2019). The findings of this study also showed the situation of practice and behavior of the participants regarding control of DM type 2. Our research expressed that only a small group controls the condition, and 61% of individuals were not serious regarding their disease due to lack of knowledge. A larger group was on oral medication, taking medication by mouth 65%, insulin

18.93%, and 16% were not taking any treatment.

The study also witnessed that 11 (2.9%) participants did not visit a general physician, 267 (71.2%) visited but not regularly, while only a small group 92(25.9%) visited regularly for medical advice or treatment. Lack of knowledge and awareness hinders the perception of taking advice on medical care about diabetic control (Nagelkerk, Reick & Meengs, 2006). his is also stated by data that practitioners face difficulties in treating a patient of DM due to a lack of knowledge about the disease. Healthcare providers make decisions while considering DM to treat the patient, so decision-making is very important for the treatment with pills, insulin, or both (Chimoriya & MacMillan, 2024)Furthermore, medical advice acceptance is very crucial for diabetic control as the treatment plan or strategy prescribed by the health care practitioner leads to better control and prevents complications in advanced age if the disease remains untreated or uncontrolled (Najafipour & Farjami, 2021).

The control and prevention of diabetes is a public health concern for the community all over the world as well as regional situations. The practice and perception of controlling the disease is not ideal, and the presence of the undiagnosed or untreated disease is the cause of many complications (Hamid, Akash & Rehman, 2021). Our study strongly overlooked the status regarding complications as a result of untreated or uncontrolled DM type 2 and found a very crucial scenario in which only 15% of participants visited a specialist doctor to take advice regarding any complication introduced as a result of diabetes. This is also evidence of a lack of knowledge regarding diabetes and its complications. The group of participants who did not visit a specialist for an expert opinion regarding complications was as crucial as other groups. This group is also at risk of diabetic complications.

Recommendations

- Establishing a public health issue, specifically among the diabetic community, needs to be considered as a public health disaster due to the increasing mortality rate and compromising quality of life among the diabetic population.
- Lack of awareness is a barrier to controlling and managing the scenario regarding behavior, perception, and practices among the community.
- Further studies may lead to follow-up guidelines to address the issue on a larger scale and benefit the population of other areas.

Limitations of the study

Lack of awareness and socio-economic factors remained the limitations, while follow-up visits. A small sample size was considered for the study, but further research may be continued in the future involving a large sample size, expanding the scope of study at the community level. Due to its significance and severity, this public health issue must be treated as a disaster.

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Analyzing the Impact of Covid-19 on Climatic Condition in Pakistan Using Geospatial

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Approach

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Abstract

Coronavirus affected the usual trends of environmental factors, globally. This study is an attempt to assess the impacts of COVID-19 on climatic conditions in Pakistan using a geospatial approach. The secondary data is used in this study. For analysis of climatic conditions satellite data of selected climatic factors (wind speed and LST) was collected from openly available websites. The climatic data were downloaded from the MODIS MERRA-2 sensor from EOSDIS Worldview NASA in NC4 File format of wind speed and data of LST from USGS Earth Explorer. The data were processed by using geospatial approaches, such as interpolation (IDW), zonal statistics, and weighted sum. By doing statistical analysis the variations in climatic conditions are assessed. The findings revealed that during the lockdown period variations were observed in climatic conditions due to limitations on anthropogenic and industrial activities. During the lockdown period of the COVID-19 pandemic not only the cases were under control but positive changes in climatic conditions were also observed. During the lockdown period of the pandemic, negative standardized anomalies in LST and wind speed were observed compared to prior years 2018 and 2019. Restriction on anthropogenic activities produces positive changes in environmental conditions.

Keywords: climatic conditions, covid-19, LST, wind speed, lockdown and geospatial approaches.

Introduction

A little cluster of cases of the disease now known as COVID-19 or coronavirus was first detected when a few patients with early symptoms of pneumonia were admitted to hospitals in the Chinese city of Wuhan on December 29, 2019 (Price et al., 2020). Globally WHO (World Health Organization) reported 28,276 confirmed cases with 565 deaths as of February 6, 2020, including at least 25 countries (Wu et al., 2020). Coronavirus was announced as a general public health emergency of International Concern in January 2020 (Bhatnagar et al., 2021) and coronavirus had turned into a global health concern of prime significance, influenced more than 400 million people with 5.7 million confirmed deaths by January 10, 2022 (Praharaj et al., 2022). Coronavirus is a positive single-stranded RNA genome encompassed by an envelope and its diameter ranges from 60nm to 140nm (Singhal, 2020). This disease has expanded expeditiously to the world and poses huge economic, environmental, health, and social challenges to the whole human population (Chakraborty and Maity, 2020).

In Pakistan first case of COVID-19 was reported on February 26, 2020, due to entry of infected pilgrims from Iran (Raza et al., 2021). A constant increase was observed in total cases of coronavirus until 12th June. 273,113 total confirmed cases were reported until 25th July 2020 (Ahsan-ul-Haq et al., 2022). The mortality rate was low in Pakistan as compared to other countries like Italy, Iran, Spain, and the USA (Amin et al., 2020). The spread of this pandemic can only be controlled by taking preventive measures. Pakistan imposed its first lockdown after three weeks since the first case reported when the total number of cases was greater than 880 (Farooq et al., 2020). The government of Pakistan did not impose a complete lockdown precipitously around the country but instead imposed it systematically (Khan et al., 2021). In Pakistan, the first lockdown was imposed on 23rd of March 2020, within the province of Sind, accompanied by a nationwide lockdown from 25th March, 2020. However, the lockdown policy varied from sector to sector such as the residential and industrial sectors. Therefore, divided the lockdown period into different stages, P1 the earlier stage from January to February, P2 before the lockdown period from the 1st of March to the 22nd of March 2020, P3 lockdown period from the 23rd of March to the 15th of April 2020, P4 loosed lockdown period from 16th of April to 30th of April 2020 and P5 selected lockdown period from 1st of May to 15th of May 2020. P4 refers to a partial or loose lockdown period when industries were not operating (Ali et al., 2021).

The association between coronavirus and climatic factors was ambiguous, which was demonstrated by both positive and negative impacts (Amnuaylojaroen et al., 2021). The positive environmental variations were reported because of the lockdown period during the COVID-19 pandemic (Evangeliou et al., 2021). COVID-19 had many positive impacts on air pollution and climatic conditions. A decrease in anthropogenic activities led to a significant decline in air pollution (Khan et al., 2021). The lockdowns during the COVID-19 pandemic brought larger changes in land surface temperature between rural and urban areas due to a reduction in anthropogenic activities (Sahani et al., 2021). The anomalies in land surface temperature during the lockdown period of COVID-19 were first studied over the worst virus-affected areas of North America and Europe. The studies discovered huge negative changes in night-time land surface temperature in Europe (0.11°C to -2.6°C) also significant changes were observed in both day and night time LST across North America from March to May in the pandemic year 2020 contrasted to the average of years before pandemic from 2015 to 2019, which can be partly due to the effects of lockdown period during COVID-19. The reduction in LST was associated with a negative change in air temperature (-0.46°C to -0.96°C). On the other side, the increase in daytime LST was observed throughout most regions of

Europe due to a decrease in solar radiation by barometrical aerosols. The negative changes in LST at night time may be associated with reduced anthropogenic activities. In North America, studies discovered a significant negative change in LST of both day and night time during the lockdown period (Parida et al., 2021).

The changes in wind speed are mainly due to land use and land cover changes (Navinya et al., 2020). An increasing trend was observed in wind speed during the pandemic between 10th March 2020 and 21st July 2020. After that time period, a decline was observed in wind speed. In Pakistan, fluctuations were observed in wind speed from 10th March 2020 to 04th October 2020 (Ali et al., 2021). The overarching goals of this research are to analyze changes in LST and wind speed during the lockdowns of the pandemic by using satellite data. However, the present study is based on previous literature and elucidates the impact of COVID-19 on climatic factors across the Pakistan and also helps to interpret the significant changes in climatic factors during the lockdown period and the reasons behind these significant changes in the study area by using geospatial approaches.

Study Area

The study area named Pakistan is located in the western zone of South Asia geographically extends from 30°22'31.2" N latitudes. It denotes Pakistan's location in the Northern Hemisphere and ranges from 69°20.707' E longitudes which represent the eastern location of Pakistan (Salma et al., 2012). Pakistan is comprised of four provinces Punjab, Sindh, Baluchistan, and KPK, and Islamabad Capital Territory. Additionally, there are two other administrative states Azad Jammu Kashmir (AJK) and Gilgit Baltistan as shown in Figure **1**. Pakistan is a land of mountains, plains, deserts, and coastal belt. The area of Pakistan is 796,095 square kilometers (Mohsin, 2020). Pakistan enjoys a wide range of seasons. Pakistan lies in the temperate zone, above the tropic of cancer. Pakistan has a bimodal distribution of rainfall. Pakistan is a developing country with a fragile health system and the financial condition of Pakistan is also not better, the impacts of the virus were more in Pakistan as compared to developed countries. The potential risk of COVID-19 risk was more in Pakistan because of Pakistan's Population dynamics and demographics (Noreen et al., 2020). This study also analyzes the impacts of the COVID-19 pandemic on the climatic factors of Pakistan and helps to create a pandemic overview in Pakistan.

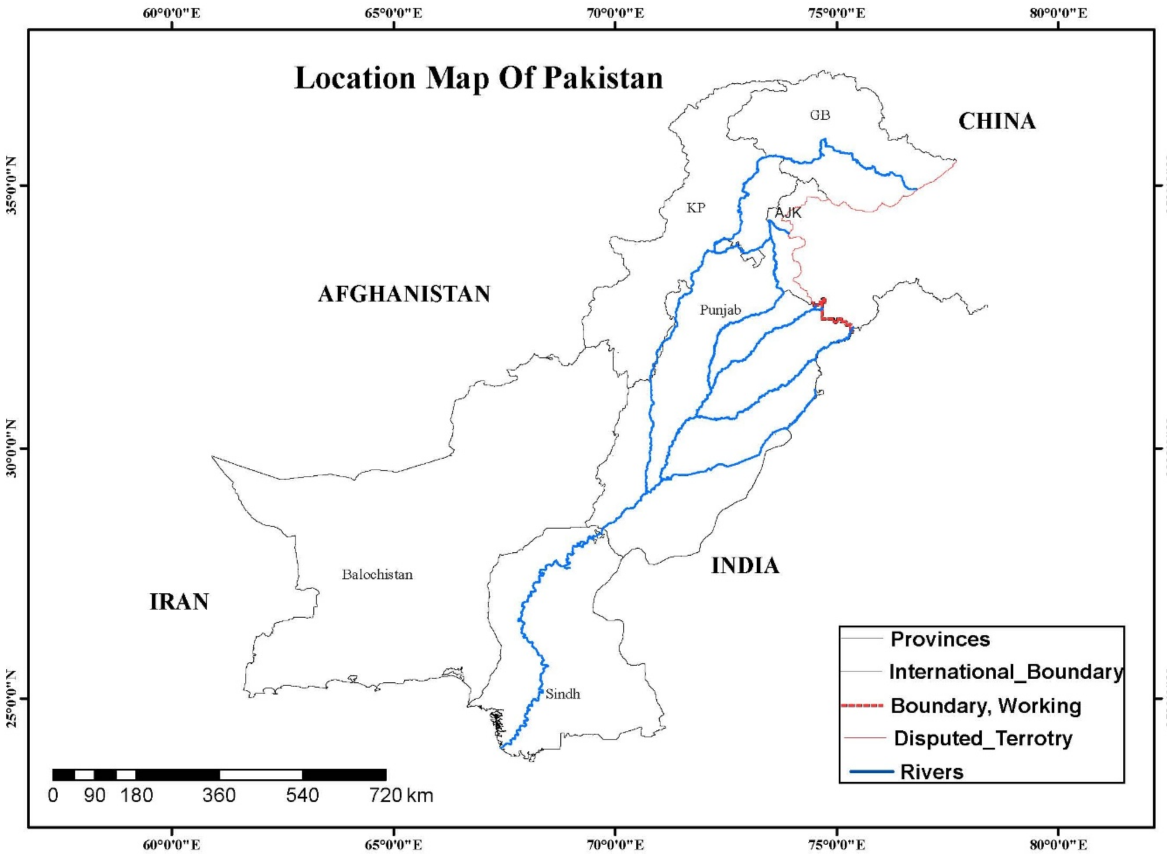

Figure 1: Study Area Map of Pakistan

Datasets used

To achieve the objectives of this study secondary data sources were exploited. For this study, satellite data and COVID-19 data were used. The data was collected through remote sources. Data has been downloaded manually from different websites. The monthly data of selected environmental factors (LST and wind speed) was downloaded from January 2018 to March 2022 and of preceding years 2018 and 2019 of pandemic and during COVID-19 pandemic. This data was collected from satellites images namely MODIS MERRA-2 sensor from EOSDIS Worldview NASA in NC4 file format of wind speed and data of LST from USGS Earth Explorer to analyze the changes in environmental condition. In this study, the satellites images of climatic data of Pakistan were downloaded of preceding years 2018 and 2019 as a proxy for conditions and compared them with data for the period 2020, 2021 and 2022 under lockdown conditions. And province wise COVID-19 monthly data set of total cases assembled from open source website covid.gov.pk from March 2020 to March 2022 of COVID-19 this time period was considered for statistical data analysis because the first case of COVID-19 in Pakistan was reported on 26th February 2020. Table **1, 2 and 3** summarized the COVID-19 data which was used in this research and collected from open source website covid.gov.pk.

Table 1: Monthly COVID-19 data of Total Cases

COVID-19 Total Cases 2020							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK
March	54	708	0	253	158	184	6
April	343	6340	6053	2627	1049	339	66
May	2589	26240	28245	10027	4393	711	255
June	12912	76262	84640	26598	10476	1489	1093
July	150333	93057	121039	34056	11743	2134	2084
August	15649	96832	129469	36118	12879	2903	2299
September	16611	99479	137106	37811	15281	3787	2731
October	19970	104271	145851	39564	15920	4261	4133
November	30406	119578	174350	47370	17187	4658	6933
December	37888	138608	215679	58701	18168	4857	8277

COVID-19 Total Cases 2021							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK

January	41418	157796	247249	67214	18823	4909	9019
February	44373	172054	258266	72424	19049	4956	10243
March	58557	223181	265680	88099	19576	5033	12805
April	75498	303182	283560	118413	22369	5310	17187
May	81257	340110	318579	132822	25218	5588	19250
June	82706	346301	337674	138068	27178	6138	20343
July	87699	356920	382865	144264	30432	8156	24501
August	99516	394738	432637	162402	32248	9919	32228
September	105516	431666	457928	174017	32926	10328	34157
October	106921	440259	470175	178074	33263	10390	34478
November	107722	443185	475820	180075	33484	10412	34556
December	108666	445107	482029	181402	33638	10429	34662

Table 2: Monthly COVID-19 Total Cases of 2021

Table 3: Monthly COVID-19 Total Cases of 2022

COVID-19 Total Cases 2022							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK
January	128429	480421	543170	194887	34417	10703	38339
February	134404	501544	568277	216174	35345	11499	42978
March	135072	505003	575257	219026	35472	11702	43261

The data of wind speed (m/s) was extracted from MEERA-2 2d_lfo_Nx which is monthly mean data collection and for Land Surface Temperature (Kelvin) (LST) data collected from USGS Earth Explorer in HDF format. For the conversion of radiance Kelvin values to LST, first digital number (DN) obtained from USGS of the image were calculated and their average was taken out and multiplied with 0.02 and then radiance was subtracted from 273.15 (Javid et al., 2019). The data has been prepared by using the ArcGIS 10.3.1 software and MS Excel. The COVID-19 data was analyzed by using Microsoft Excel Spreadsheet and presented in the form of tables. The COVID-19 and climatic data both were processed by using Arc GIS. After that Inverse Distance Weighted (IDW) was used for visualization and to show the trends of COVID-19 data and variations of climatic factors. IDW is type of deterministic method of interpolation that estimates cell values by averaging the value of given sample data points in the neighborhood of each processing cell. Finally, zonal statistic implemented to show districts wise visualization of both COVID-19 and climatic data. Furthermore, maps were produced to show spatial distribution across Pakistan by using Arc Map Tools. The weighted sum analysis approach provides the ability to weight and combine series of raster inputs to create an integrated analysis. The weighted sum multiplies all the input raster values by specified weight. Statistical Analysis was performed to show changes in environmental factors at district level of Pakistan. By using this method, a generalized visualization of variation in climatic conditions in areas of Pakistan due to COVID-19 is shown.

Results

In this research impacts of the COVID-19 pandemic on climatic conditions are assessed and also how the lockdown period during the pandemic caused variations in environmental conditions. In this study it has already been mentioned cause of this pandemic, preventive measures were taken such as wearing masks, social distancing, limiting transport, closure of industries, and lockdowns were imposed to control the spread of COVID-19, lockdowns not only minimized the spread of COVID-19 but also brought positive changes in environmental conditions. In this study analysis are performed at both level district and province level. Tables represent impacts of lockdown on environmental conditions at district-level and images across the country. In Pakistan the first lockdown was imposed in the month of March 2020 to June 2020 known as strict lockdown. In the month of July 2020, the government again imposed a partial lockdown. In May 2021 the government again imposed a lockdown known as Eid lockdown. By June 2021 COVID-19 had hit Pakistan hard. Until March 2022 the most affected province by coronavirus was Sindh with 575257 total reported cases. And the least affected was GB with 11702 total cases. The total cases in March 2022 were 251334. The lockdown not only controlled the spread of COVID-19 cases but also caused changes in climatic conditions. Figure 2 depicts how during strict lockdown the cases of COVID-19 were under control. When the government loosened the lockdown, an increasing trend was observed in total cases in different parts of the country. Figure 3 **Error! Reference source not found.**shows how COVID-19 during the partial lockdown affected the country. Figure 4 depicts how COVID-19 affected Pakistan after the month of October 2020. Similarly, Figure 6 and 7 show the terrible increase in COVID-19 cases. And Figure 8 presents how pitifully coronavirus affected the Pakistan till March 2022.

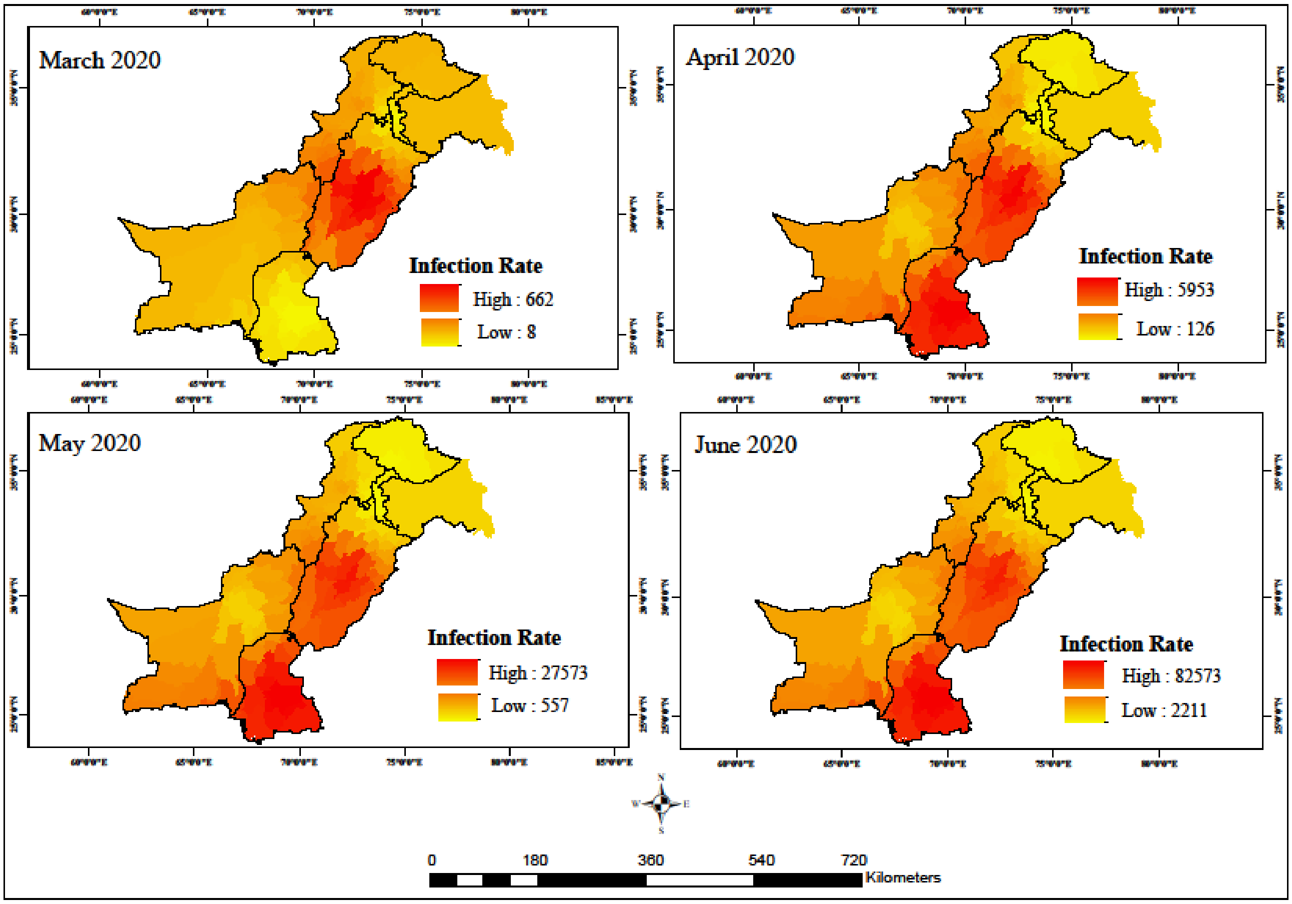

Figure 2: Spatial Distribution of Total Cases of Covid-19 during Strict Lockdown Period

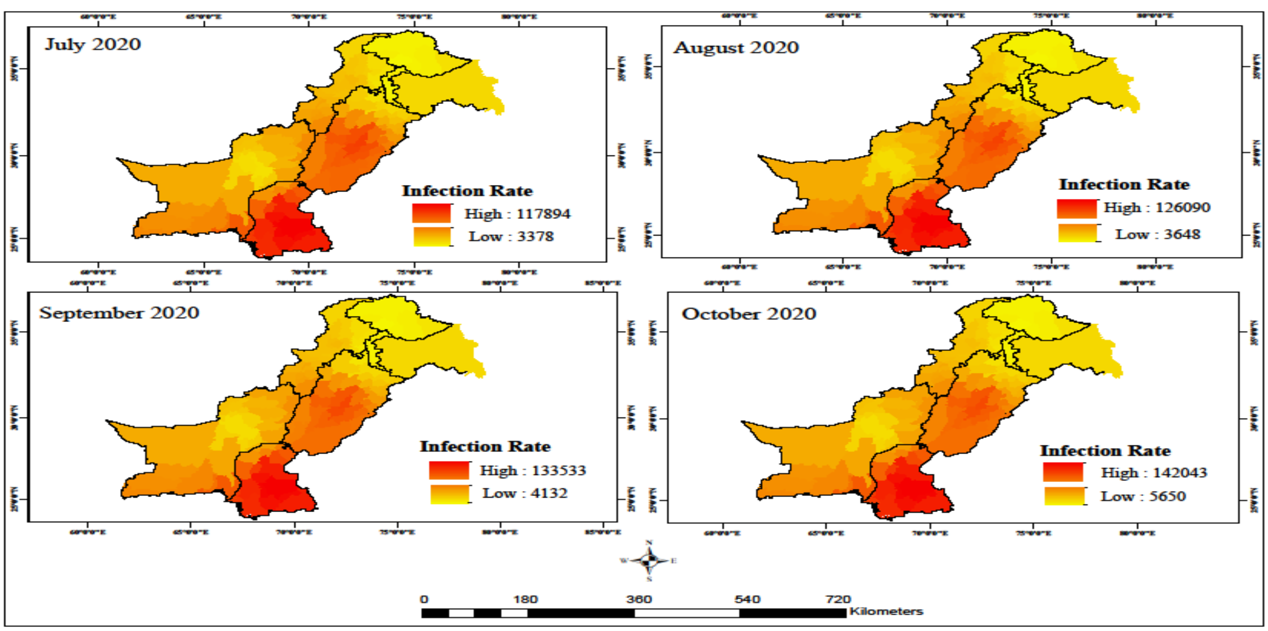

Figure 3: Spatial Distribution of Total Cases of Covid-19 during Partial Lockdown Period

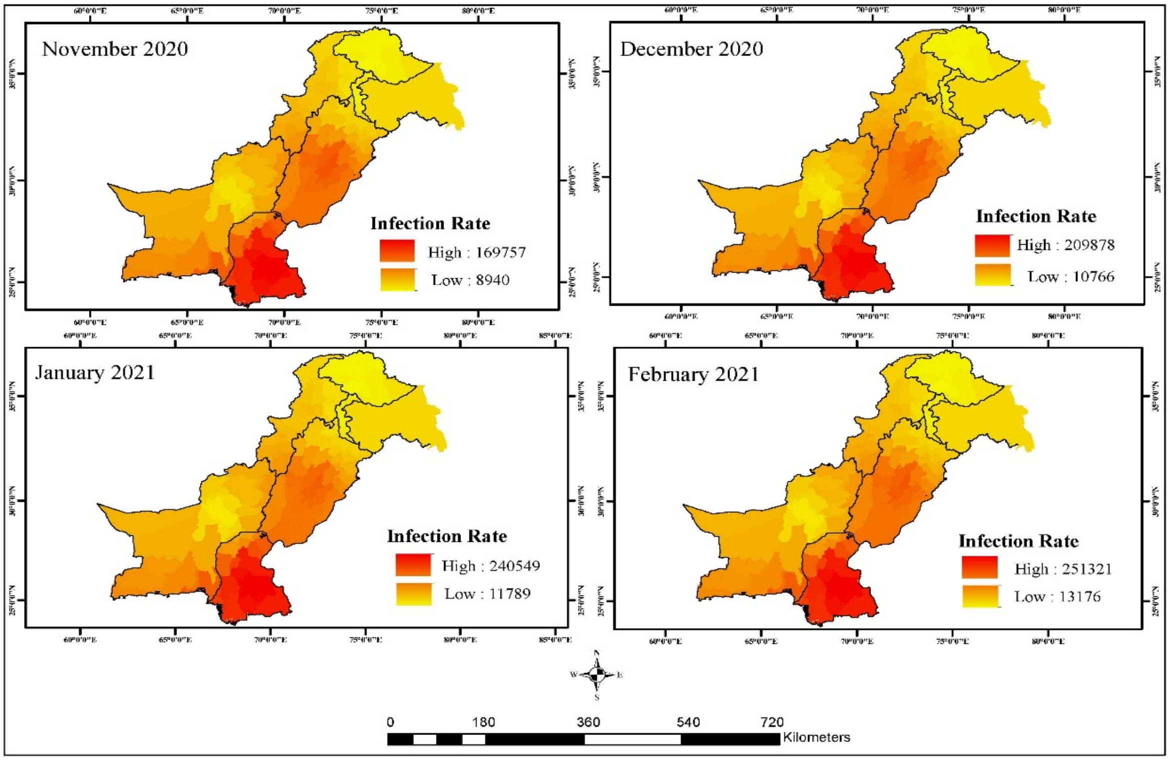

Figure 4: Spatial Distributions of Total Cases of Covid-19 after Lockdown Period

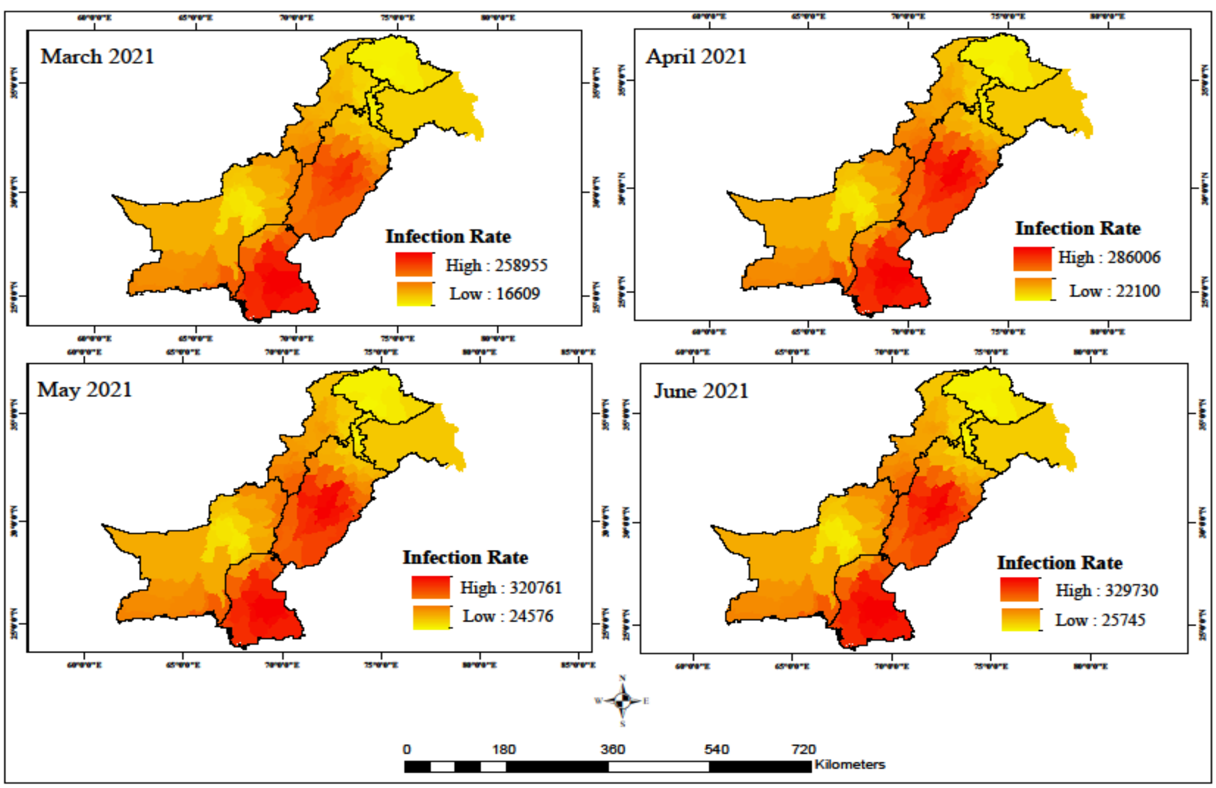

Figure 5: Spatial Distribution of Total Cases of Covid-19

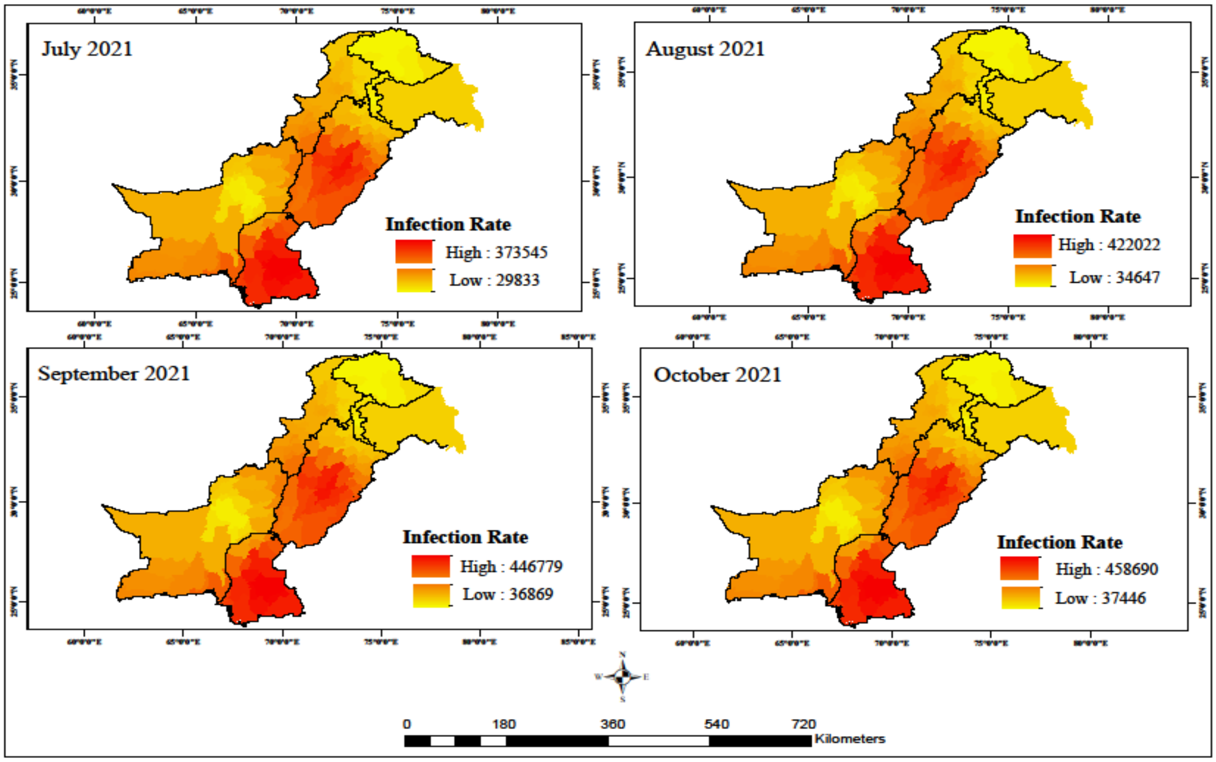

Figure 6: Spatial Distribution of Total Cases of Covid-19

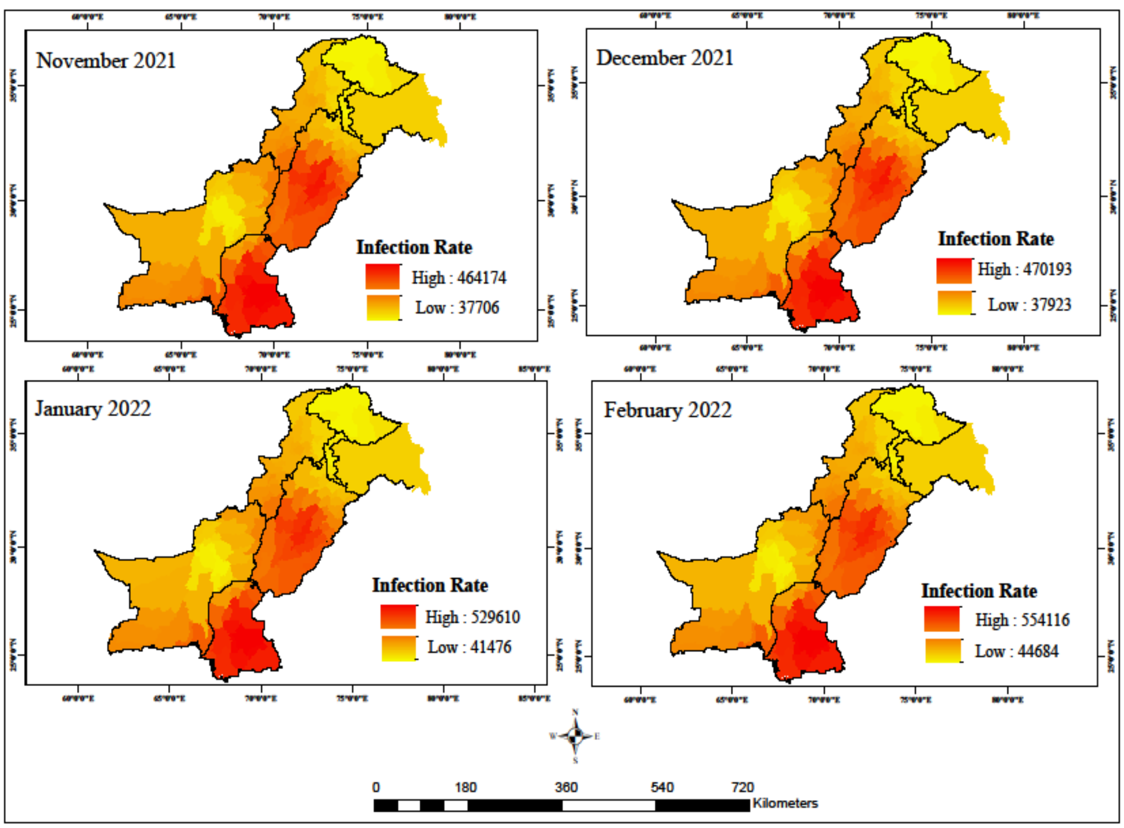

Figure 7: Spatial Distribution of Total Cases of Covid-19

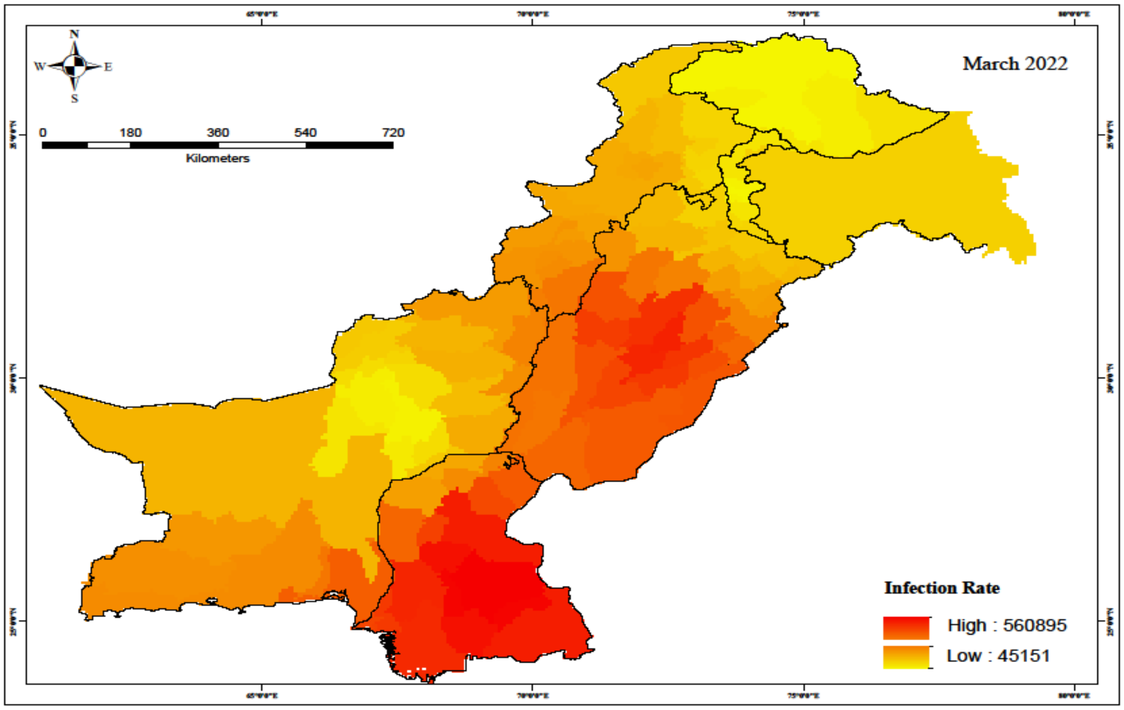

Figure 8: Spatial Distribution of Total Cases of Covid-19

A substantial variation in climatic factors was observed over Pakistan during the lockdown period. The results show a clear distinction between climatic factors before and after the lockdown period over the country. In the COVID-19 pandemic during the lockdown period decreasing trend was observed in the monthly district-wise mean of wind speed. In March 2020, the monthly average wind speed decreased to 4.23m/s from 4.38m/s and 4.36m/s compared to March 2018 and March 2019 respectively. A similar trend was also observed during the lockdown period of April 2020. There was a decline in the monthly district-wise average wind speed from 4.66m/s in April 2018 and 4.55m/s in April 2019 to 4.28m/s in April 2020. Figure 9 and 10 represent the spatial distribution of wind speed before the lockdown in March and April 2018 and 2019. Figure 11 shows the spatial distribution of wind speed during the lockdown period of March and April 2020. The monthly district-wise mean wind speed decreased. In May 2020 wind speed was 4.85m/s which decreased from 4.97m/s and 4.91m/s respectively prior to the years 2018 and 2019. Figure 16 shows the spatial distribution of wind speed during the lockdown period of May 2020 and Figure 14 and15 portray the spatial distribution of wind speed before the lockdown period of May 2018 and 2019. In June 2020, the wind speed also decreased due to lockdown from 5.26m/s in June 2018 and 5.14m/s in June 2019 to 4.58 m/s in June 2020. A similar trend was also observed during the 2021 lockdown in the month of May 2021.

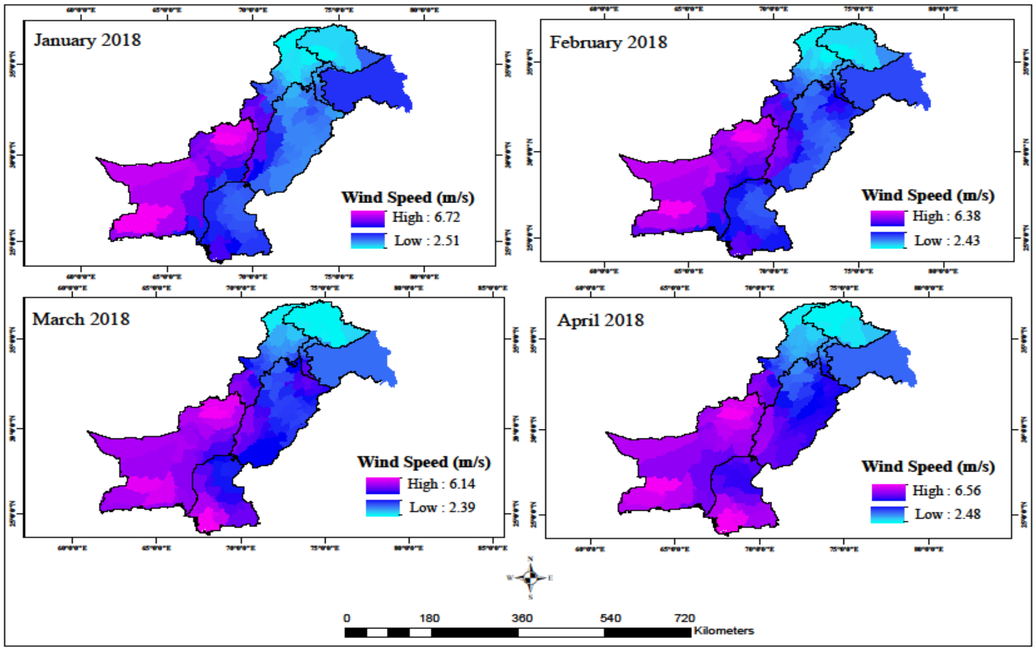

Figure 9: Spatial Distribution of Wind Speed in 2018 before Covid-19 Pandemic

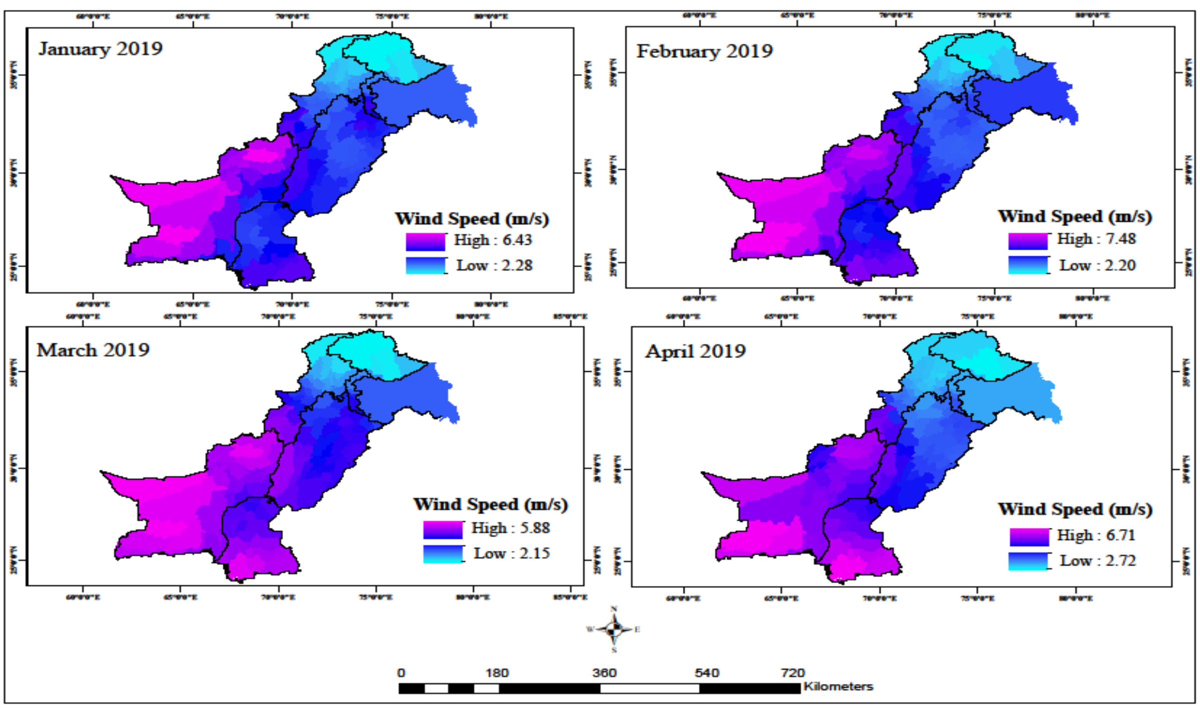

Figure 10: Spatial Distribution of Wind Speed in 2019 before Covid-19 Pandemic

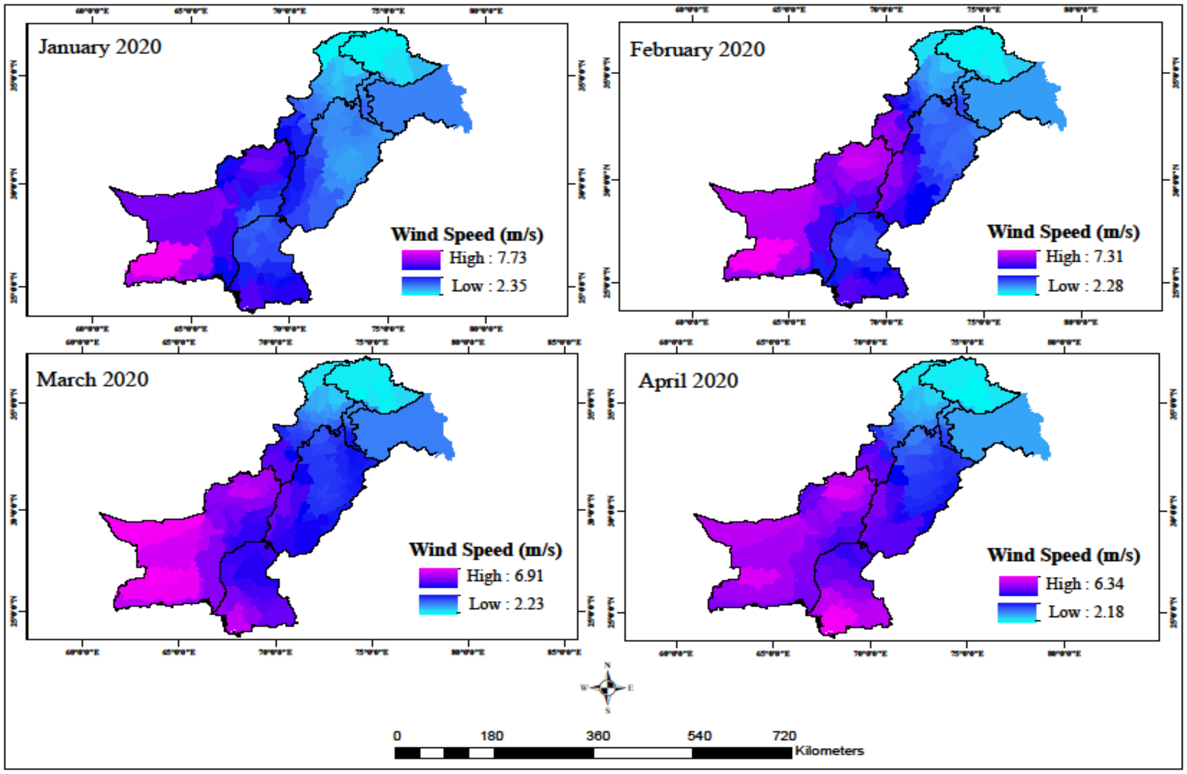

Figure 11: Spatial Distribution of Wind Speed during Pandemic 2020

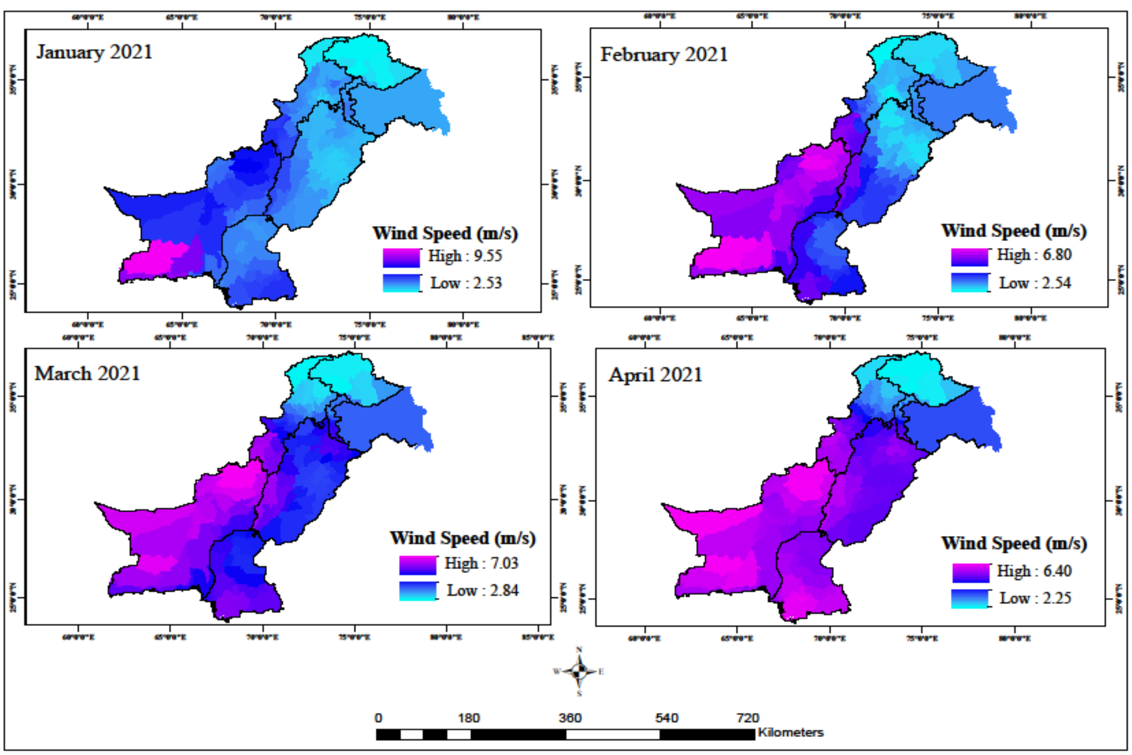

Figure 12: Spatial Distribution of Wind Speed during Pandemic 2021

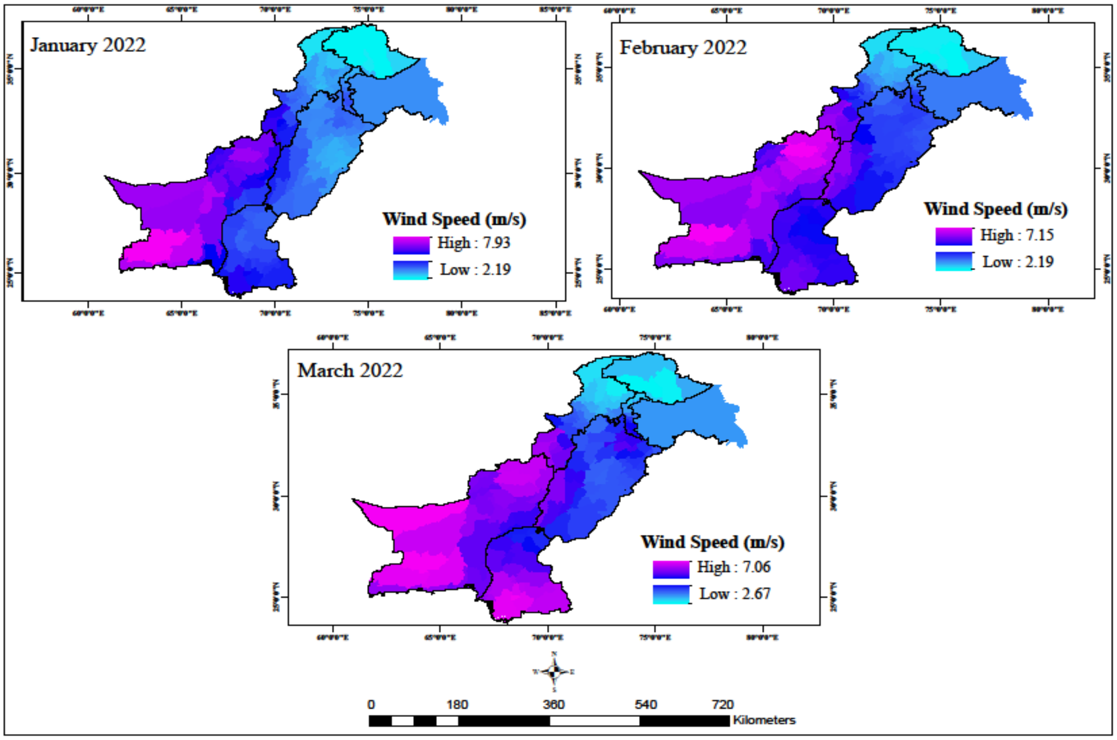

Figure 13: Spatial Distribution of Wind Speed during Covid-19 Pandemic 2022

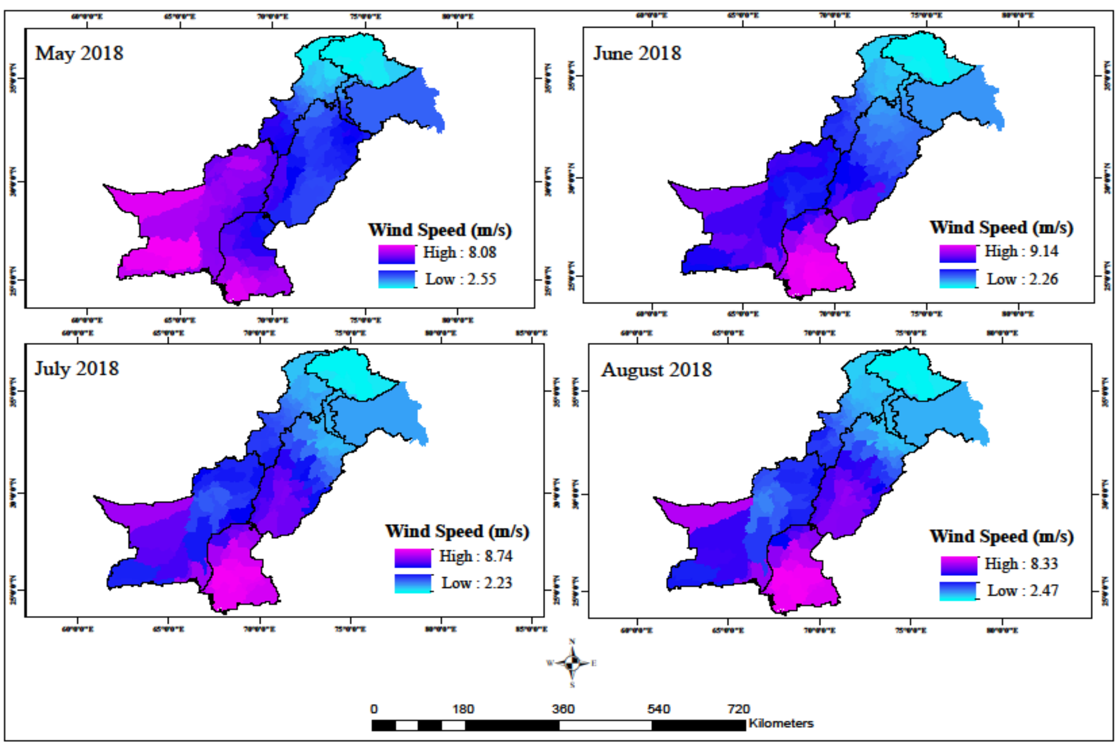

Figure 14: Spatial Distribution of Wind Speed 2018 before Covid-19 Pandemic

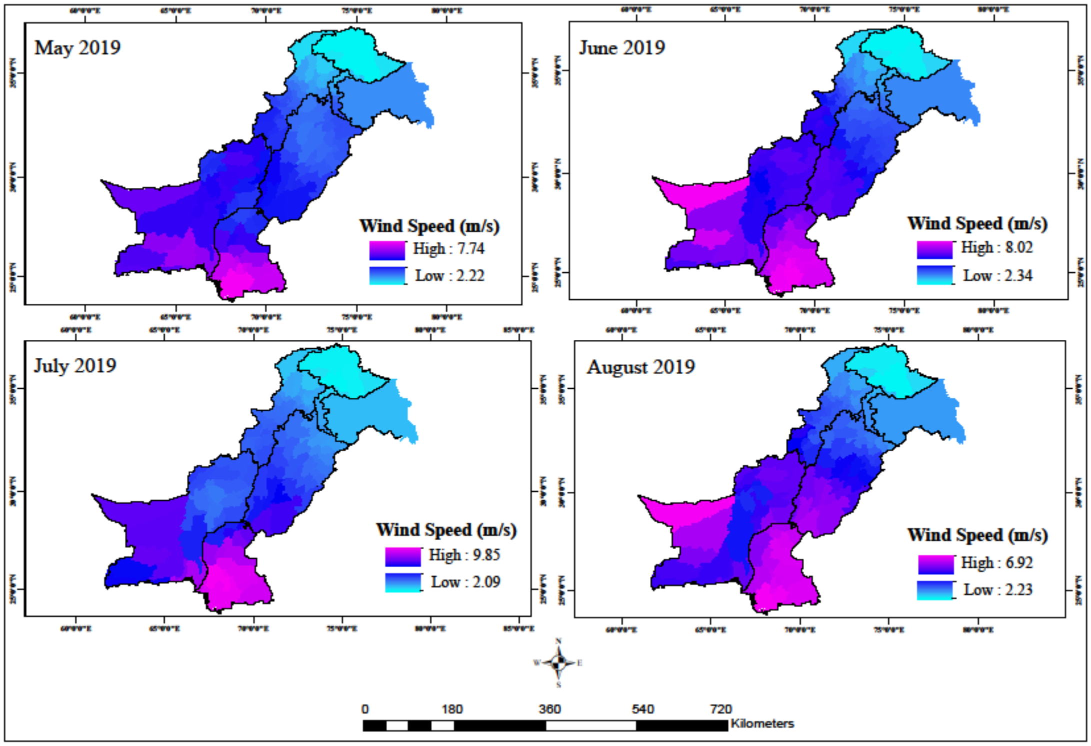

Figure 15: Spatial Distribution of Wind Speed 2019 before Covid-19 Pandemic

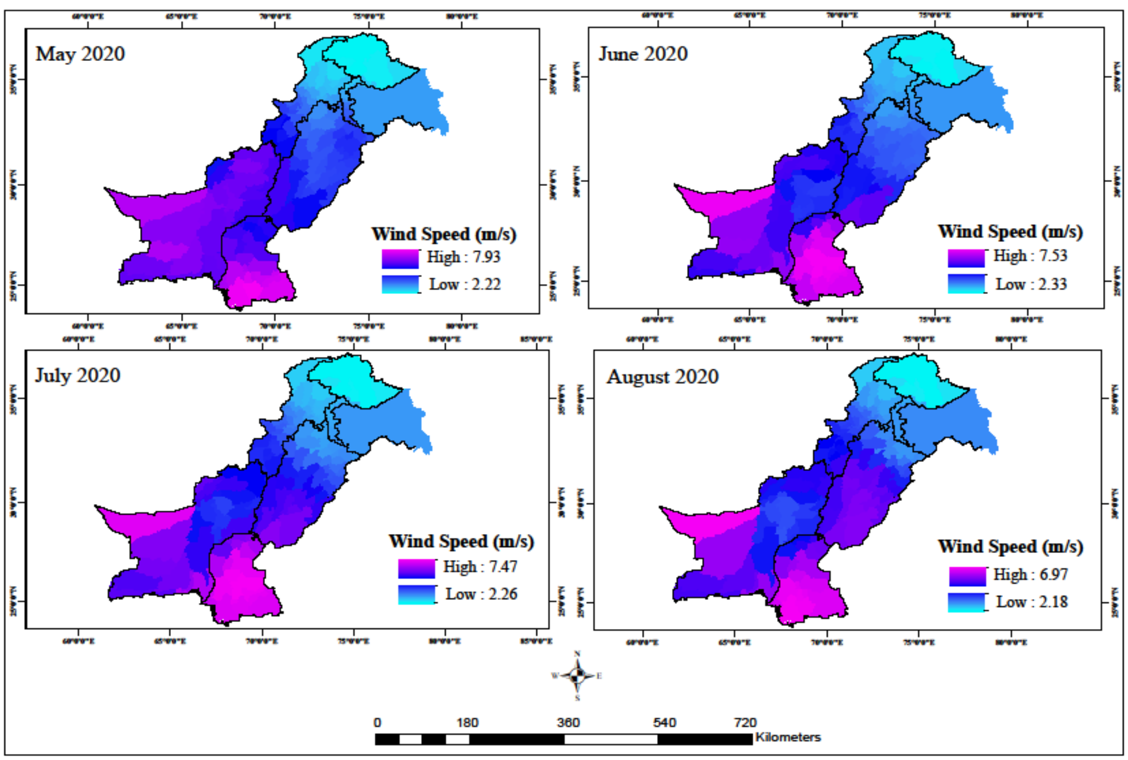

Figure 16 Spatial Distribution of Wind Speed 2020 During Covid-19 Pandemic

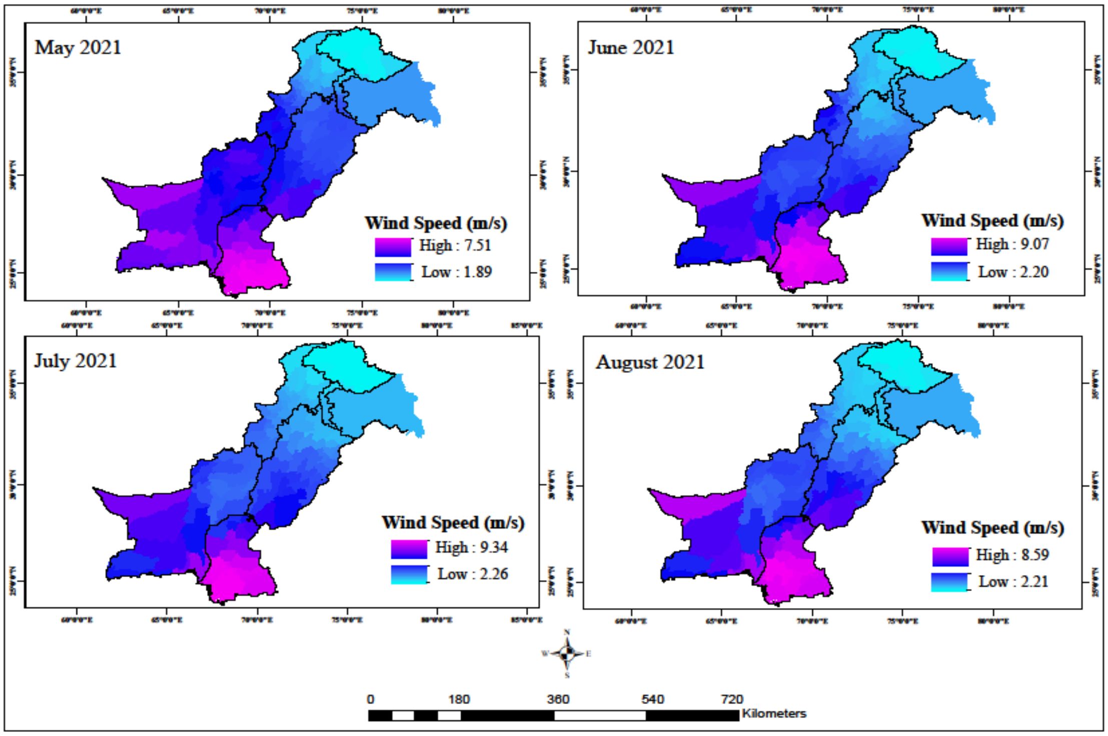

Figure 17: Spatial Distribution of Wind Speed 2021 during Covid-19 Pandemic

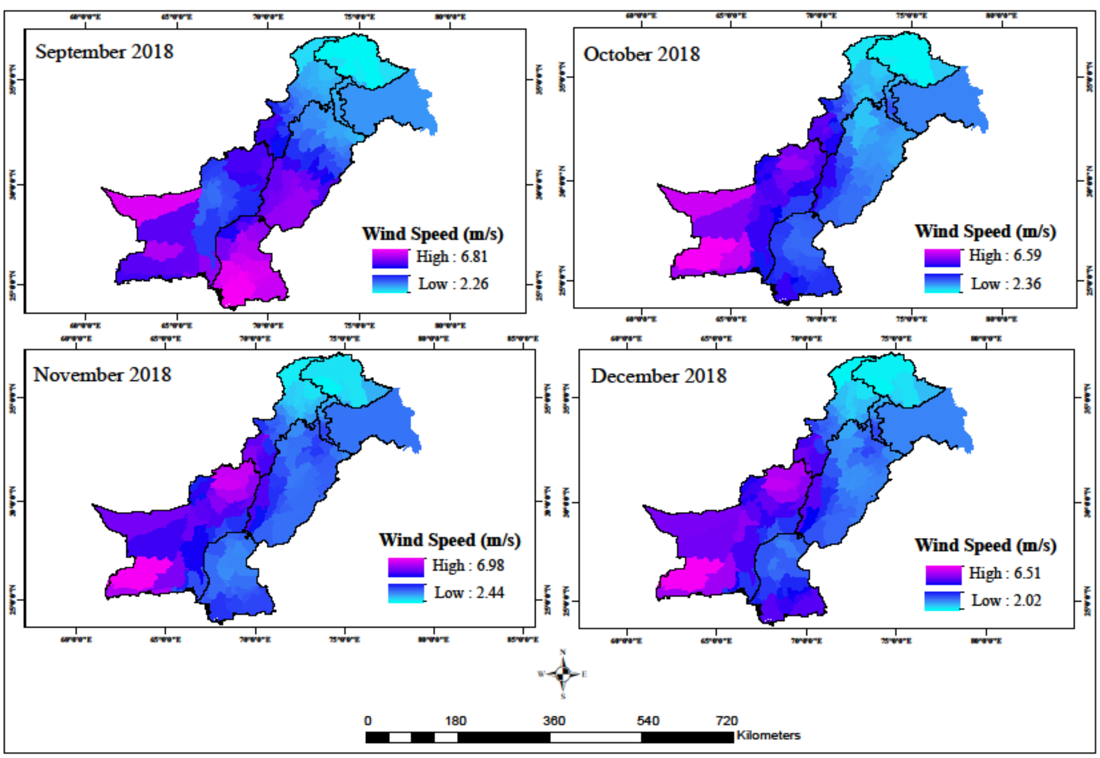

Figure 18: Spatial Distribution of Wind Speed 2018 Before Covid-19 Pandemic

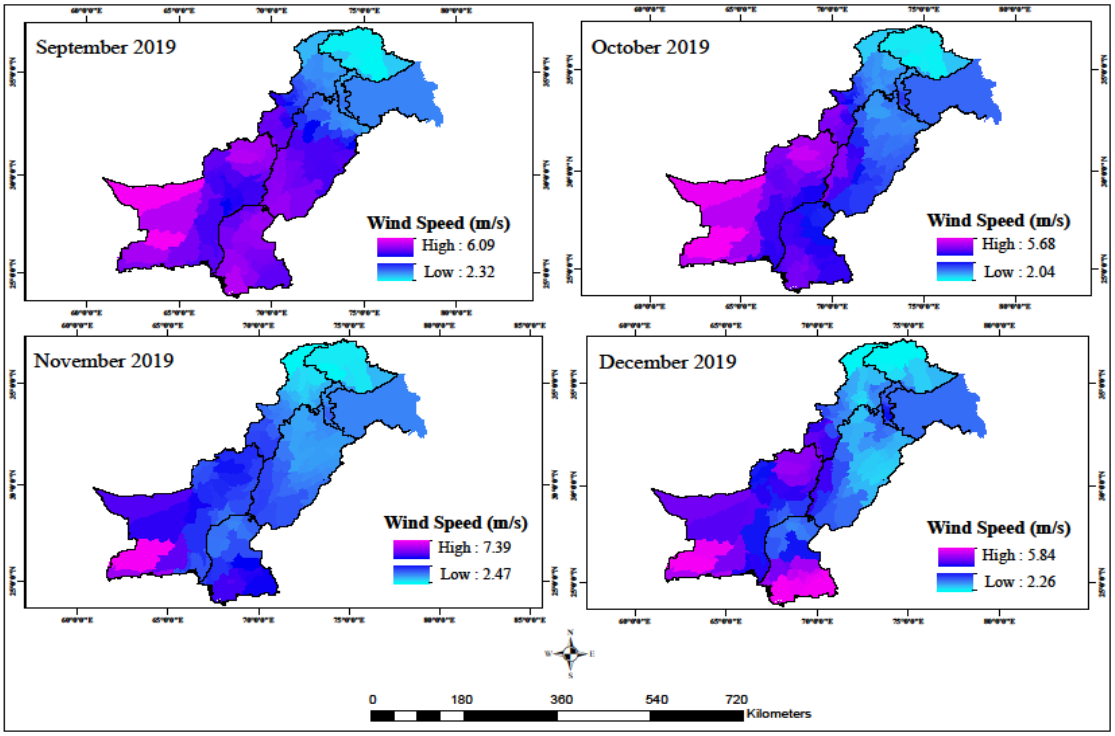

Figure 19: Spatial Distribution of Wind Speed 2019 before Covid-19 Pandemic

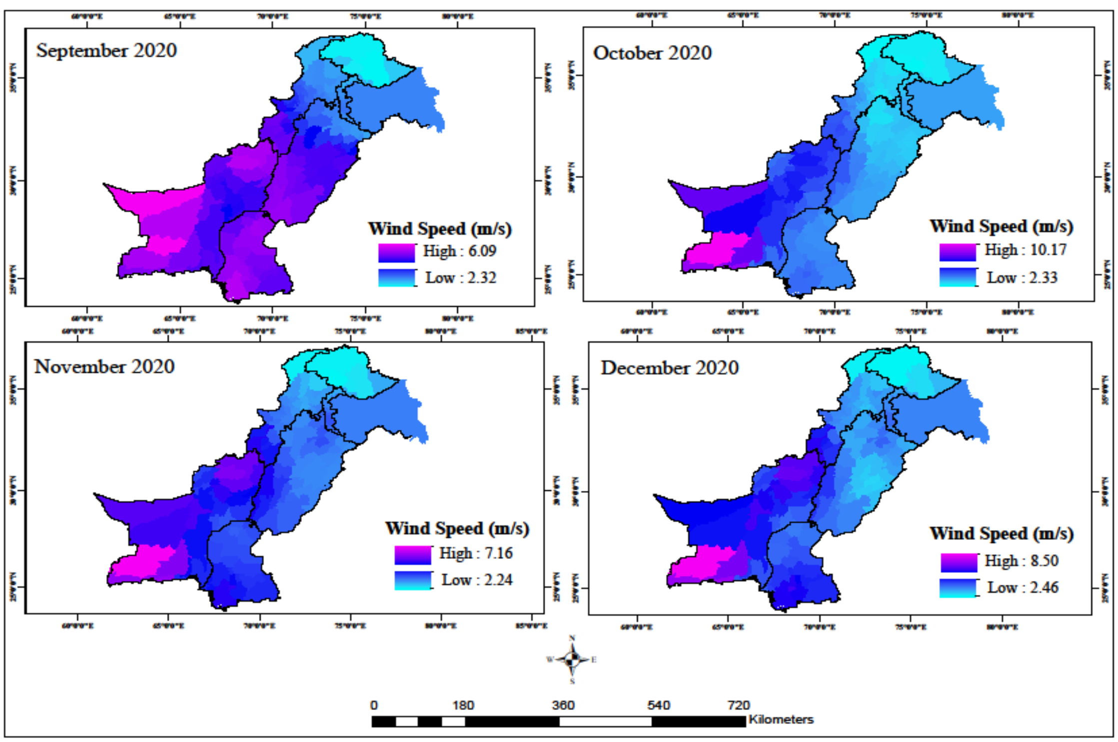

Figure 20: Spatial Distribution of Wind Speed 2020 during Covid-19 Pandemic

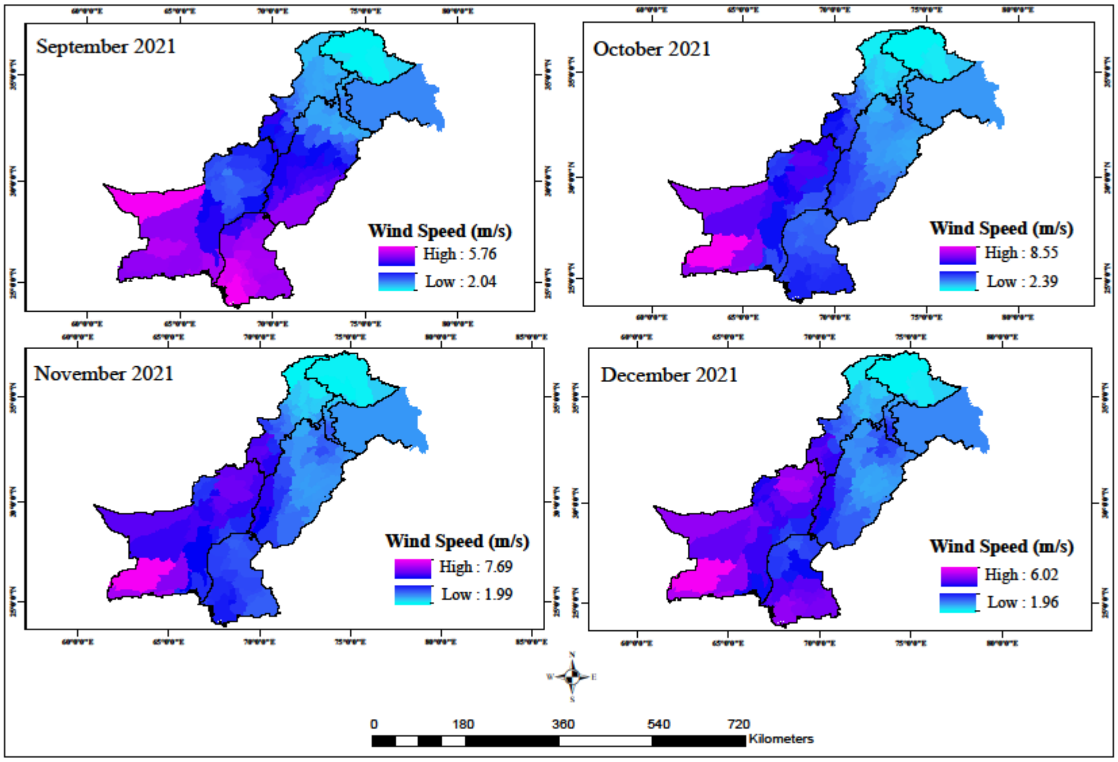

Figure 21: Spatial Distribution of Wind Speed 2021 during Covid-19 Pandemic

Table 4 : Statistics of Wind Speed During Lockdown

Wind Speed (m/s)	2018	2019	2020	2021
March	4.38	4.36	4.23	4.86
April	4.66	4.55	4.28	4.76
May	4.97	4.91	4.85	4.52
June	5.26	5.14	4.58	4.91

Figure 14 and 15 show wind speed distribution before the lockdown period of May 2018 and 2019. The monthly district-wise mean wind speed decreased in May 2021 (decreased to 4.52m/s May 2021 from 4.97m/s in May 2018 and 4.91m/s in May 2019. Figure 17 depicts the spatial variation of wind speed during the lockdown period of May 2021. After June 2020 again contrasting variation was observed in the values of wind speed this was because of the loosening of the lockdown. From the obtained results variations in wind speed were very clear during the lockdown period. Figure 9, 10, 14, 15 18 and 19 depict the spatial distribution of wind speed before the COVID-19 pandemic of 2018 and 2019 respectively. Figure 11, 12 16, 17, 20 and 21 show the spatial distribution of wind speed during the COVID-19 pandemic 2020 and 2021, sequentially. Similarly, Figure 13 shows wind speed district-wise distribution during the COVID-19 pandemic from January to March 2022. During the pandemic years 2020 and 2021 the annual average wind speed increased compared to the previous year 2019. Table 4 represents district–wise average of wind speed during the lockdown period of the pandemic.

The reduction in LST during the lockdown period was observed over Pakistan. The results of this study revealed that a 5°C reduction in the district-wise average of LST over Pakistan was observed in the month of March 2020 against the month of March 2018 (from 28°C in 2018 to 23°C in 2020) and as compared to the March 2019 the decline was 1°C (from 24°C in 2019 to 23°C in 2020). Figure shows the spatial distribution of LST over the country during the lockdown of March 2020 compared to 2018 and 2019 March before the lockdown period in Figure 22 and 23 respectively. The decline in LST was also observed in the month of April 2020. Figure 24 portrays the distribution of LST during the lockdown period of April 2020. The month of April 2020 showed a 2°C negative anomaly in LST against April 2018 (from 33°C in 2018 to 31°C in 2020) and as compared to the 2019 the decline was 1°C (from 32°C in 2019 to 31°C in 2020). Figure 22 and 23 depict the spatial distribution of LST before lockdown in April 2018 and 2019 sequentially. The decline in LST was also noticed in the month of May 2020 and LST had shown a negative anomaly of 1°C compared to the May of 2018 and 2019 (from 38°C to 37°C in both years 2018 and 2019). Figure 29 depicts the spatial distribution of LST during the lockdown period of May and June 2020. Figure 27 and 28 depict the distribution of LST before the lockdown period of May and June of 2018 and 2019 respectively. A decrease in the month of June 2020 was also noticed. The LST decreased 1°C in June 2020 compared to previous years 2018 and 2019 (from 38°C in June 2018 to 37°C in June 2020 and similarly in June 2019 from 38°C to 37°C). The same pattern was also remarked for LST in the month of May 2021 because of the lockdown and LST had shown a negative anomaly of 1°C as compared to 2018 and 2019 (from 38°C to 37°C in both years 2018 and 2019). Figure 30 shows the spatial distribution of LST during the lockdown period of May 2021. The drop in LST could be associated with lockdown or generally cooler weather. After the month of June 2020, we again started to observe the increase in LST because of the loosening of the lockdown that increased the anthropogenic activities. Figure 22, 23, 27, 28 31 and 32 depict the spatial distribution of LST before the COVID-19 pandemic period.

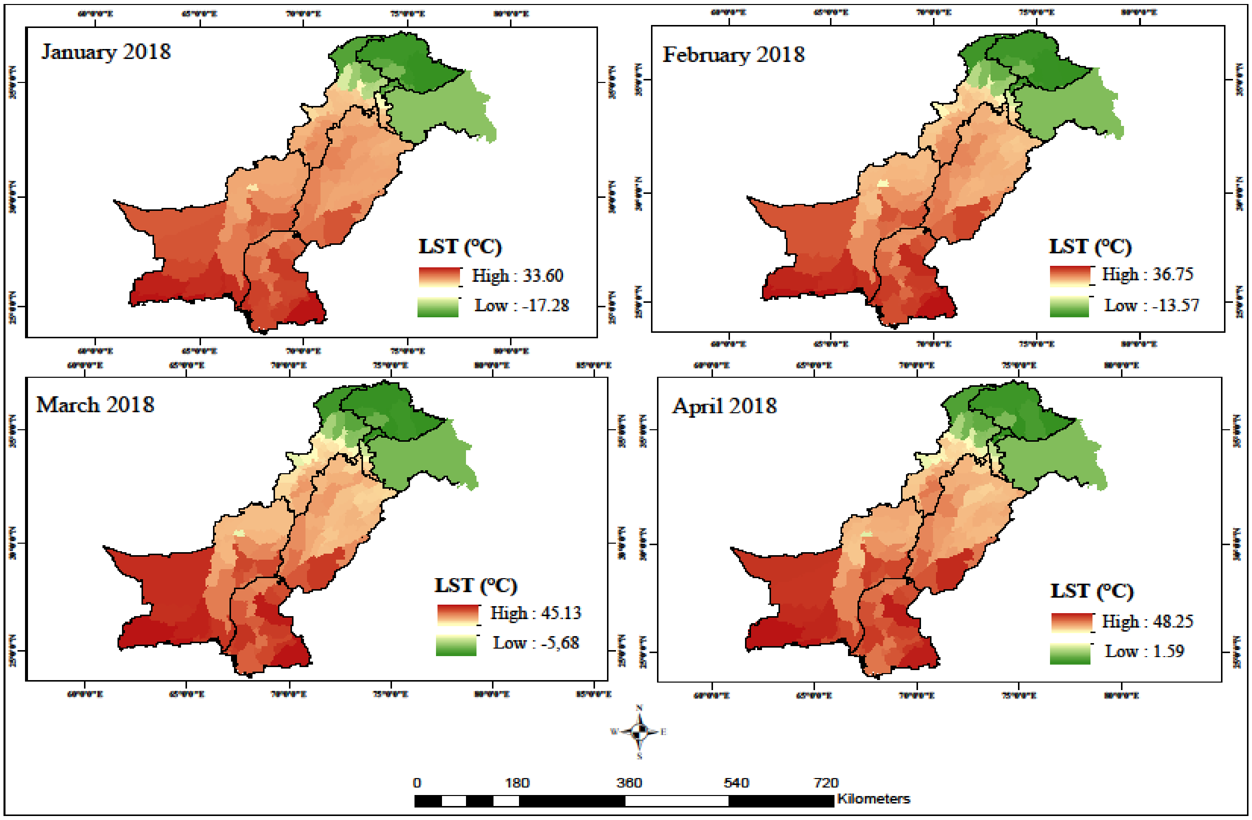

Figure 22: Spatial Distribution of LST before Covid-19 Pandemic 2018

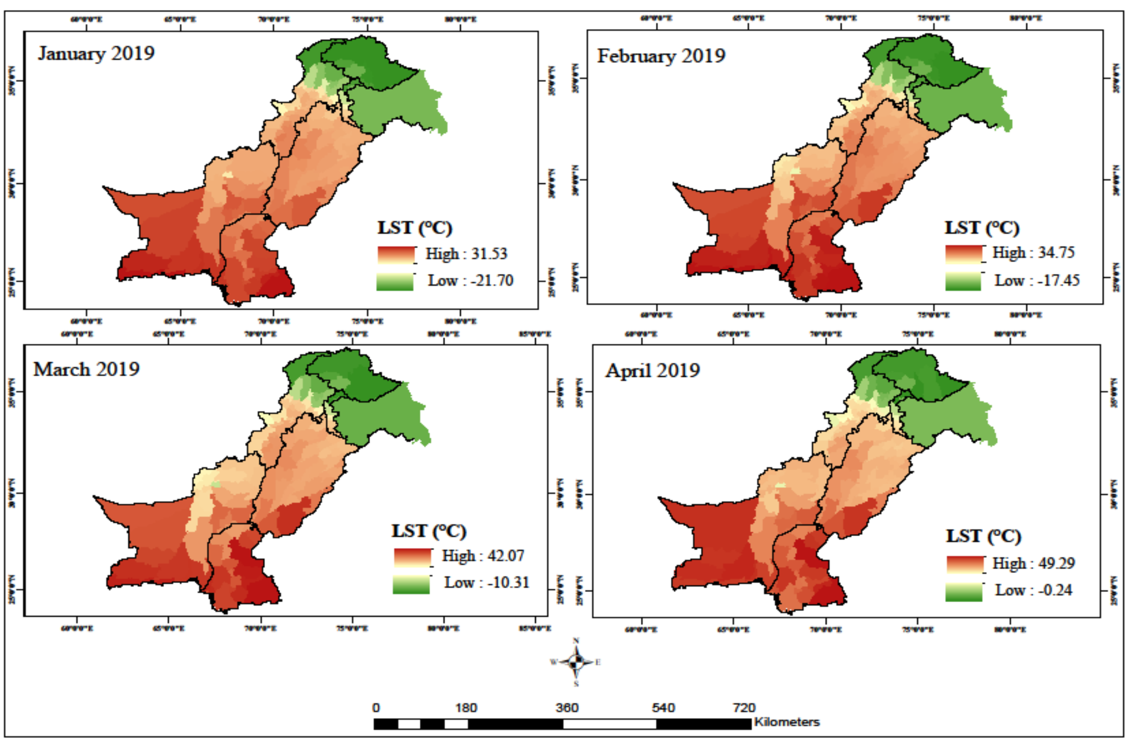

Figure 23: Spatial Distribution of LST Before Covid-19 Pandemic 2019

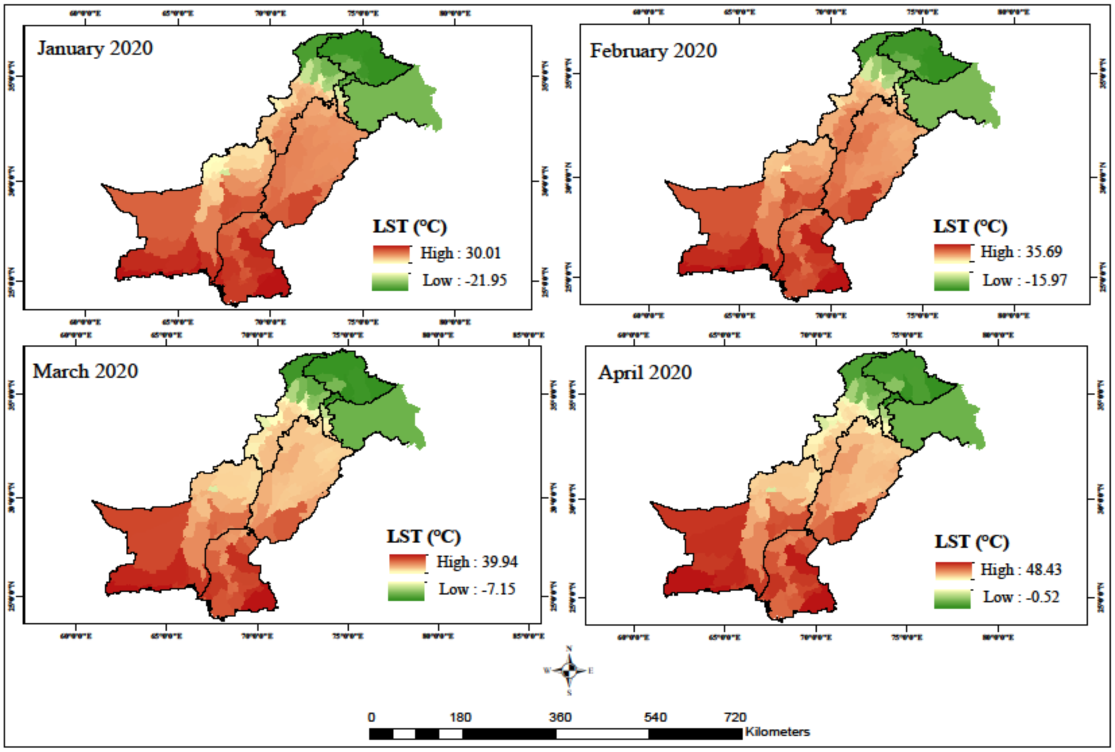

Figure 24: Spatial Distribution of LST During Covid-19 Pandemic 2020

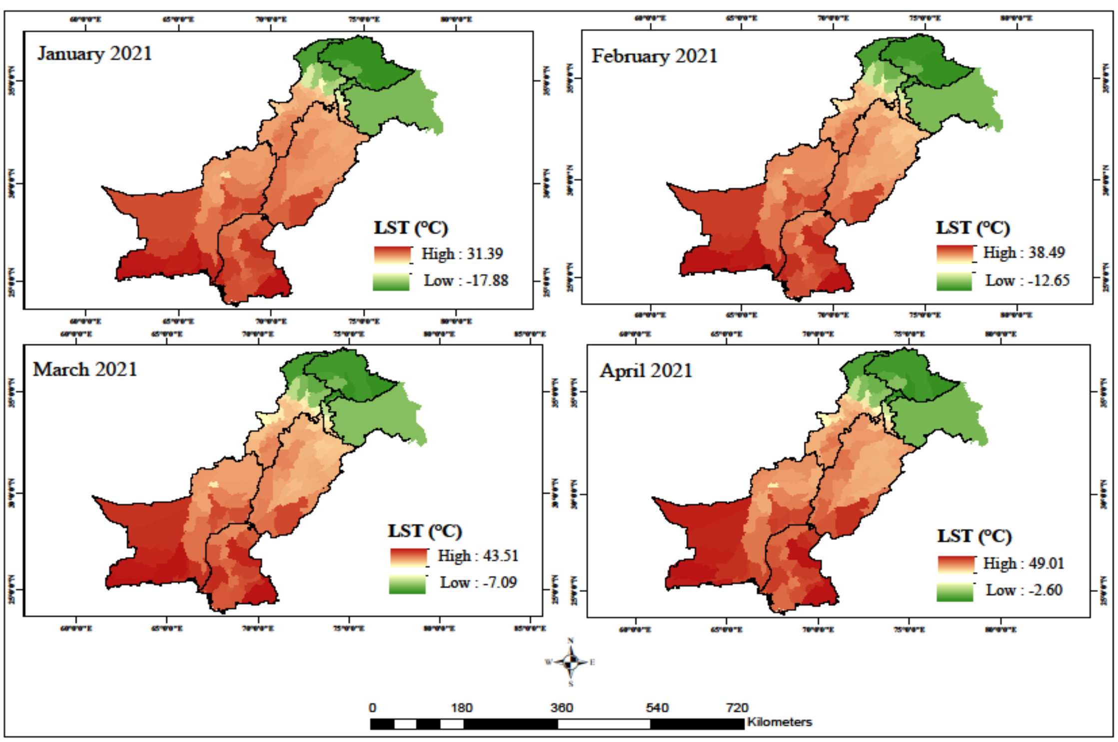

Figure 25: Spatial Distribution of LST During Covid-19 Pandemic 2021

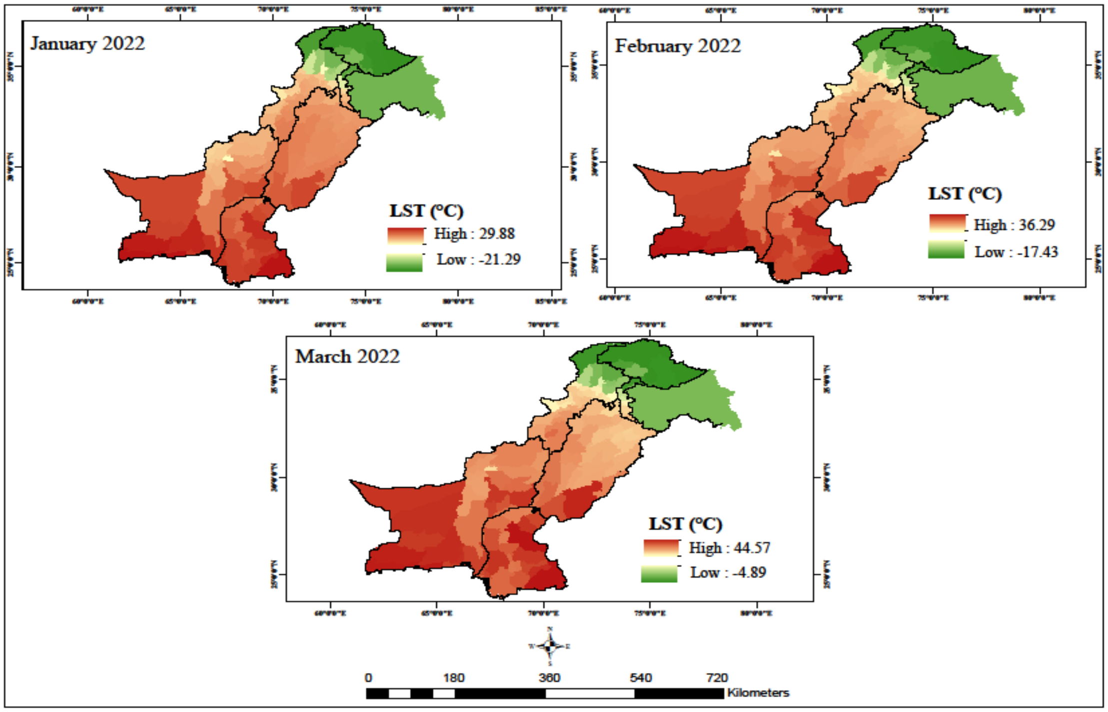

Figure 26: Spatial Distribution of LST During Covid-19 Pandemic 2022

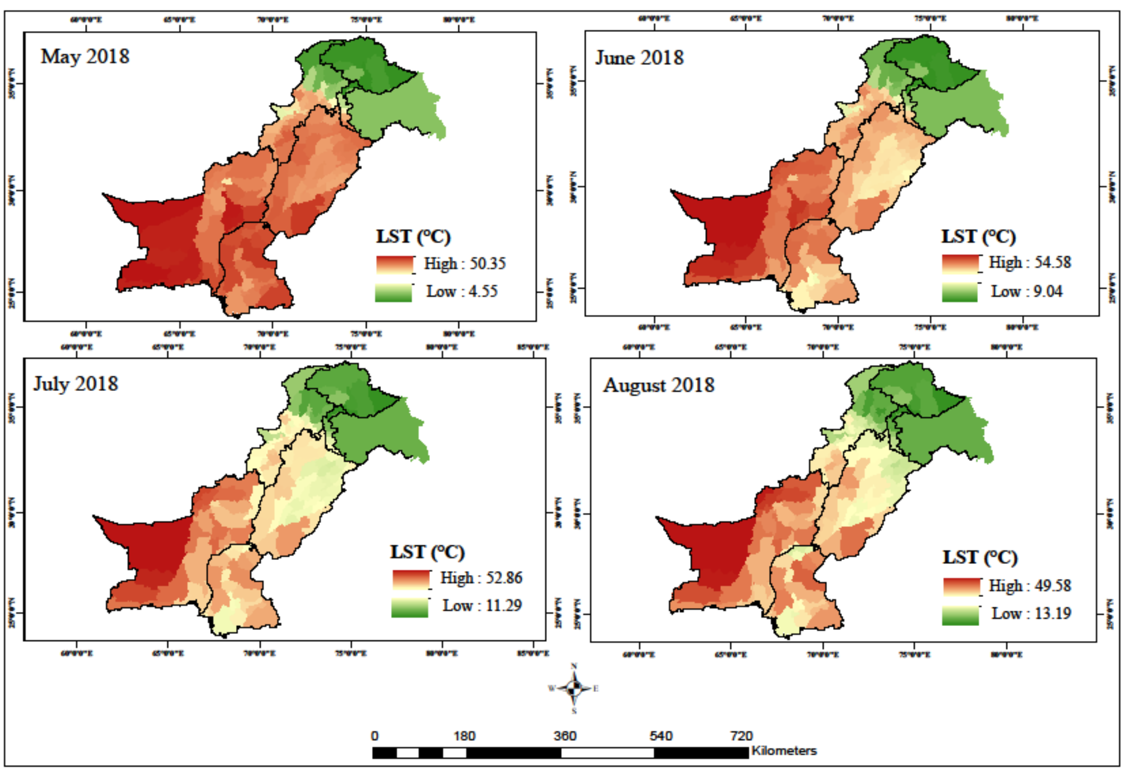

Figure 27: Spatial Distribution of LST Before Covid-19 Pandemic 2018

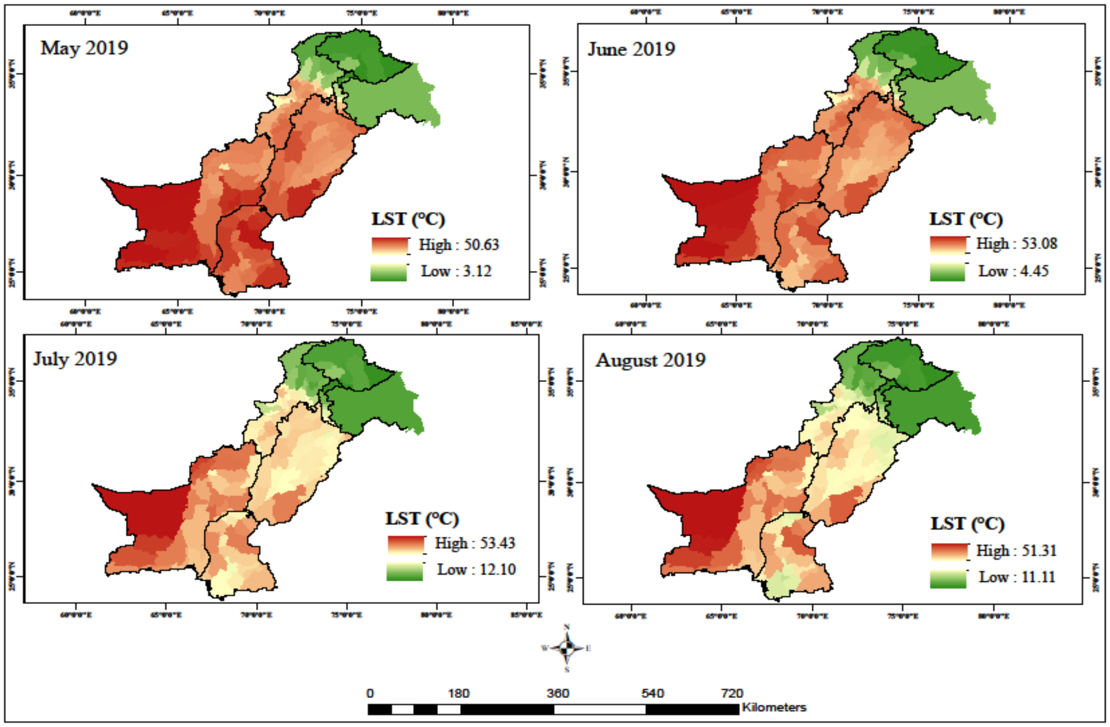

Figure 28: Spatial Distribution of LST Before Covid-19 Pandemic 2019

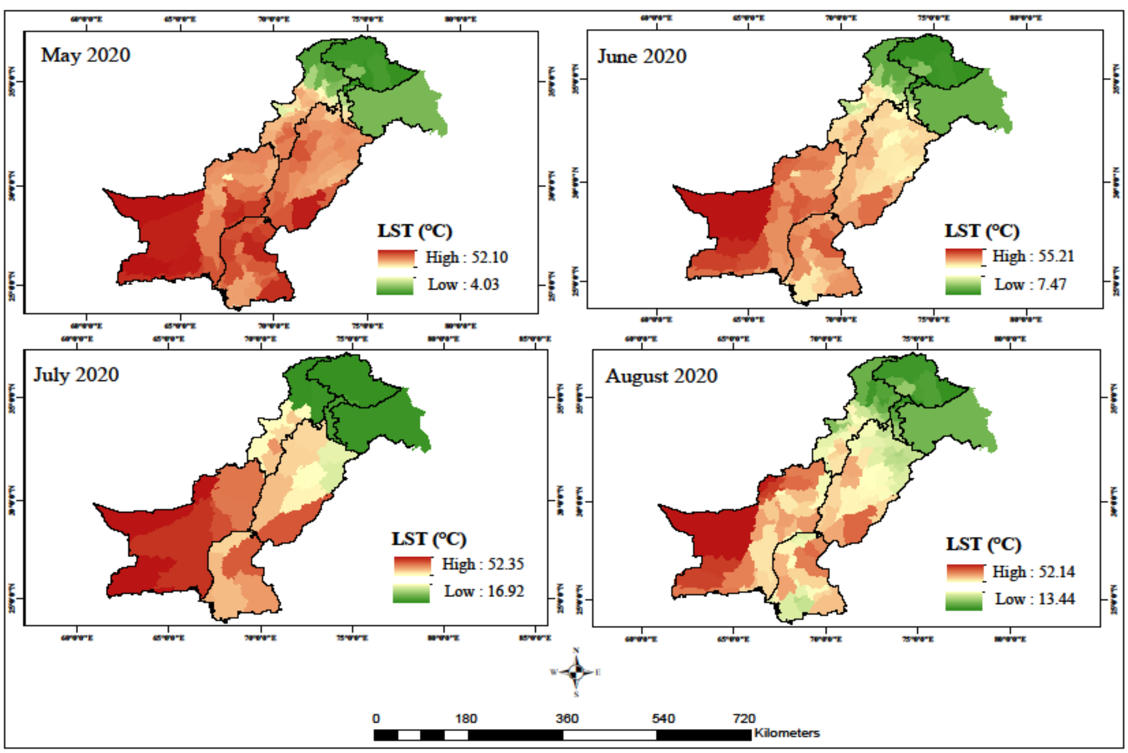

Figure 29: Spatial Distribution of LST During Covid-19 Pandemic 2020

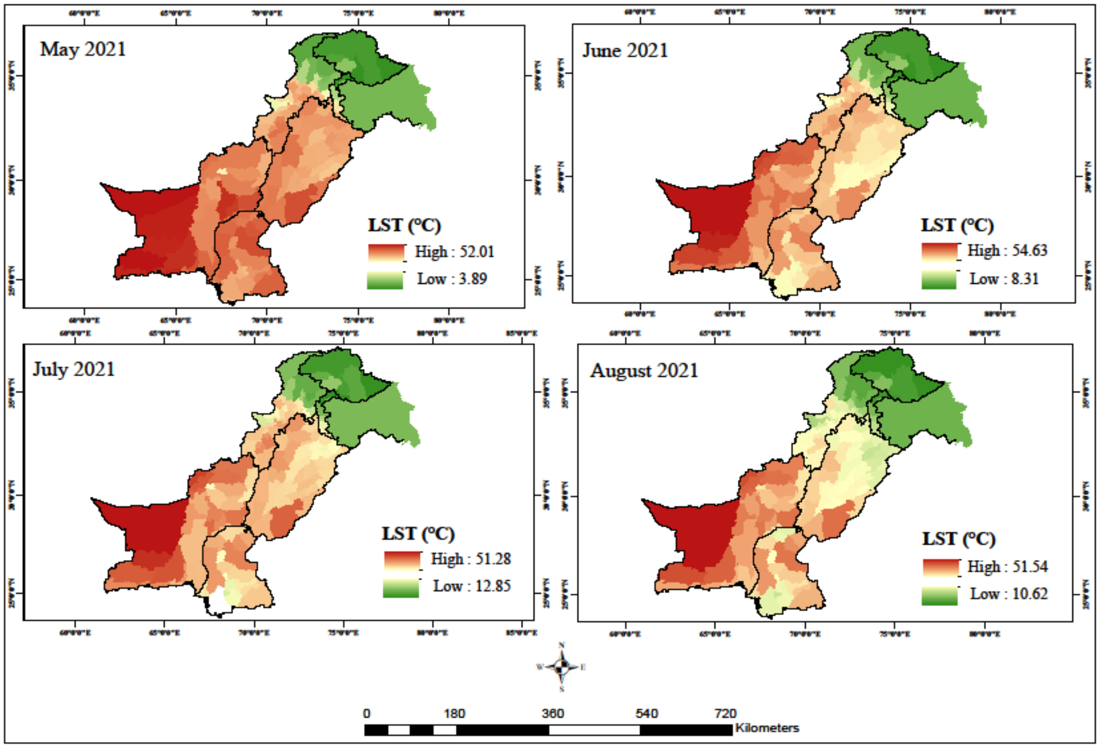

Figure 30: Spatial Distribution of LST During Covid-19 Pandemic 2021

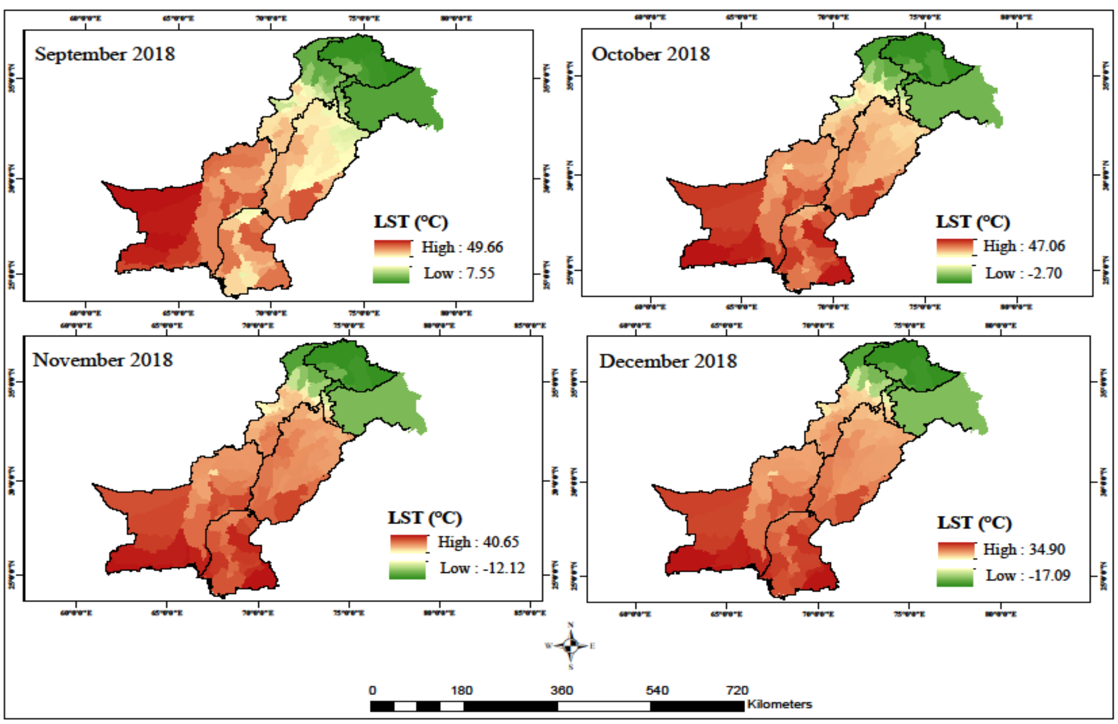

Figure 31 Spatial Distribution of LST Before Covid-19 Pandemic 2018

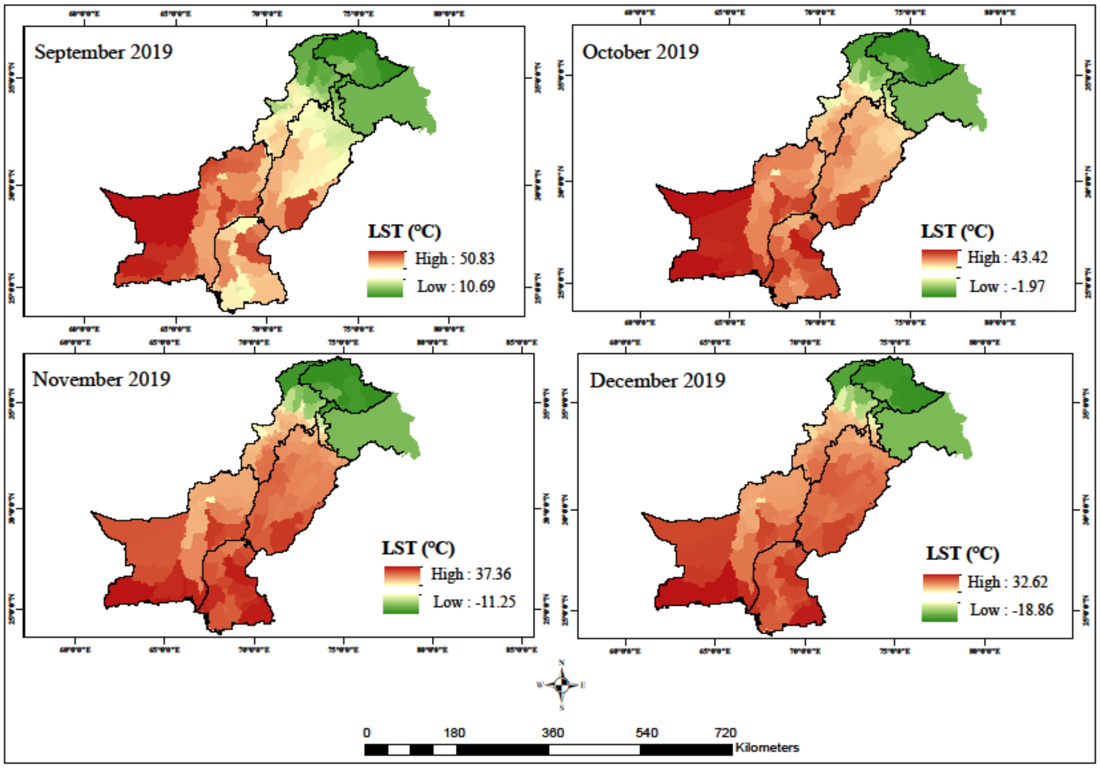

Figure 32: Spatial Distribution of LST During Covid-19 Pandemic 2019

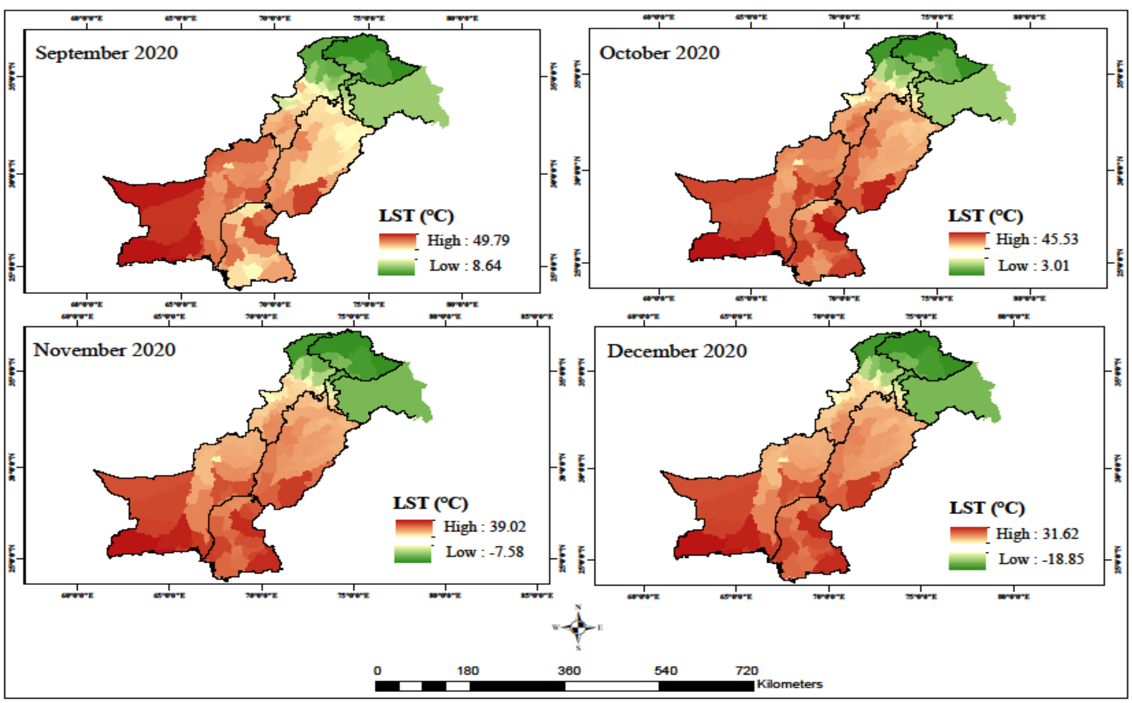

Figure 33: Spatial Distribution of LST During Covid-19 Pandemic 2020

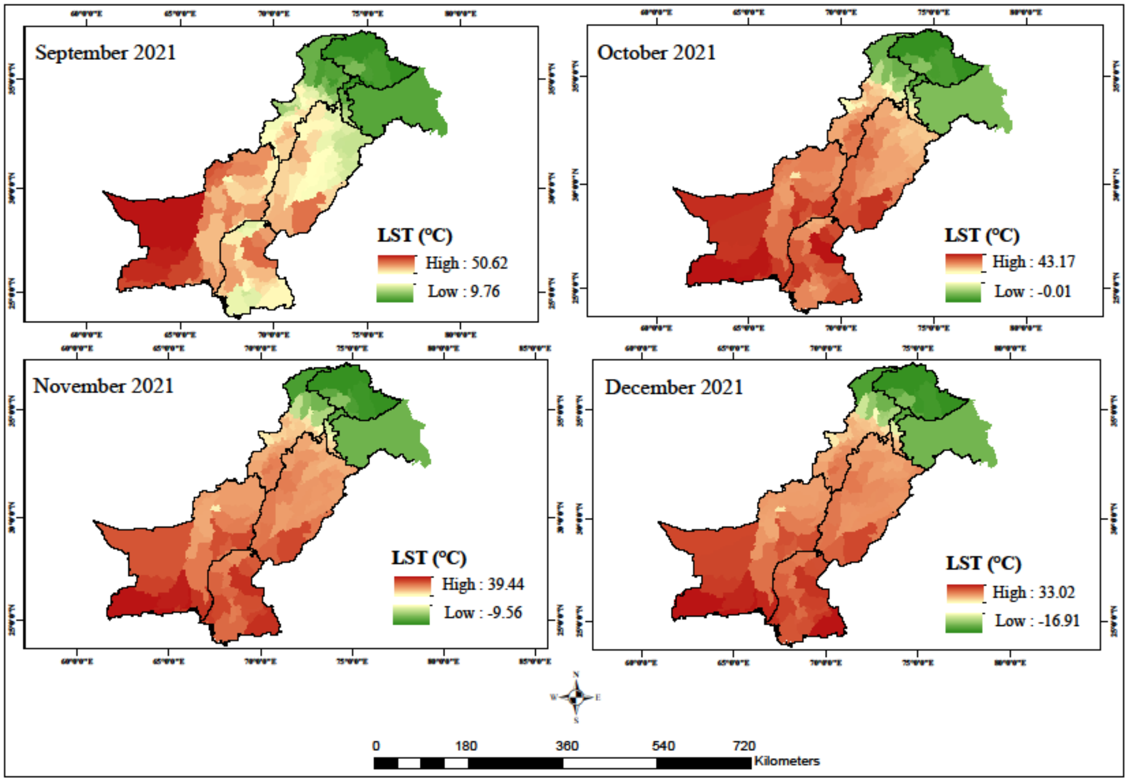

Figure 34: Spatial Distribution of LST During Covid-19 Pandemic 2021

Table 5: Statistics of LST during lockdown

LST(°C)	2018	2019	2020	2021
March	28	24	23	27
April	33	32	31	33
May	38	38	37	37
June	38	38	37	37

The main variations due to the lockdown period were observed during the 2020 pandemic year. Figure 24 and 29 and Figure 33 show the distribution of LST during the pandemic year 2020. The decrease in 2021 was basically due to a generally cooler weather pattern. Figure 25 and 30 and 34 portray spatial distribution during the COVID-19 pandemic of 2021. Figure 26 shows the distribution of LST during COVID-19 from January to March 2022. The variations in climatic conditions are very clear from the obtained results. A decreasing trend was observed during the lockdown period in wind speed and LST. Figure 35 shows the overall condition of selected environmental factors (wind speed and LST of prior years of the pandemic 2018 and 2019. Table 5 represents the district-wise average of LST during the lockdown period.

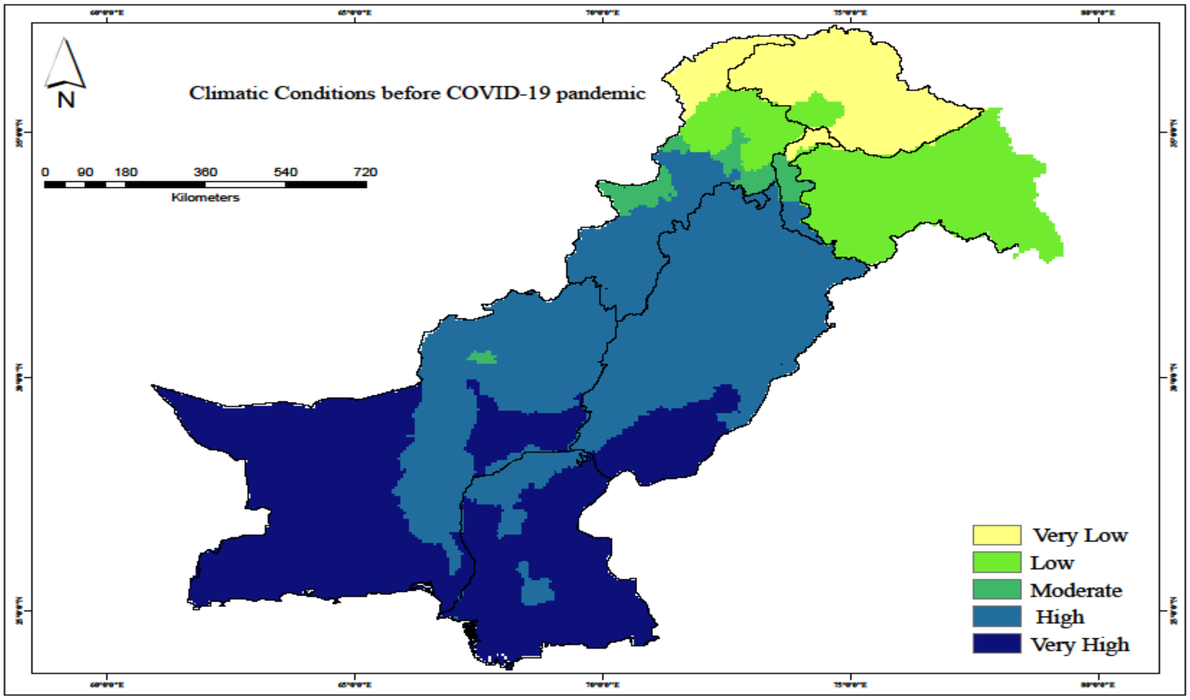

Figure 35: Spatial Distributions of Overall Environmental Conditions before Pandemic (LST, Wind Speed)

Figure 36 depicts how COVID-19 caused changes in climatic conditions during the COVID-19 pandemic in 2020, 2021 and 2022. The changes in climatic conditions were associated with lockdown period during the COVID-19 pandemic and also with a reduction in air pollutants resulting in changes in the trend of climatic conditions.

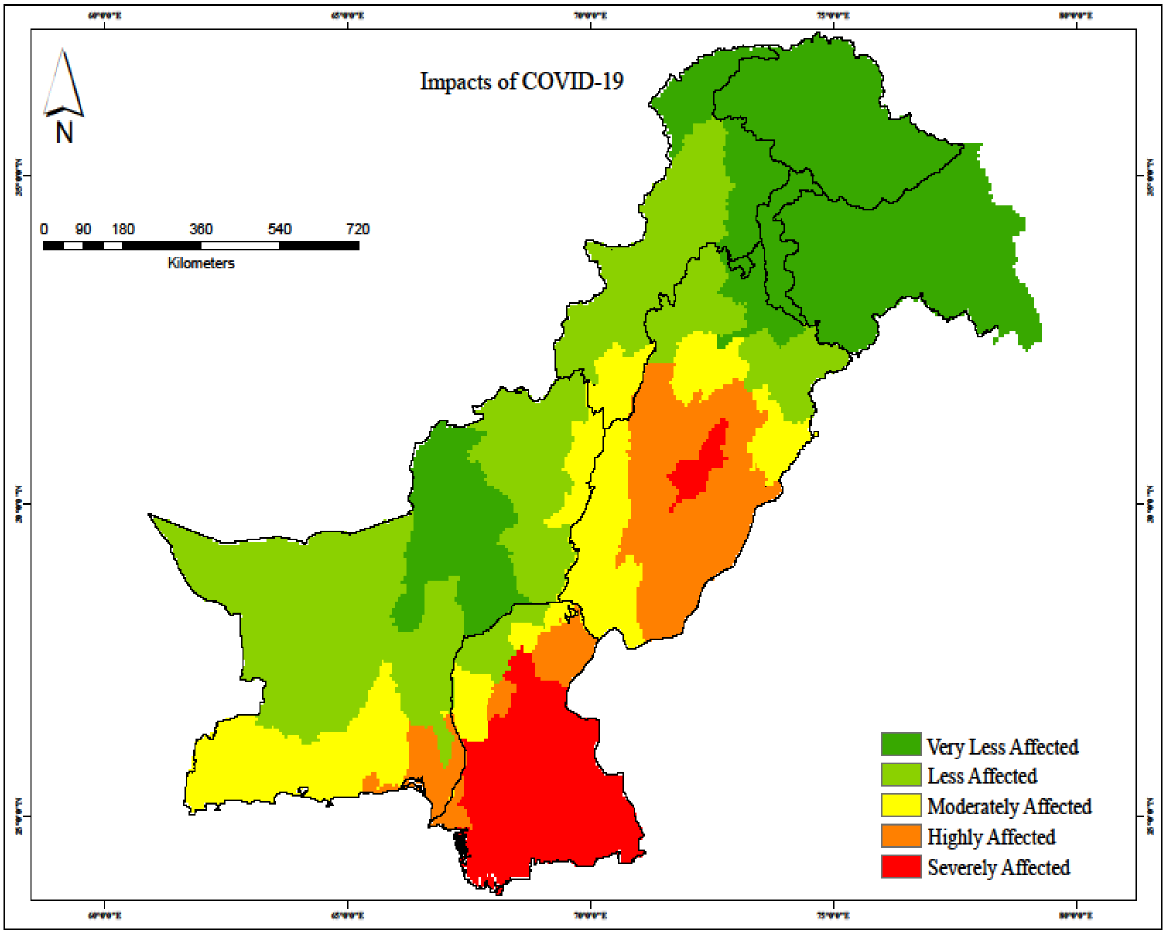

Figure 36: Impacts of Covid-19 on Climatic Conditions

Discussion

In this study the impacts of COVID-19 on environmental conditions and how preventive measures such as lockdown helped to control the spread of coronavirus and caused variations in climatic conditions were assessed over the country. From the obtained results of this research, it could be observed that the most affected province by COVID-19 was Sindh. To limit the spread of COVID-19 the government of Pakistan imposed the lockdown that not only controlled the spread of coronavirus cases but also caused variations in the climatic conditions over the country. The decreasing trend was observed in LST and wind speed in the study domain during the strict lockdown period of 2020 and 2021. These variations in climatic conditions were mainly due to a decrease in anthropogenic activities, restricted transport and closure of industries during the lockdown period of the pandemic. A similar decreasing trend in LST was also observed over different parts of Europe during the lockdown period (Parida et al., 2021). The similar decreasing trend in wind speed was also observed over the different cities of India (Navinya et al., 2020).

Lockdown policies during this pandemic around the world had led a way to explain human effects on the environment. This research is of great help to understanding the variation that occurred during the COVID-19 pandemic because this study is based on long-term data analysis and discussed all lockdown periods during the COVID-19 pandemic. And in this study, only secondary data is used and only statistical analysis is performed to understand the impacts of COVID-19 on environmental conditions at district level. In the future more, advanced satellite data can improve the results and ground-based data on metrological factors can be more useful to compare variations for this kind of research paper.

Conclusion

This study provides the impacts of COVID-19 on climatic conditions in Pakistan. The COVID-19 epidemic had improved temporarily climatic conditions around the world, owing to the large-scale reduction in human activities, transport, and industrial activities which caused positive changes in environmental conditions. The results of the present study showed a generally decreasing trend in LST and wind speed around the country during the lockdown period of the pandemic was observed. The variations were mainly due to lockdowns, limited transport and reduction in industrial production. These climatic factors and anthropogenic emissions returned to their standard levels as the government removed the preventive measure such as lockdown and restrictions on transport and also resumed industrial activities. However, this study provides improvements in climatic conditions can be achieved by adopting sustainable usage of transport and industrial production. Furthermore, only secondary data of climatic factors is used in this research to understand the impacts of COVID-19 on climatic conditions over the country. By using ground-based data for comparison the obtained results could be more accurate.

Recommendations

- The officials of government should make policies such as a brief lockdown and sustainable production of industries to control the concentration of atmospheric pollutants resulting in improvements in environmental conditions.
- The officials should take preventive measures to reduce fossils fuel usage resulting reduction in aerosol concentrations. This will cause positive changes in environmental conditions.
- The most significant outcome of this study is to suggest to policymakers and officials that such purposeful actions to reduce atmospheric pollution and even population density in cities can have serious consequences for human life.

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Authors' contributions

The authors declared that this research was done by the both authors named in this manuscript and all liabilities pertaining to claim relating to the content of this article will be borne by both of them. Hazeema Mumtaz conceived the research and drafted the manuscript. Kanwal Javid revised the manuscript. Both authors performed a review of the manuscript before approving its publication in this journal.

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Competing Interests

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Drought Risk Assessment of Muzaffargarh District by Using Geospatial Techniques

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Abstract

Drought is a major natural hazard characterized by extended periods of insufficient precipitation, posing serious threats to both ecosystems and human livelihoods. This study evaluates drought risk in Muzaffargarh District, Pakistan, by combining geospatial techniques such as remote sensing (RS) and geographical information systems (GIS). Landsat ETM+ and OLI imagery from 2002, 2008, 2013, and 2018 were used to compute the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). The study found that LST increased from 38.77 °C in 2002 to 42.54 °C in 2018, while NDVI values decreased from 0.989 to 0.576. This inverse trend confirms declining vegetation cover and rising surface temperatures, which are important indicators of increasing meteorological and agricultural drought risk. Regression analysis confirms a negative correlation between LST and NDVI ($R^2 = 0.4167$), indicating the region's vulnerability to climatic stress. The supervised classification of LU/LC data reveals significant urban expansion and vegetation loss between 2002 and 2018. The resulting drought risk maps identify increasingly dry zones, providing critical spatial insights for policymakers and stakeholders as they develop targeted and proactive drought mitigation plans.

***Keywords**:* Drought, GIS, LST, meteorological drought, NDVI, remote sensing.

Introduction

Drought is one of the most complex and devastating natural hazards, affecting millions of people worldwide, particularly in arid and semi-arid areas. It is characterized by a prolonged deficiency in precipitation, resulting in water scarcity, crop failure, and socioeconomic distress. (WHO 2021). Climate change has increased the frequency, severity, and duration of droughts, posing significant challenges for water resource management and food security (IPCC et al. 2023). Pakistan, as a predominantly agrarian economy, is especially vulnerable to droughts. Southern Punjab's Muzaffargarh District is not an exception; it has experienced ongoing dry spells that have negatively impacted livelihoods and agricultural productivity (Ahmad et al. 2020).

Traditional drought monitoring approaches frequently deficiency spatial resolution and fail to deliver timely warnings at the local level. The integration of geospatial techniques, with remote sensing (RS) and geographic information systems (GIS), has been established as a reliable and cost-effective technique for drought risk assessment (Nepal et al., 2021). These technologies permit unceasing monitoring of vegetation health, land surface temperature, soil moisture, and rainfall anomalies, all of which are key gauges of drought. The Normalized Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), and the Standardized Precipitation Index (SPI) are broadly used indicators to measure drought vulnerability and spatial degree (Amarasingam et al. 2022). In Muzaffargarh, a comprehensive drought risk assessment is vital for making knowledgeable decisions and planning. The district's varied agro-climatic zones, reliance on seasonal rainfall, and growing demand for water resources necessitate the usage of advanced geospatial tools for real drought monitoring and mitigation. This study purposes to assess drought risk in Muzaffargarh District by investigating multitemporal satellite data and climatic variables through geospatial techniques. The consequences are anticipated to provision local authorities and stakeholders in developing targeted drought preparedness and resilience strategies.

Research objectives

This study aims to:

- To evaluate the underlying factors contributing to drought risk in the study area through geospatial analysis.
- To track changes in vegetation health and surface temperature over time.
- To investigate how land use and land cover changes contribute to drought risk.

Study area

Muzaffargarh District is located in south-central Punjab province, Pakistan, at latitude 30°4′10″N and longitude 71°11′39″E. The district covers 8,249 km² and borders the Chenab River to the east and the Indus River to the west. The region is divided into four tehsils: Muzaffargarh, Jatoi, Alipur, and Kot Addu, with 111 union councils in total.

- The districts of Khanewal and Multan are located on the eastern side of District Muza ffargarh, across the Chenab; the district of Layyah borders the district on the north; an d the districts of Bahawalpur and Rahimyar Khan Border to the south. The districts of Dera Ghazi Khan and Rajanpur are located on the western bank of the Indus River, w hile District Jhang is located in the northeast.

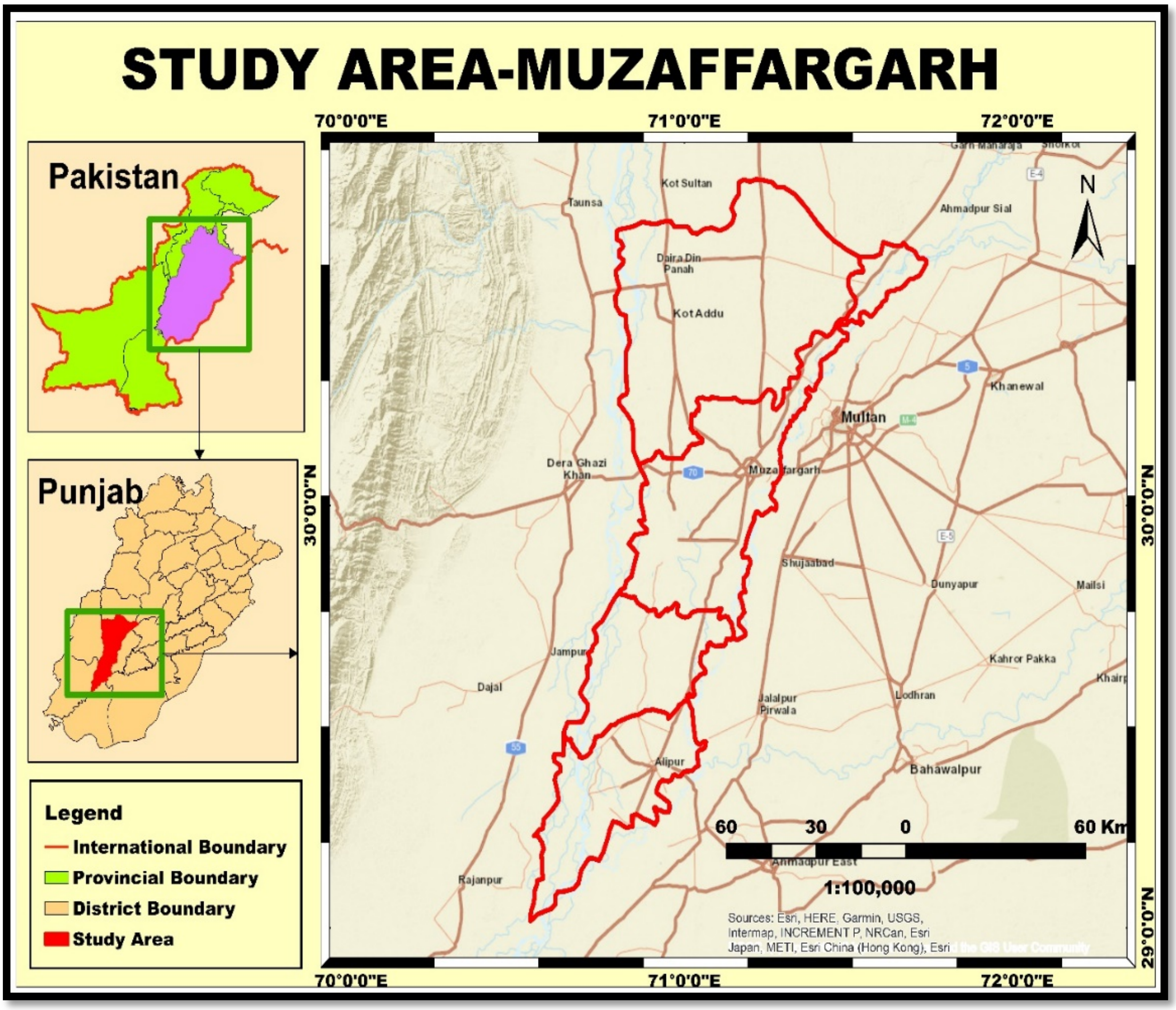

Figure 1: *Study Area Map*

(Source: USGS Earth Explorer)

Climate

Mostly the area of Muzaffargarh is dry and also consists of the barren lands and sand dunes known as the thal area, but the other portion of the area, whether flooded from the river or irrigated by inundation canals, is less dry.

- The climate of Muzaffargarh is arid, with scorching summers and moderate winters. The city has seen among Pakistan's most severe weather. The months of May through Septem ber are hot, but between mid-August and mid-September, a cool breeze might begin to bl ow, which would lower the temperature. In December and January, there are cold nights with heavy frost, which seriously damages vegetables, cotton, mangoes, and sugarcane.
- The temperature that was recorded was roughly 1°C at the lowest point and 54°C at the m

aximum.

- The maximum temperature graph displays how many days per month reach certain tempe ratures. Figure 2 shows that the maximum temperature that is of 40°C the Muzaffargarh is in June to July, the whole month in 2018.

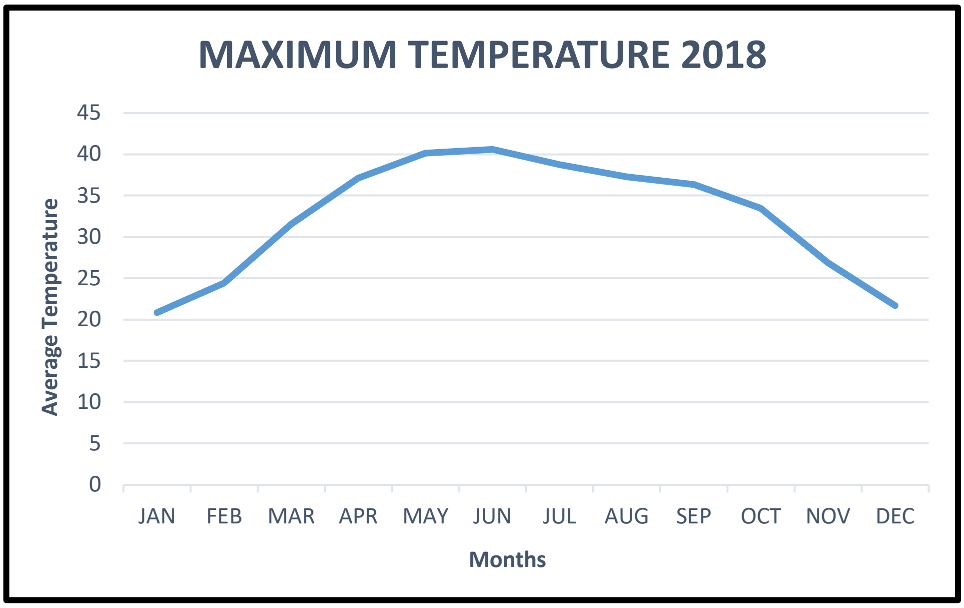

Figure 2: *Graphical representation of the maximum temperature in Muzaffargarh (2018)*

Material and Methods

The overview of used methodology used to work out the proposed research. Reliable indices to distinguish the spatial and temporal dimensions of drought existence and its concentration are necessary to evaluate the impact, and also for decision-making and crop research priorities for improvement. The methodological framework is illustrated in Figure 2.

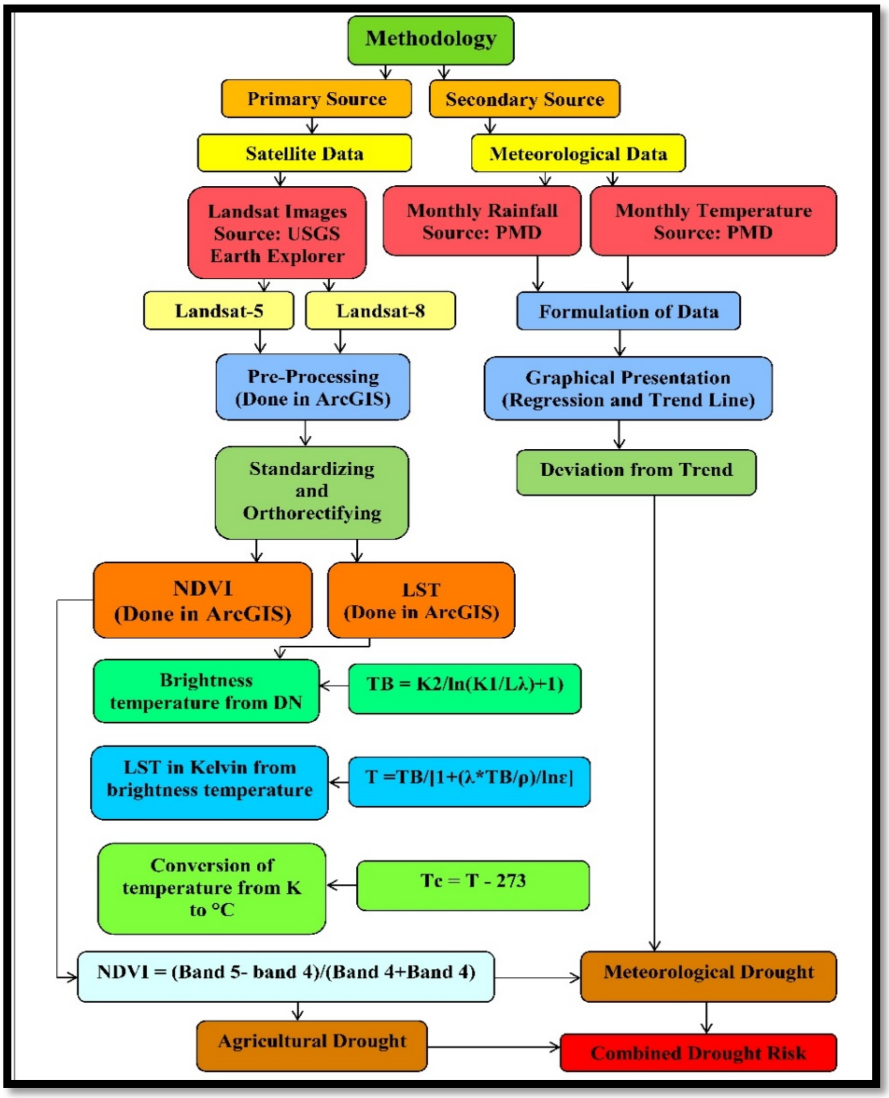

Figure 3: *Methodological Framework*

Dataset used

The satellite data, that has been taken from the United States Geological Survey (USGS) (http://earthexplorer.usgs.gov), Landsat 5 and 8 Enhanced Thermal Mapper (ETM+) and Operational Land Imager (OLI), images (path 150 rows 39, path 151 rows 39 and path 151 row 40) with the 30 m resolution, of July, for the years 2002, 2008, 2013 and 2018 as mentioned in Table 1 used for applying the analysis by using the Remote Sensing and Geographical Information System techniques. In this study, the secondary data source, as Pakistan Meteorological Department (PMD), brings meteorological data on monthly rainfall and monthly temperature, which has been collected for the period 16 years, ranging from 2002-2018.

Table 1. Detailed Information about satellite imagery. (Source: USGS Earth Explorer)

Satellite	Dates of Images	Resolution	Reference system/Path/Row
Landsat 5	14/07/2002	30m	WRS/150/39
Landsat 5	21/07/2002	30m	WRS/151/39
Landsat 5	21/07/2002	30m	WRS/151/40
Landsat 5	14/07/2008	30m	WRS/150/39
Landsat 5	05/07/2008	30m	WRS/151/39
Landsat 5	21/07/2008	30m	WRS/151/40
Landsat 8	12/07/2013	30m	WRS/150/39
Landsat 8	19/07/2013	30m	WRS/151/39
Landsat 8	19/01/2013	30m	WRS/151/40
Landsat 8	10/07/2018	30m	WRS/150/39
Landsat 8	01/07/2018	30m	WRS/151/39
Landsat 8	01/07/2018	30m	WRS/151/40

Data analysis

Satellite imagery was analyzed using key drought indices such as the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and supervised classification for Land Use and Land Cover (LU/LC). The Pakistan Meteorological

Department (PMD) provided secondary climatic data in addition to satellite data. Microsoft Excel was used to establish and examine the mean temperature and precipitation averages for the year. The line graphs were formed by applying regression analysis to these variables, which assisted in influential and identifying the study area's drought risk. A vigorous measure of the Earth's surface energy balance, land surface temperature (LST) is extensively recognised as a vital variable in the investigation of land-surface processes at both regional and global scales (Yadav et al. 2024). In this study, LST was performed by means of satellite thermal bands—Band 6 for Landsat 5, and Bands 10 and 11 for Landsat 8. The satellite imagery for Muzaffargarh, Pakistan, experienced knowledgeable preprocessing, which comprised mosaic generation and geometric correction.

Satellite data was transformed into real-world spatial coordinates during image processing by applying the WGS 1984 datum and the Universal Transverse Mercator (UTM) projection system. Table 2 shows the full sequence of image processing and analytical procedures used in this LST:

Step no. 1: Conversion of DN values to the spectral radiance by using the equation

$$\mathbf{L\lambda = ML*Qcal + Al}$$

Lλ is the cell value as radiance (Ebaid 2016). ML is the radiance multi-band value, Al is the radiance add band value, and Qcal is the thermal band used in it.

Step no.2: Radiance values from the TM 5 / L8 thermal band were then changed to radiant surface temperature, that is, top-of-atmosphere brightness temperature, using thermal calibration constants (Ebaid 2016) by the given equation:

$$\mathbf{TB = K2/ln(K1/L\lambda)+1)}$$

Step no.3: In the very last step in we got the outcomes that are the temperature, which was in kelvin, converted into Celsius (Cº) through this equation:

$$\mathbf{T= T(K)-273.15}$$

Table 2. Processing steps, as well as the conversion of DN numbers to LST

Processing Steps	Formulas	Explanation
Conversion of DN (Digital Number) to At-Satellite Brightness	TB = K2/ln(K1/Lλ)+1)	• K1 Band specific thermal conversion constant (in watts/meter squared *ster*µm) • K2 = Band-specific thermal conversion consta nt (in kelvin) • Lλ =spectral radiance at sensor aperture meas ures (in watts/ meter squared *star*µm) • λ =wavelength of emitted radiance • ρ =h*c/σ (1.438*10^-²m-K)

Temperature.		• h=Plank's Constant (6.62*10^-34 j-s) • σ = Boltzmann Constant (1.38*10^-23 j/K) • c =velocity of light (2.998*10^8 m/s) • ε =emissivity, which is given at: ε = 1.009+0. 047 ln(NDVI)
Calculation of Land Surface Temperature in Kelvin	T=TB/[1+(λ*TB/ρ)/lnε]	• T = land surface temperature in Kelvin • Tc = land surface temperature in Celsius.
Conversion from Kelvin to Celsius	Tc = T – 273	

The Normalized Difference Vegetation Index (NDVI) is one of the most extensively used and reliable vegetation indices for monitoring plant health and assessing drought conditions (Whig et al. 2024). Tucker and Choudhury applied it to drought monitoring for the first time in 1987. In this study, vegetation-related features were extracted from the Muzaffargarh district 3-band satellite imagery using the NDVI technique.

NDVI = (NIR- RED)/(NIR+RED)

Or

NDVI = (Band 5 – Band 4)/(Band 4 + Band 5)

NIR signifies near-infrared reflectance, and RED characterizes red reflectance. This ratio demonstrates the difference between healthy vegetation, which strongly reflects NIR and absorbs RED, and stressed or non-vegetated surfaces, which do not exhibit this spectral behavior. Using this index on Landsat satellite imagery, variations in vegetation cover across space and time were successfully identified, allowing for a detailed assessment of vegetative stress and potential drought conditions in the region.

Variations in land use and land cover (LU/LC) pose a threat to our comprehension of environmental change on a global scale. In this study, supervised classification of LU/LC dynamics in the Muzaffargarh district was carried out using ArcGIS 10.5.

- The process began with the satellite images being organized. For each tile, multispectral images were formed by combining Landsat 5 bands 1–6 and Landsat 8 bands 1–11. After extracting the study area from the larger dataset, a mosaic process was carried out using a reliable spatial reference system.

- To confirm the land features in the study area, ground truthing was carried out by superimposing a base map in ArcGIS. Initiating the pertinent tool and generating training samples in polygonal form over the removed image tiles was the first step in supervised classification. Water, vegetation, and built-up areas were the three main LU/LC categories into which these samples were detached. After that, a GCS (Geographic Coordinate System) signature file encompassing the training data was saved.
- Importing the GCS signature file into the ArcGIS workspace was the last step by step. Applying the symbology of the layer, each land cover class was given a distinct color: brown for built-up areas, green for vegetation, and blue for water bodies. The inclusive distribution of land cover and its variations over time were accurately and clearly represented by this classification.

Results

Abundant geospatial analyses, such as the Index of Normalized Difference Vegetation (NDVI), Land Surface Temperature (LST), and supervised classification for Land Use/Land Cover (LU/LC) mapping, were performed using the Landsat satellite sequence. To confirm outstanding spatial resolution, all maps were made at a scale of 1:10,000. Agricultural and meteorological drought risks have been mixed to generate a composite risk map, which demonstrates that the study area is likely to knowledge compounded hazards due to the convergence of these drought categories.

Land cover change

In this study, LU/LC variations were analyzed using a supervised classification method, chiefly applying the Maximum Likelihood Classification (MLC) technique. The land cover was classified into three major groups: water, vegetation, and built-up areas, by normal remote sensing classification practices. The investigation of the Muzaffargarh district over 16 years (2002-2018) exposes a significant change in land use patterns.

The most notable change is rapid urbanization, which has resulted in a significant increase in built-up areas. This trend coincides with both population growth and the arrival of refugees in the region. As urbanization has increased, vegetative cover has decreased, indicating a significant shift in land use. These spatial changes are displayed by LU/LC maps created with ArcGIS 10.5. Although the built-up area has grown, vegetation still occupies a larger portion of the district. However, the consistent decline in vegetation suggests a possible change in local climatic conditions, particularly an increase in land surface temperature. This pattern demonstrates a direct relationship between land use changes and the risk of meteorological drought, which can lead to agricultural drought. The temporal LU/LC maps for 2002 and 2018 show in Figure 4 visual evidence of these changes, emphasizing the importance of sustainable land management in mitigating environmental risks.

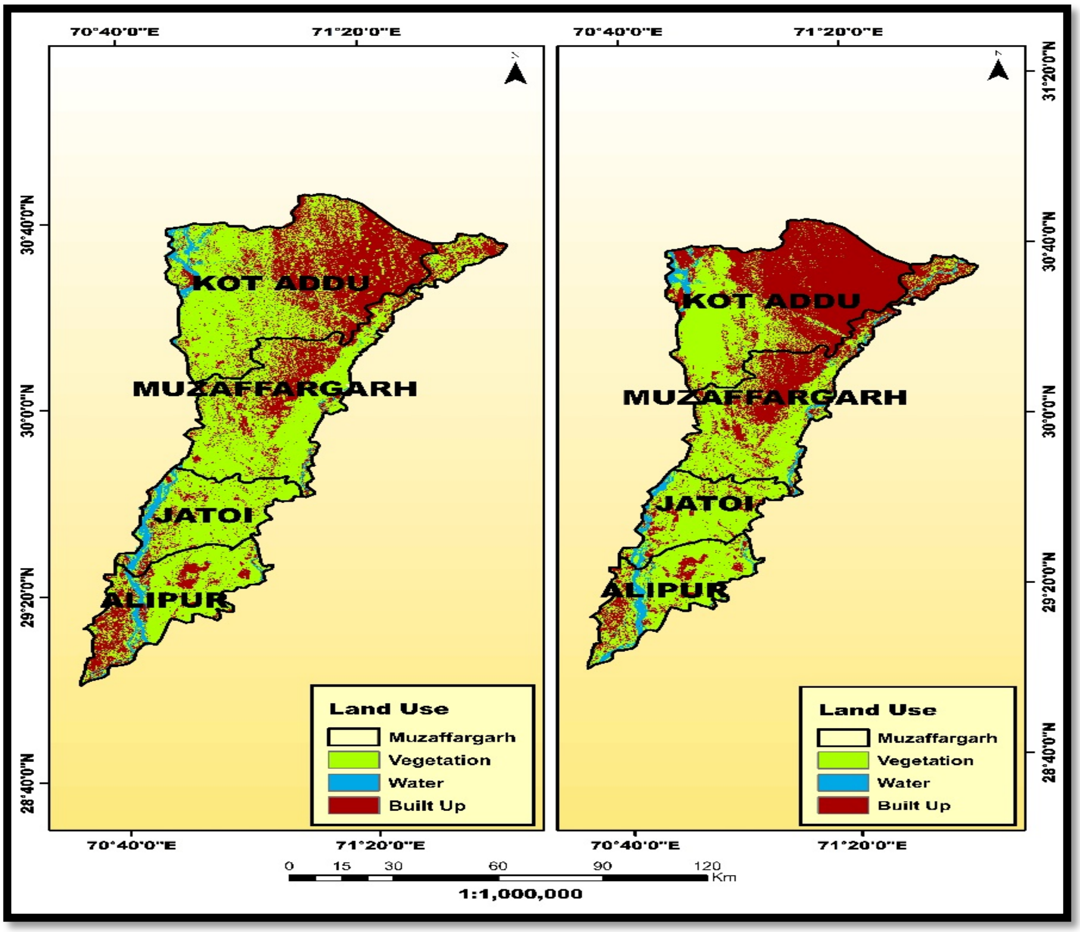

Figure 4: *Temporal Variation in Land Use Mapping (2002-2018)*

Land surface temperature (LST)

Globally, urban temperatures have been steadily increasing (Patel and Patel 2024). Several studies have used satellite-based measurements to accurately calculate Land Surface Temperature (LST) (Mustaquim 2024). The present analysis shows in Figure 5 a significant increase in maximum temperature from 38.77 °C in 2002 to 42.54 °C in 2018. The line Graph 1 and 2 depicts the trend in average maximum and minimum land surface temperature (MMaxT and mminT) for the years 2002, 2008, 2013, and 2018. This consistent temperature rise indicates an increasing risk of meteorological drought. Furthermore, the rise in LST has had a direct impact on vegetation health and coverage, accelerating the onset of agricultural drought.

Over the 18-year study period, the maximum Normalized Difference Vegetation Index (NDVI) value decreased significantly, from 0.989 in 2002 to 0.576 in 2018. This decrease reflects the declining vigor and extent of vegetative cover, particularly cropland, which is extremely vulnerable to climatic stress. A comparison of NDVI and LST maps reveals that the study area experienced increasingly dry conditions in 2018. The spatial correlation between rising surface temperatures and declining vegetation highlights throughout Table 3 the region's increased vulnerability to drought, emphasizing the importance of proactive mitigation strategies and sustainable land management practices.

Table 3. Summary of Land Surface Temperature (LST)

Year	LST Value (C°)	
	Maximum	**Minimum**
2002	38.77419	21.012
2008	38.7097	21.324
2013	39.4871	21.42
2018	42.5432	21.54

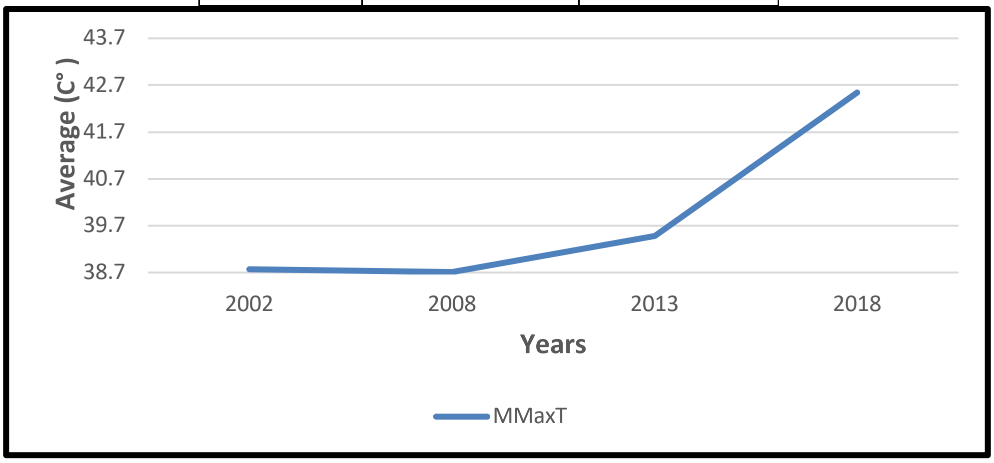

Figure 5: Temporal variation in maximum temperature of Muzaffargarh in the month of July (2002-2018). (Source: PMD)

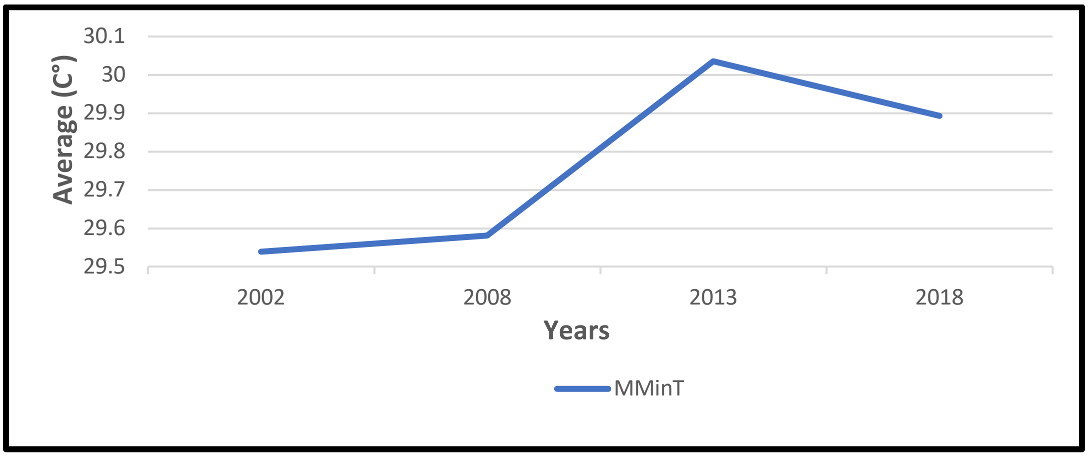

Figure 6: Temporal variation in minimum temperature of Muzaffargarh in the month of July (2002-2018). (Source: PMD)

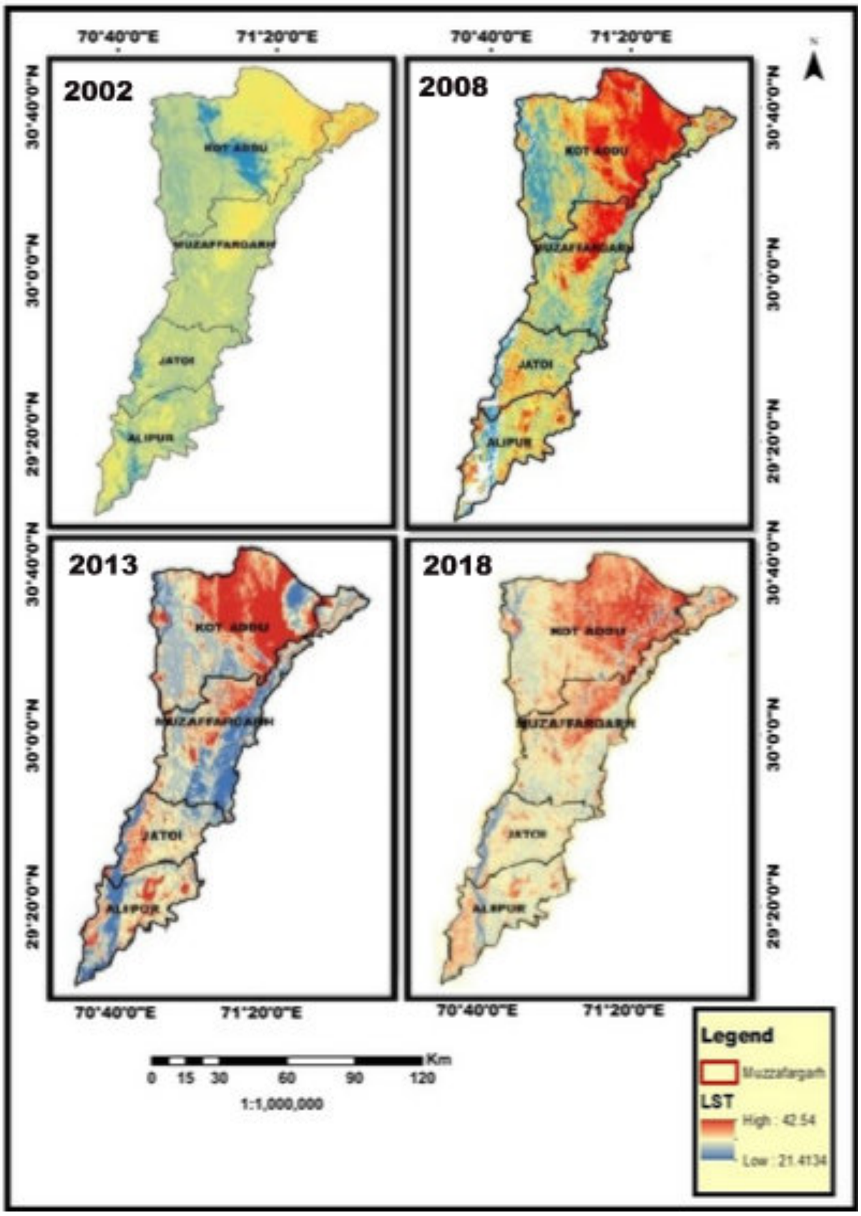

Figure7: *Temporal Map of Land Surface Temperature (LST) (2002-2018*)

Normalized difference vegetation index (NDVI)

NDVI was used to derive vegetation cover classes, allowing for the identification of spatial and temporal variations between 2002 and 2018. NDVI values fell dramatically during this time, from a high of 0.989 in 2002 to 0.576 in 2018, indicating, through Figure 6, a significant decline in vegetation health and density. This decline is primarily due to climate change, specifically rising atmospheric and land surface temperatures. According to international classification standards, much of the study area has shifted from moderate vegetation to increasingly dry conditions, as shown in Table 4. This shift indicates an increased risk of agricultural drought, which could harm crop productivity and local livelihoods. The observed trend emphasizes the critical need for climate-resilient agricultural practices and sustainable land use planning.

Table 4. Classification of NDVI

NDVI Ranges	Drought
<0	Extreme Drought
0-0.2	Dry
0.2-0.4	Moderate
0.4-0.6	Wet
>0.6	Extreme Wet

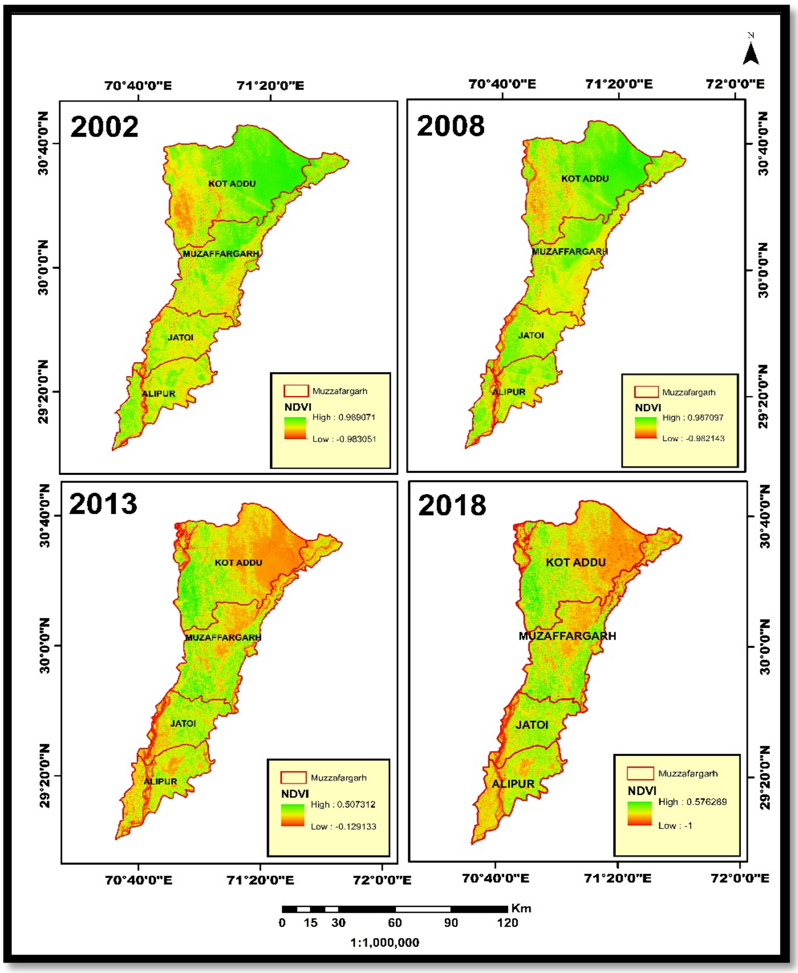

***Figure 8:** Temporal Variation in Normalized Difference Vegetation Index (NDVI)*

The NDVI values in Muzaffargarh District indicate as well in Table 8, a clear decline i n vegetation health over time. The maximum NDVI values for 2002 and 2008 were relatively high (0.989 and 0.987, respectively), indicating dense and healthy vegetation cover. However, by 2013, the maximum value had fallen significantly to 0.507, with only a slight recovery to 0 .576 in 2018. Similarly, minimum NDVI values indicate increased vegetation stress, with the lowest value recorded in 2018 (-1.0). These trends indicate a consistent degradation of vegetat ion cover, most likely due to rising temperatures, urban expansion, and climatic stress, implyi ng an increased risk of agricultural droughts.

Table 5. Summary of Normalized Difference Vegetation Index (NDVI)

Year	NDVI	
	High	**Low**
2002	0.989071	-0.98305
2008	0.987097	-0.98214
2013	0.507312	-0.12913
2018	0.576289	-1

Correlation and linear regression analysis were performed between NDVI and LST anomaly. Graph 3 displays a clear view that there is an inverse correlation between land surface temperature (LST) and normalized vegetation index (NDVI). This directly indicates the risk of drought in this research target area. The graph demonstrates a negative linear relationship between temperature and NDVI, represented by the regression equation:

$$y=-0.0924x+4.4492$$

This means that for every 1°C increase in temperature, the NDVI drops by about 0.0924 units, indicating a decline in vegetation health.

- The coefficient of determination ($R^2 = 0.4167$) indicates a moderate negative correlation. Temperature changes account for approximately 41.67% of the variation in NDVI.
- The NDVI values decrease as the temperature rises from 38.77°C (2002) to 42.54°C (2018), indicating that vegetation cover and surface temperature are inversely correlated.
- This tendency supports the theory of increased drought risk, which holds that vegetation stress, a decline of greenness, and possible agricultural drought are caused by increasing temperatures.

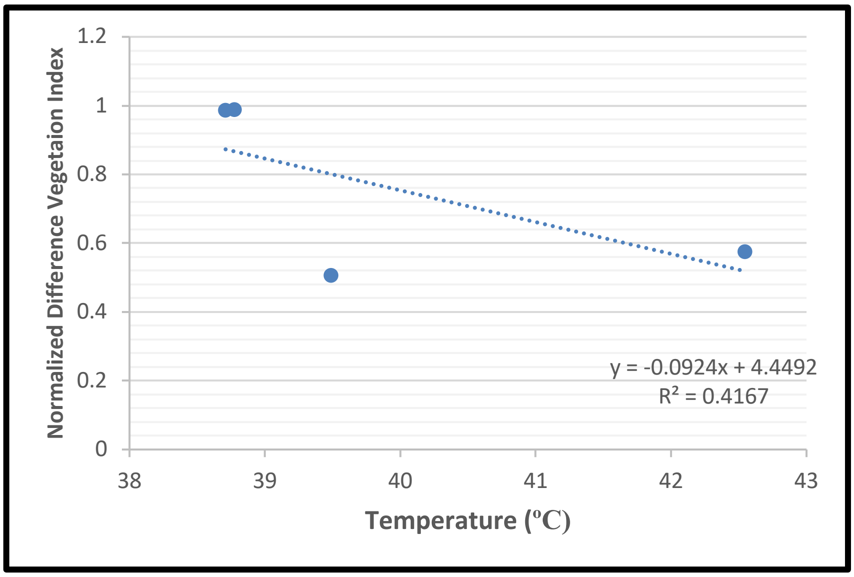

Figure 9: *Correlation between Land Surface Temperature and Normalized Difference Vegetation Index*
(Source: PMD)

Discussion

This study's objective was to measure the Muzaffargarh district's risk of agricultural and meteorological drought using geospatial methods. A mutual occurrence worldwide, droughts have distressing belongings on agriculture, ecosystems, and socioeconomic systems (WHO 2021). The absence of long-term, high-resolution rainfall data for the target area was a component of the study's restrictions. Nevertheless, this limit was addressed by using satellite-derived indices like the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and Land Use/Land Cover (LULC) classification. To professionally map and track situations of drought, a amount of studies have employed NDVI and LULC analysis (Mahajan and Dodamani 2015). Forest and shrubland areas have progressively decreased over time, according to historical trends in land cover shifts, while agricultural land, built-up areas, and water bodies have improved (Gandhi et al. 2015). In this study, a alike trend was detected, with supervised classification of LULC data and NDVI analysis revealing a gradual decline in vegetation cover from 2002 to 2018, representing increased agricultural drought vulnerability.

LST has been widely used in prior studies as a proxy for surface moisture circumstances and drought risk (Latha 2021). Our analysis reveals a rising trend in surface temperatures across the district, typically in recent years, which further supports the presence of meteorological drought. The inverse relationship between NDVI and LST, also engrained in earlier studies (Mahajan and Dodamani 2015; Sun and Kafatos 2007), was validated settled regression analysis in this research. The negative correlation experiential through the summer season strengthens the notion that improved surface temperatures contribute to vegetation stress and decline. Overall, the integration of NDVI, LST, and LULC data brings a comprehensive thoughtful of drought dynamics in Muzaffargarh. This approach not only enables spatial identification of drought-prone areas but also offers a scientific basis for developing risk mitigation strategies. Such multi-source geospatial analyses are energetic for effective drought monitoring, early warning systems, and adaptive land management planning under changing climatic circumstances (IPCC, 2023).

Conclusion

Prolonged precipitation deficiencies, or drought, pose thoughtful problems for agriculture and the situation. By pursuing agricultural and meteorological droughts using geospatial tools like the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), this study measures the risk of drought in the Muzaffargarh District. It has been demonstrated that declining rainfall lowers NDVI values, suggesting the beginning of drought and vegetation stress. From 2002 to 2018, research was led in Muzaffargarh, which is situated between the Chenab and Indus rivers. In accumulation to notable land use moves from vegetation to built-up areas, the results validate a steady rise in surface temperatures and a consistent decline in vegetation cover. This trend designates which drought vulnerability is increasing. Regression analysis demonstrates that LST and NDVI have an inverse relationship, highlighting surface temperature rise as a key factor influencing the risk of agricultural and meteorological drought.

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Flood Risk Reduction Using Integrated Community-Based Disaster Risk Management and Geo-Spatial Approaches in Gin River Basin, Sri Lanka

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Abstract

Floods present considerable risks to the sustenance of livelihoods, infrastructure, and social fairness within the Gin River Basin, Sri Lanka, necessitating an integrated methodology for efficient risk mitigation. This article investigates the implementation of Community-Based Disaster Risk Management (CBDRM) combined with geospatial techniques to reinforce community resilience and involvement in reducing flood hazards. Encompassing an area of 932 square kilometers, the research site displays various climatic conditions impacted by monsoons and diverse topography spanning from mountainous forested inclines to agricultural floodplains. The methodology involved the selection of 100 households and stakeholders for data collection through quantitative surveys and qualitative interviews, focusing on demographic characteristics, livelihood trends, flood impacts, and coping strategies. Data was acquired from both primary and secondary resources, encompassing governmental publications and hydrological observation stations. The Delphi method was employed to enhance the CBDRM model customized for the area. The investigation pinpointed crucial socio-economic variables influencing community engagement in flood risk governance. The outcomes of the study underscored the recurrent flood occurrences intensified by climate variations, underscoring the necessity for a multifaceted strategy encompassing both physical and non-physical interventions. The strategy for lessening flood risks integrates traditional local knowledge, participatory risk evaluations, and sophisticated geospatial technologies like OpenStreetMap for instantaneous flood delineation. Proposed physical interventions involve the establishment of new sluices, refurbishment of pump houses, and the erection of flood embankments, while non-structural actions emphasize prompt warning systems, land utilization supervision, and community enlightenment. This holistic approach accentuates the significance of community responsibility, regional proficiency, and sustainable developmental techniques in augmenting flood resilience. The findings aim to enhance the wider conversation on disaster risk reduction and provide practical solutions for managing flood hazards in the Gin River Basin.

***Keywords**:* CBDRM, demographic, DELPHI, flood hazards, flood resilience

Introduction

The Millennium Development Goals (MDGs), adopted globally in 2000, highlight the importance of addressing vulnerability, disaster management, and risk assessment in development (WMO, 2017). Disasters, both large and small, can undo years of progress, severely impact livelihoods, and increase the risk of extreme poverty, disease, and poor health. Floods, in particular, are frequent hydrological disasters causing significant economic damage, threatening human lives, and disrupting infrastructure. Their impacts on businesses, public services, and the environment exacerbate social and economic inequalities, affecting community resilience and participation in flood-risk management. Effective community involvement in disaster risk reduction (DRR) requires understanding the socio-economic factors influencing participation, such as poverty, education, and access to services (Ashvin et al., 2021).

This paper attempts to address the importance of enhancing community resilience is underscored by Sri Lanka's experience in DRR over the past two decades. Despite traditionally high resilience, government and civil society efforts have primarily focused on preparedness and recovery, affecting attitudes and knowledge about disaster risk (David, 2021). Community-based institutions play a crucial role in managing flood risks, with indigenous knowledge providing valuable coping strategies. For instance, in Bangladesh, communities adapt by raising houses and storing emergency provisions. Sri Lanka, frequently affected by floods, experiences significant disruptions and damage during monsoon seasons (Pakneshan et al., 2023). Understanding the magnitude and frequency of floods is essential for effective planning and management. Models like the disaster-resistant and disaster-resilient communities emphasize minimizing vulnerability and enhancing community participation in DRR efforts (Chamal et al., 2023).

Research objectives

The main objective of this study is to determine Flood Risk Reduction using integrated Community-Based Disaster Risk Management and Geo-spatial Approaches in GIN River Basin, Sri Lanka. The sub-objectives of the study are to analyze the flood risk reduction in the Gin River area, prepare a flood risk reduction plan using integrated community-based disaster risk management (CBDRM) and geospatial approaches, and to align the CBDRM with a suitable existing model of flood risk reduction.

Study area

The study area, as delineated by latitudes 6°18'-6°24'N and longitudes 80°19'-80°35'E, encompasses the Gin catchment, situated between longitudes 80°08'E to 80°40'E and latitudes 6°04'N to 6°30'N, covering an estimated area of 932 square kilometers. The climatic conditions in this region are shaped by the influence of the southwest monsoon (May to September) and the northeast monsoon (November to February), interspersed with inter-monsoon showers during the remaining months. Precipitation levels exhibit variation in accordance with elevation, ranging from more than 3500 mm annually in the upper regions to below 2500 mm in the lower areas. (Salajegheh, 2013) The catchment area, entirely situated within the wet zone, showcases mountainous forested slopes in the higher elevations, while the middle and lower parts feature human habitation, agricultural activities, and forested areas. Thawalama, positioned in the mid-section of the catchment, primarily comprises human settlements and cultivated lands within the expansive floodplain of the Gin River (Wickramaarachchi, 2016). This zone borders the Sinharaja Rain Forest, a designated natural world heritage site, and incorporates anthropogenic practices like tea and rubber cultivation, domestic gardens, and regenerated forests.

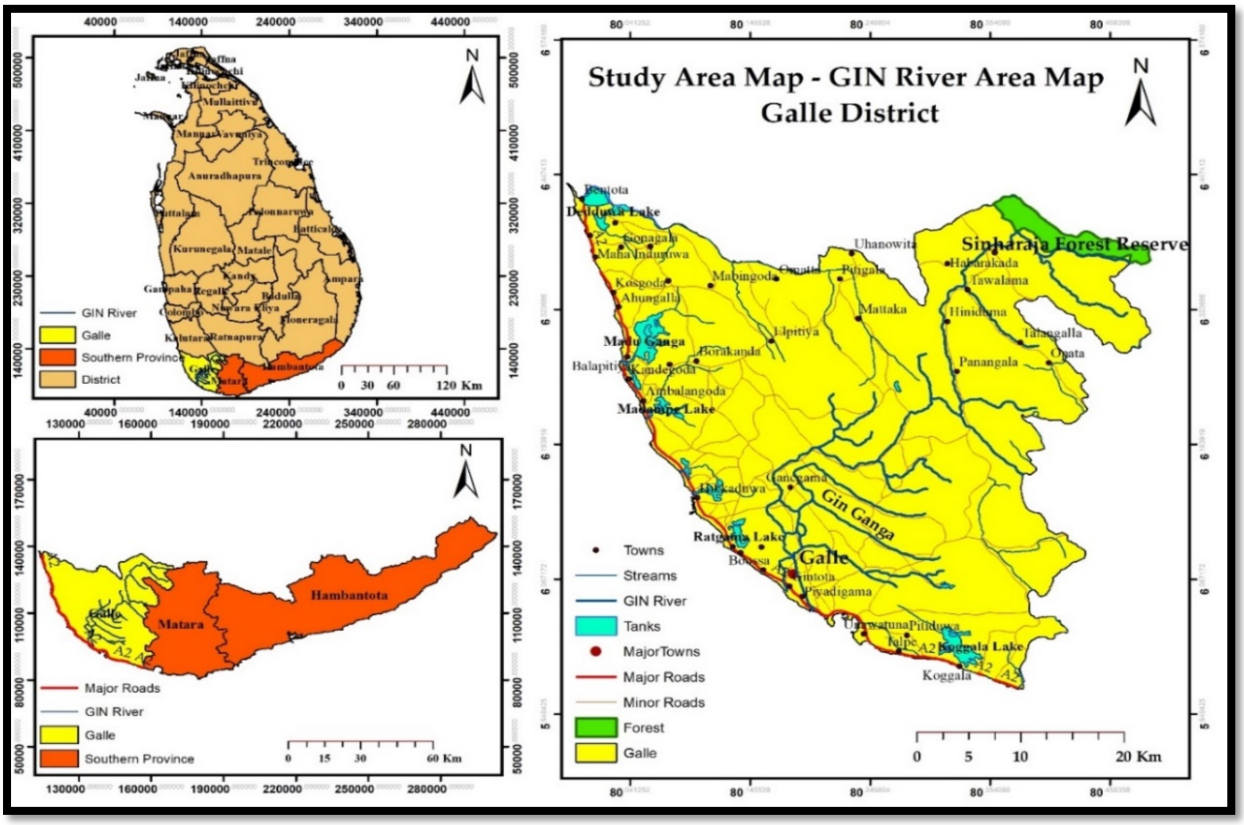

Figure 1: Study Area Map

Topography

The geographical features of the locality are defined by steep-sided, northwest-oriented strike ridges and valleys, characterized by basement rocks comprising highly resistant Precambrian metamorphic formations. The flow patterns of tributary streams are influenced by geological formations, where smaller streams rely on seasonal precipitation, whereas larger streams exhibit perennial flow. The Gin River basin, classified as a fifth-order stream, spans an area of 947 square kilometers with a river length of 112 kilometers, originating from elevated terrains exceeding 1300 meters (Kumari et al., 2018).The data for this research endeavor was obtained from the hydrological monitoring station at Thawalama (6°20'33"N, 80°19'50"E), covering an upstream catchment area of 470 square kilometers. (Dennis et al., 2019). The average annual precipitation within the catchment region is around 3,200 mm.

Material and Methods

The methodology involved purposively selecting 100 households, institutions, community leaders, and practitioners at household, district, and community levels due to time and financial constraints. Both quantitative and qualitative approaches were used to study community-based disaster risk management (CBDRM), focusing on disaster preparedness and recovery. Data collection methods included narrative literature review, secondary data (e.g., government reports), and primary data (e.g., interviews, focus group discussions, key informant interviews, and field observation). The Delphi technique was employed in three stages to refine the final CBDRM model for the Gin River basin (Hua et al., 2020).Quantitative data was gathered through household questionnaires covering demographics, livelihood patterns, flood impacts, vulnerable groups, and coping strategies. Qualitative data was collected via key informant interviews with district-level stakeholders, NGOs, religious institutions, and community representatives, discussing topics such as livelihood patterns, income sources, flood impacts, vulnerability causes, coping strategies, and development options (Ekeu-Wei, (2018).

Data Analysis

The disaster risk reduction method consists of six consecutive steps that can be used either in advance of or during a disaster to lower risks in the future. Each stage develops from the one before it and leads to additional action. The stages in the disaster risk reduction process are given in the figure below:

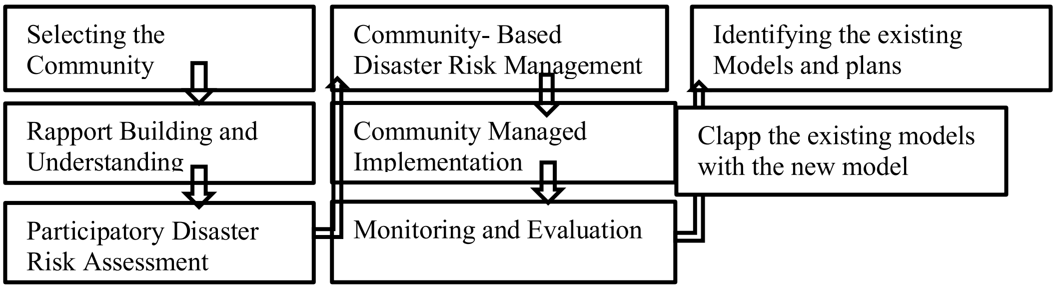

Figure 2: Disaster Risk Reduction Process (Adpc 2006)

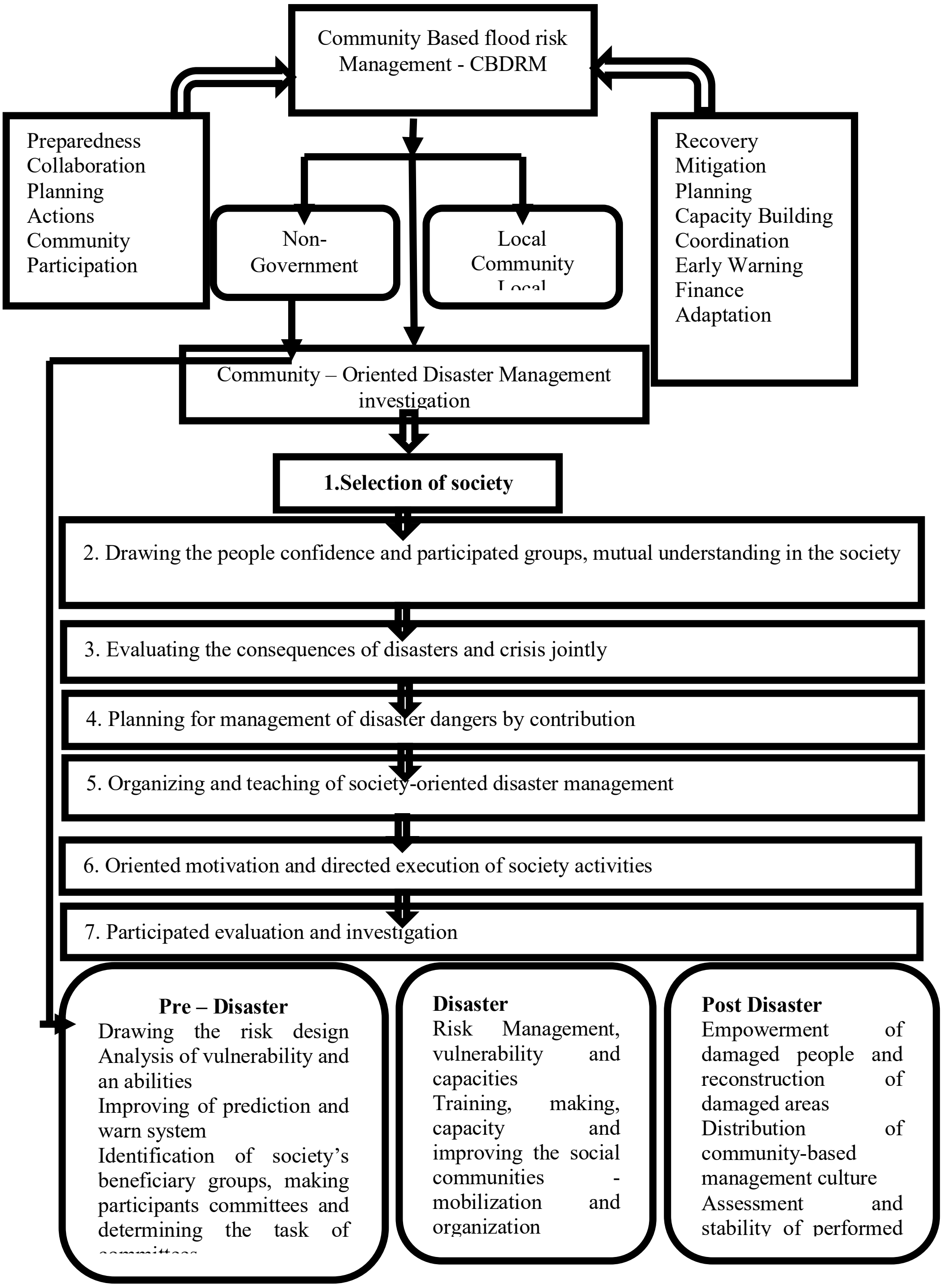

Figure 3: Methodological Framework

Results

However, the area is prone to recurring flood events, posing significant challenges to both the local communities and infrastructure. As climate change exacerbates weather patterns, the vulnerability of this region to flooding has become more pronounced, necessitating comprehensive studies and interventions to mitigate these risks (JMMU et al., 2020).

Several research endeavors have underscored the multifaceted aspects of flood risk within the GIN River basin. These studies often investigate the complex interplay of environmental factors, land use practices, hydrological patterns, and anthropogenic influences contributing to the heightened flood vulnerability. They explore diverse methodologies encompassing hydrological modeling, spatial analysis, and socio-economic assessments to understand the dynamics of flood occurrences and their impacts on the region. Furthermore, the GIN River basin has witnessed various efforts aimed at flood risk reduction and management. These initiatives span a spectrum from structural interventions such as embankments and reservoirs to non-structural measures like community-based preparedness and early warning systems. The effectiveness of these strategies, their sustainability, and their alignment with local socio-economic contexts form pivotal focal points in the ongoing discourse on flood risk reduction in this region (Kanchana et al., 2020).

This paper aims to synthesize and critically analyze existing research on flood risk reduction in the GIN River area of Sri Lanka. By examining the current state of knowledge, identifying gaps, and evaluating the efficacy of mitigation strategies, this study seeks to contribute to the ongoing dialogue on enhancing resilience against flooding in this ecologically rich and socially vibrant region.

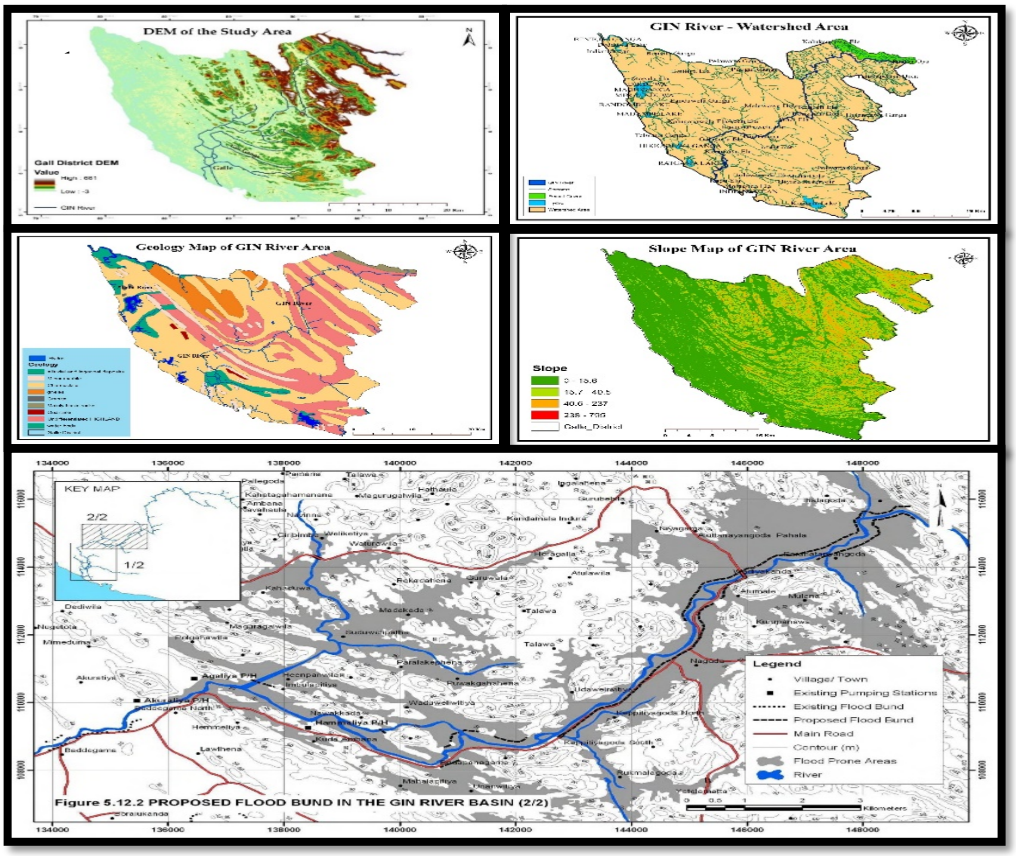

Figure 4: Gin River Area Dem, Gin River Watershed Area, Gin River Slope Map, Gin River Area Geology Map, Flood Prone Areas In Gin River Map

Society Participation

As per the definition provided by the World Health Organization (WHO) in 2002, community participation is characterized by individuals actively engaging in decision-making processes, identifying pertinent issues, and executing development policies and services (WMO. 2017). This approach enables individuals to exert influence on the design of development initiatives, decision-making processes, and the allocation of resources. Participation involves collaborative decision-making and societal supervision, covering all essential activities required to address present needs. It capitalizes on the inherent capacities of individuals, granting them the ability to effectively oversee their health and manage their lives through the acquisition of knowledge, skills, and self-assurance (Sadegh Nejad, 2009). To participate people in society, the different roles are determined for people which are as fallow:

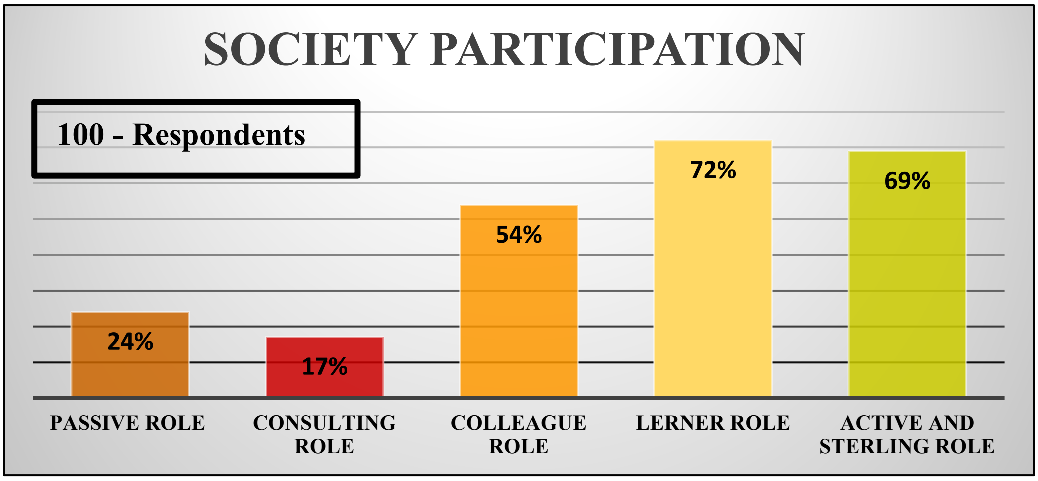

Figure 5: Society Participation (Source- Compiled by Author, 2022)

- **Passive role:** fallowing and obeying of rules and plans of decision makers and lawmakers
- **Consulting role:** using of people views
- **Colleague role:** people cooperation in management processes
- **Lerner role:** learning knowledge and necessary skills for people interventions
- **Active and sterling role:** people cooperation as a partnership (Jahangiri, 2010)

In flood analysis within the GIN River area, various socio-economic factors significantly impact both the vulnerability of communities to floods and the subsequent recovery and resilience-building efforts (Rojanamon et al., 2009).

Community-based flood disaster risk management is crucial in Sri Lanka to enhance resilience and preparedness against the frequent flood hazards that pose a threat to the nation. The damage inflicted on structures and infrastructure by floods underscores the necessity for integrating disaster risk reduction (DRR) mechanisms within the current systems. Despite the advocacy for sustainability by the Green Building Council of Sri Lanka, the complete integration of DRR into its framework remains incomplete. Consequently, Community Disaster Management Committees (CDMC) are being formed in at-risk areas such as the Gin River region. (Perera, B, H, N., Wickramaarachchi, N, C., 2022) These committees offer DRR information, carry out vulnerability assessments, and provide training for effective disaster preparedness and response. Furthermore, there is a development of multi-stakeholder networks to facilitate the exchange of knowledge between government bodies and flood-prone communities.

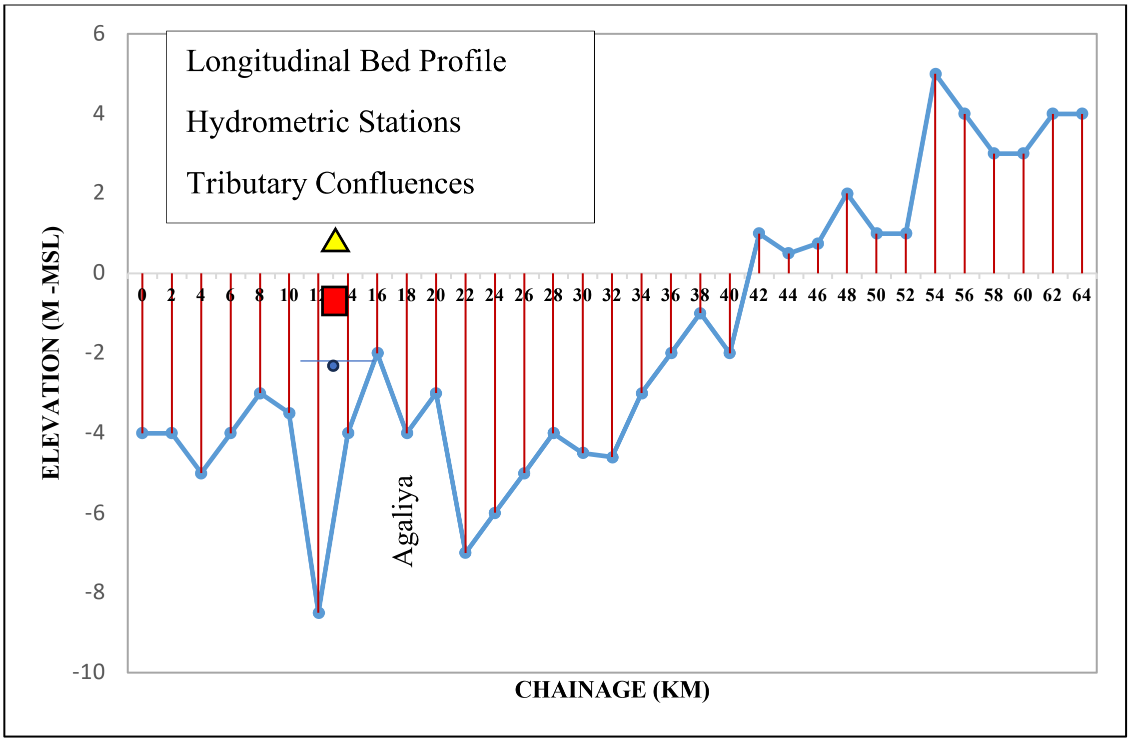

Figure 6: Longitudinal Profile of Gin River (Source: LHI, 2021)

Diverse methodologies are being utilized to effectively involve communities in flood disaster risk management. These methodologies encompass Participatory Risk Assessment (PRA), Vulnerability and Capacity Assessment (VCA), community hazard mapping, and the establishment of community-based early warning systems. Additional strategies include simulation drills, workshops for capacity enhancement, formulation of community-based disaster management plans, and mobilization of local resources. Attention is also given to gender and social inclusivity, the reinforcement of local institutions, nurturing partnerships, promoting sustainable livelihoods, and engaging communities in recovery and rehabilitation endeavors. These strategies underscore the significance of community ownership and empowerment, utilizing local expertise to bolster flood disaster resilience in Sri Lanka.

Existing flood management Master Plan Gin River Basin

Structural Measures

Table 1: Proposed Major Structures in Master Plan (Gin River)

	Kind of structure	Major dimensions
Short Term	1. New sluices	9 nos.
	2. Rehabilitation of existing pumps	10 pump houses
	3. Mound dike	A=51,000 m^2 (3 sites)

Plan	4. Flood bund	Left bank (L=8,360 m, H=5.4m) Right bank (L=7,620m, H=5.3m)
Long Term Plan	5. Flood bund (heightening)	Left bank (L=8,360 m, H=6.6m),Right bank (L=7,620m, H=6.3m)
	6. New pump house	8 nos.

Non-structural Measures (To proceed in parallel with the short-term plan)

Table 2: Non-Structural Measures to be promoted (Gin River) (Source: JICA Study Team)

Measures	Major Items
1. Early warning and monitoringsystem	- 8 rain gauge stations - 5 hydrometric stations
2. Restriction of further development in urban area	- Management and monitoring of land use - Prohibiting housing development in flood prone area - Flood zoning with hazard mapping,
3. Promotion of water-resistantarchitecture	- Heightening of building foundation - Construction of column-supported - Housing, change to multi-storied housing - Water proofing of wall/housing materials, etc.
4. Promotion of flood fightingactivities	- Information dissemination in the communities - Evacuation to safer area, - Removal of properties in house/building, etc.
5. Resettlement	- Mound dike
6. Institutional strengthening ofimplementing agency	- Consensus building for project implementation - Integration with urban development and land use development plans

Flood Risk Reduction Plan Using the Cbdrm and Geospatial Approaches

A plan for reducing the risk of floods has been examined in Sri Lanka using the Community-Based Disaster Risk Management (CBDRM) and geospatial methods. The focus of the research was to identify areas that are vulnerable to flooding and develop models to evaluate the levels of flood risk. The studies integrated different criteria, such as the built environment, physical environment, and socio-economic environment, to categorize vulnerability and assess the levels of risk (Reaves, 2013). Open-Source applications, like OpenStreetMap (OSM), were employed to gather on-site information and identify areas that are inundated by floods. (Dr.Sanjar Salajegheh, 2013) Advanced models were utilized to assess the advantages of local infrastructure adaptation measures and determine the costs of not responding to changing flood risks (Gireesan, 2013). The spatial variations of drought and flood hazards were also analyzed in the Northern Region of Sri Lanka. These studies offer valuable insights and tools for the development of effective plans to reduce flood risks using CBDRM and geospatial approaches in Sri Lanka.

Creating a flood risk reduction plan for the Galle District in Sri Lanka using integrated Community-Based Disaster Risk Management (CBDRM) and geospatial approaches involves a comprehensive and collaborative process. Here's a general outline of the steps Researcher identified by the outputs (Pacific et al., 2008).

Step 1: Understand the Context

Risk Assessment: Conduct a detailed risk assessment of flood-prone areas in the Galle District. This includes identifying vulnerable communities, assets, infrastructure, and natural features that are at risk.

Step 2: Engage Stakeholders

Stakeholder Mapping: Identify and engage key stakeholders, including local communities, government agencies, NGOs, academic institutions, and private sector entities.

Step 3: Data Collection and Analysis

Geospatial Data Collection: Gather geospatial data such as elevation, land use, drainage systems, and flood history. This data will be essential for creating flood hazard and vulnerability maps.

Step 4: Community Participation

Participatory Mapping: Involve local communities in mapping flood-prone areas, safe shelters, evacuation routes, and critical infrastructure. Their knowledge is crucial for accurate planning.

Step 5: Risk Mapping

- Flood Hazard Mapping: Use geospatial data to create flood hazard maps indicating areas at risk of flooding based on elevation and historical flood patterns.
- Vulnerability Mapping: Combine socio-economic data (population density, poverty rates, etc.) with flood hazard maps to identify vulnerable communities and assets

Step 6: Risk Assessment

Integrated Risk Assessment: Combine hazard and vulnerability information to assess the overall flood risk in different areas of the district.

Step 7: Strategy Development

- Community-Based Strategies: Collaborate with local communities to develop strategies tailored to their needs. This could include early warning systems, community training, evacuation plans, and resource mobilization.
- Infrastructure Improvement: Identify critical infrastructure in flood-prone areas and develop plans for upgrading or relocating them.

Step 8: Early Warning Systems

Community Early Warning Systems: Design and implement community-based early warning systems that utilize both modern technology and local knowledge.

Step 9: Capacity Building

Training and Workshops: Conduct capacity-building workshops to enhance community members' skills in disaster preparedness, response, and first aid.

Step 10: Monitoring and Evaluation

Implementation Monitoring: Continuously monitor the implementation of the flood risk reduction plan and gather feedback from the community.

Regular Review: Regularly review and update the plan based on new data, lessons learned, and changes in the flood risk landscape.

Step 11: Collaboration and Coordination

Stakeholder Coordination: Ensure effective collaboration among all stakeholders involved in the plan's implementation.

Step 12: Public Awareness and Education

Community Outreach: Conduct public awareness campaigns to educate the community about flood risks, safety measures, and the importance of their participation.

Step 13: Documentation and Reporting

Figure 7: Identified Flood risk reduction plan for the GIN River Area

Communities and institutions involved in disaster management were forced to take proactive measures to lessen the impact of disasters due to the rising trend of disasters. The Sri Lankan government and other DM actors have begun to recognize the Community Based Disaster Risk Management (CBDRM) method as a fundamental tactic for increasing community capacity and resilience. The Government Road Map and the National Disaster Management Plan have designated Sri Lankan Red Cross Society as one of the primary actors in delivering CBDRM measures (Mohamed et al., 2023).

In accordance with the framework established by the government, SLRCS CBDRM interventions concentrated on conducting participatory risk profiling through evaluations of hazard, vulnerability, and capability, followed by the creation of community risk reduction plans, forming community groups to serve as village disaster management committees, training and outfitting local reaction teams, Identifying and implementing small-scale, community-managed mitigation activities, conducting simulation exercises and drills, installing signboards to indicate safe evacuation routes, executing DM awareness campaigns, and distributing information, education, and communication materials are just a few examples (Miyami et al., 2022).

The CBDRM program includes a school programming that is put in place to foster a culture of readiness within the school community. This entails the creation of a school-based disaster management unit, the creation and training of safety teams, the creation of plans and maps for the reduction of disaster risk at the school level, the execution of disaster mitigation and preparedness operations at the school level, and the conducting of practice drills.

Combining the Gin River Cbdrm Process with Existing Cbdrm Approach Model

The harmonization of the GIN River Community-Based Disaster Risk Management (CBDRM) approach with the participatory methodologies of the Participatory Learning and Action (PLA) model presents a compelling opportunity to fortify community resilience, instigate sustainable solutions, and cultivate an all-encompassing flood risk reduction strategy within the GIN River basin of Sri Lanka. (Wickramaarachchi, 2016) The GIN River CBDRM approach, tailored to the region's specifics, lays the foundation by engaging local stakeholders, leveraging community insights, and pinpointing flood vulnerabilities unique to the basin. (Kodikara et al., 2019). This initiative champions community involvement and context-sensitive strategies to mitigate risks.

Conclusion

In conclusion, the objectives set forth to analyze flood risk reduction in the GIN River area have paved the way for a holistic approach towards managing and mitigating potential flood hazards. By employing integrated Community-Based Disaster Risk Management (CBDRM) techniques alongside geospatial methodologies, a comprehensive flood risk reduction plan has been crafted. This plan considers the unique vulnerabilities of the GIN River area and harnesses suitable existing models of flood risk reduction, thereby fostering a proactive and adaptive strategy aimed at enhancing resilience and ensuring the safety of the communities within this region against the threat of floods.

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Assessment of Risk Factors, Disease Control, and Health-Seeking Behavior of Diabetes Mellitus among Urban Slum Populations

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Abstract

This cross-sectional descriptive study aims to specify the trend, major risk factors, and control of Diabetes mellitus (DM) patients in urban slum areas. A significant progression in adult populations globally has made it a major public health issue and a disaster of recent times. Lack of awareness, social constraints, and absence of community participation to address this public health issue contributed to a socio-economic burden on society. The study concluded the trends, major risk factors, and behavior regarding Diabetes Mellitus. A total of 164 males and 211 females were included in the study with a median age of 53.03 years. Following demographic information, the risk factors, duration of DM presence, practice regarding control, type of treatment taken, and the medical advice to manage the disease were observed as variables of the study. Risk factors such as hypertension 65%, dyslipidemia 41%, obesity 29%, and ischemic heart disease 33% were observed significantly. A high ratio of 62% among the study population did not control the disease properly. Only 35% of people knew the presence of the disease for 6-15 years. Only 26% of participants visited a general physician for medical advice regarding DM. Diabetes mellitus needs to be addressed due to lack of awareness, poor perception, and behavior among the diabetic community of urban slum areas. Further study on a large scale, considering a larger sample size and expanding the community area, may be helpful to establish guidelines to fight against this public health disaster.

Keywords. Diabetes mellitus, prevalence of diabetes, diabetic complications, diabetic awareness, urban slums communities

Introduction

Diabetes Mellitus (DM) is a non-communicable chronic disease also termed hyperglycemia, which is a raised blood glucose level in the body. This is because of the condition referred to as insulin resistance, in which insulin is not produced or does not work properly to convert glucose into energy. The main types of DM are listed as type 1, type 2, and gestational diabetes (Khali & Azar 2024; Solomen & Chew, 2017)**.** This is estimated at present that about 537 million (3 in 4) of the adult world population are living with DM, and this number is specifically rising so predicted that 643 million in 2030 and 783 million by 2045, as stated by IDF Diabetes Atlas. This scenario is more alarming in low and middle-income countries than in high-income countries. Another big challenge to global health is that DM is more prevalent globally due to the fact to remain the condition is uncontrolled or untreated (Mishra & Pandey, 2024)**.** According to IDF, the prevalence of DM in the adult population in Pakistan, by 2021 is about 12-13 million (12.3%, 1 in 8 adults) and expected to rise to around 18-19 million (15.4%, 1 in 6 adults) by 2045.

This alarming condition made Pakistan a more targeted point regarding DM progression among the general adult population (Basit & Fawad, 2018). The adult diabetic population nearly 44.7% are living as undiagnosed and this is a cause of a global burden of socioeconomic scenario and needs to be addressed regarding effective prevention, early detection, and proper management of diabetes (Wali, Rafique, 2020; Tokhirovna, 2024). There are several risk factors of DM, are known as non-modifiable risk factors including family history, age, and ethnic background, but modifiable risk factors are a sedentary lifestyle, smoking dietary behavior, cardiovascular issues, hyperlipidemia, excessive alcohol consumption, and mental stress (Wang & Li,2021). Complications of DM include serious conditions such as microvascular conditions such including diabetic retinopathy, diabetic nephropathy, and diabetic neuropathy, as well as macrovascular conditions, such as cardiovascular issues, stroke, and peripheral arterial diseases. Additionally, the population suffering from DM is expected to get infections and slower wound healing **(**Casqueiro & Casqueiro, 2012).

In a community-based study conducted in Nepal, hypertension was recorded as the leading risk factor for DM, in the list of global disease burdens of a public health issue of underdeveloped countries found as 29.4%, in this study, while 25% of individuals suffered from hypertension and < 50% were known about their disease[i]. In the Chinese population, the rate of hypertensive conditions evolved to 26-29% among the adult population (Swedish Council on Health Technology Assessment, 2008). As a genetic and environmental factor of diabetes, obesity has been found a considerable increase in ratio worldwide (Ruze & Liu, 2023). Obesity and DM have a significant ratio of 29% among our study population mentioned already in the study. DM was also established as a strong risk factor for cardiovascular diseases and available research data explained the high prevalence of CVD as a result of both Type 1 and Type 2 DM and a cause of atherosclerosis as well as heart attack (Heather & Hafstad, 2022). Arterial fibrillation was also established as increasing in prevalence all over the world and a significant risk factor of sudden death in the Type 2 DM population of the older age group

> 75 years of age Mozaffarian, Kamineni, 2009; Volgman, & Nair, 2022). The study conducted by the American Diabetic Association settled a standard protocol to address the behavior, treatment, and comorbid conditions, and in older patients over the age of 65 years, this was established that in kidney diseases, the patient must be evaluated regarding kidney functions, also (Pecoits-Filho & Abensur, 2016).

Longer duration of uncontrolled and untreated DM represents the evidence of more complications resulting from DM (Park, & Cho, 2024). Better diet control established good glycemic control as a result of the best strategy to control Type 2 DM among the adult population, and in the middle age group including the overweight and obese population were best-treated population of higher body mass index which was moderately control of the DM scenario (Chiavaroli & Lee, 2021). The diabetic population has little knowledge about the disease, and 94% of people know about the disease, but only 17% know about the risk factors and preventive measures of DM. The knowledge about the disease was recorded higher among the diabetic population those have diabetes in their relatives and families (Tellawy & Alfallaj, 2021).

Hypertension is a condition with DM type 2 and interlinked with each other, so the prevalence is increasing worldwide due to arteriosclerosis so be considered as an emerging cardiovascular disease (Balakumar & Maung, 2016). Moreover, data expressed that the association between high blood pressure and DM more significant cause of many other cardiovascular complications, so needs to be conscious for the treatment and control of hypertension and diabetes both together (Przezak, Bielka, & Pawlik, 2022). Dyslipidemia is another comorbid condition to be considered in patients with DM, due to the raised value of triglycerides and low high-density lipoprotein cholesterol (HDL-C), which is more prevalent and evident. The finding showed that cardiovascular diseases are also associated and have a high prevalence in the diabetic population (Kaze, & Santhanam, 2021) Ischemic heart diseases like cardiomyopathy, myocardial infarction, and heart attack have high mortality rates with DM type 2, and adopting a standard protocol to monitor diabetes and heart issues on regular basis (Shrivastava & Ramasamy, 2013), (Heather, & Hafstad, 2022). Duration of occurrence of DM is a more prevalent factor about 25% among the population of older age group as a main health burden, so has a higher risk of increasing in frequency in the next decades. This is now established from the data that normally the older age group of population has the more complications because in this group the duration of DM is directly associated with the growing age, eventually greater the age longer the duration of diabetes if present (Huang &

Laiteerapong, 2014; Izzo, Massimino, & Riccardi, 2021). The control of DM is directly associated with the lack of awareness of the disease, and lifestyle also has an impact on the control of DM. An active lifestyle may be very helpful in coping with the effects and complications of diabetes. Research showed that about 23% population takes care of and shows good response to the medication for the treatment of DM (Shrivastava & Shrivastava, 2013). The adherence rate also has a direct impact on treating diabetes among the population with pharmacological ways such as oral medication or insulin, so clinical depends upon the uptake of the machines as medical advice enhances good clinical outcomes (Alharbi & Alaamri, 2023).

The biology of type 2 DM is one of the risk factors, and the absence of enough production of insulin or insulin produced by the pancreas not being able to work properly. Accumulation of fat in the liver due to static lifestyle resulting in physical inactive behavior. Poor hygienic environment, social isolation, sleep disturbance, air, and noise pollution are the strong risk factors of DM. Smoke, green area elimination, burden of traffic cause severe stress, enhancing the disease condition. (Dendup & Feng, 2018). Strong associations of rapid population growth, unhealthy air quality index, urbanization, and thickly populated areas, specifically urban slums, are at high risk of developing worse condition of DM .among adult and especially in old age group in general population (Hankey & Marshall, 2017).

Materials and Methods

This cross-sectional study was conducted among the general population involving 375 individuals with a simple random sampling technique and calculated by the formula,

$$n = Z^2 \,(p\ q)\,/d^2$$

$$= Z^2\, p\,(1-p)/d^2$$

$$= (1.96)^{2\,\times}\, 70.4\,(100-70.4)/5^2$$

$$= 30.96 \times 70.4\,(29.6)\,/25$$

$$= 8252\,/\,25$$

$$= 330$$

With a 10% attrition rate, 330 +33 = 363

For convenience, 375 individuals were included in the study.

All new and follow-up patients residing in urban slums of Lahore visiting Gulab Devi Teaching Hospital Lahore, with known patients of DM type 2, were included in the study for a dilated retinal examination in the eye department. A self-structured questionnaire was used to collect the data, and all patients for the study were interviewed with informed consent. After data collection, data were analyzed on SPSS version 26. Categorical variables were computed and presented in tables, charts, and graphs. In the descriptive analysis, frequency tables were generated. Cross tabulation and association of variables were done by chi-square test, P – P-value < 0.05 was considered as significant. ANOVA was used to analyze the difference between the mean of groups, and an independent sample t-test was used to analyze the difference between the means of two unrelated groups.

Results and Analysis

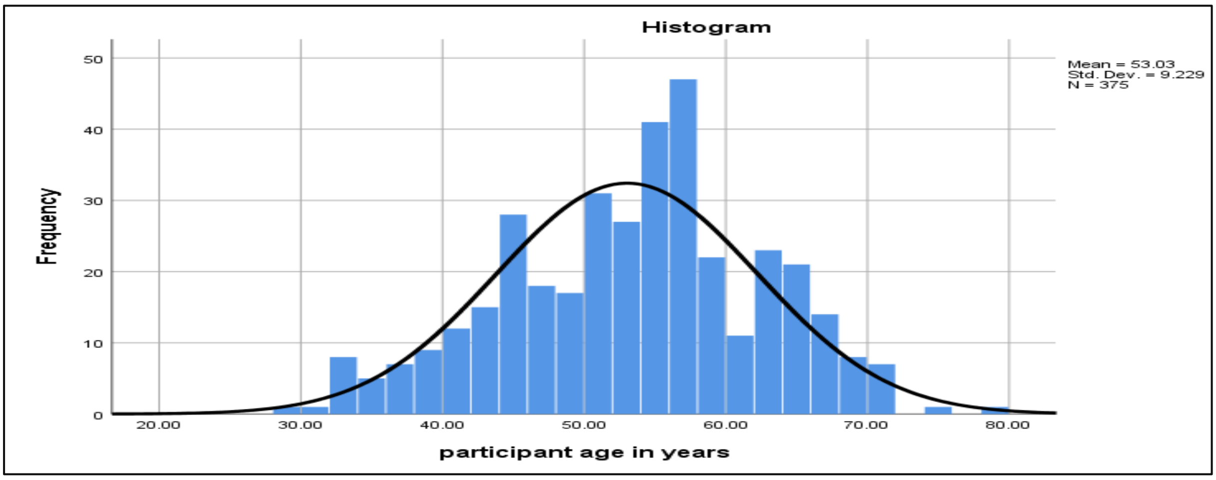

Figure 1: Age Distribution of the Participants

Figure 1 shows the age and gender of the study population and explains that the median age was 53.03 years, with a standard deviation of 9.23. The total number of participants included in the study was 375.

Table. 1 Demographic Presentation of the Participants

	Category	*f*	%
Gender	Males	164	43.73
	Females	211	56.26
	Illiterate	132	35.2
	Primary9o78	72	19.2
Educational Status	Secondary	113	30.13
	Graduate	58	15.46
	Govt. Job	31	8.26
	Private job	35	9.33
	Labor	34	9.06
Profession	Retired	39	10.4
	Housewife	176	46.93
	Unemployed	60	16

Out of 375 participants in the study, 164 (43.73%) were males, and 211(56.26%) were females. The ratio of females was higher than that of males. The educational status of the participants was as follows: 132 (35.2%) illiterate, 72 (19.2%) primary level, 113 (30.13%) secondary level, and 58 (15.46%) were graduate.

The professional status of participants was recorded as Govt. Job 31 (8.3%), Private Job 35 (9.3%), Labor 34 (9.1%), Housewives 176 (56.9%), Retired 39 (10.4%), and Unemployed 60 (16.0%) (Table 1).

Table 2 Major Risk Factors of Diabetes Mellitus

Risk Factors	*f*	%
Hypertension	244	65.06
Dyslipidemia	155	41.33
Obesity	109	29.06
Ischemic Heart Disease	123	32.8

This table explains the co-morbidities of DM, as hypertension was evident in 244 (65.1%), dyslipidemia in 155 (41.3%), obesity in 109 (29.1%), and ischemic heart diseases in 123 (32.8%) (Table 2).

Table 3 Duration of Diabetes Mellitus

Duration in years	*f*	%
3-5	81	21.6
6-10	129	34.4
11-15	128	34.13
16-20	30	8.0
>20	7	1.86

Table 3 shows the duration of the diabetes best known by the individual was observed in the category of 3-5 years 81 (21.6%), 5-10 years 129 (34.4%), 11-15 years 128 (34.1%), 16-20 years 30 (8.0%), and more than 20 years 7 (71.9%).

Table 4 Control of Diabetes mellitus

Control	*f*	%
Very Strict	16	4.26
Strict	126	33.6
Not Strict	230	61.33

Table 4 explains the behavior towards the control of the DM, and data was recorded as individuals who control the disease very strictly were 16 (4.26%), strictly 129 (34.4%), and not strictly 230(61.33%).

Table 5 Type of Treatment Adopted by Individual

Treatment taken	*f*	%
Pills	244	65.06
Insulin	71	18.93
No medication	60	16

The table 5 shows the practice regarding taking any treatment to control the disease as 244 (65.06%) were on oral medication, 71 (18.93%) were insulin-dependent, and 60 (16.0%) were not taking any treatment to control the disease.

Table 6 Visit to General Physician

Visit to Physician	*f*	*%*
Regular	97	25.86
Not Regular	267	73.6
Never	11	2.93

The table 6 shows that participants 97 (25.86%) visited regularly, 267 (73.6%) not regularly, and 11 (2.9%) never visited to physician to take advice for the disease.

Discussion

Awareness and socio-economic status are both directly influencing factors of increasing diabetes in the adult population. (Saeed & Saleem, 2018). In our study, we concluded that the individuals involved in the study were of a median age of 53.03 years with a standard deviation of 9.23, which predicts the condition that the prevalence was significant in the old age group. It was also observed that the ratio of female patients was high at 53% as compared to female participants were 43%. Our data established a higher ratio of 35.2% in the illiterate category, the category of the primary level was 19.2%, and secondary level was 30.1%, the graduate level was recorded as 15.5%. Socio-economic and literacy status were considerable factors in this study. The profession also affects the behavior and practice to control and prevent non-communicable diseases as the busy schedule in many professions, awareness and self-care strategies are the main factors established in studies. (Agha & Usman, 2014) The professional status of participants was recorded in our research, as Govt. Job 31 (8.3%), Private Job 35 (9.3%), Labor 34 (9.1%), Housewives 176 (56.9%), Retired 39 (10.4%), and Unemployed 60 (16.0%). In this study, the highest ratio was recorded among housewives (56.9%), and the second largest group was recorded among the unemployed population. The larger group of housewives was the dominant group of participants in the study.

The comorbidities were experienced in this study, including hypertension 244 (65.1%), dyslipidemia 155 (41.3%), obesity cases 109 (29.1%), and ischemic heart diseases 123 (32.8%). In a study done on Madrid's general population, the comorbid conditions were found to be hypertension 70%, dyslipidemia 67%, and obesity 32%, in the study. (Barrio-Cortes & Mateos-Carchenilla, 2024). This study showed the equal proportions of results as suggested by other researchers. The results found that the duration of DM was also a significant factor in the emergence of many complications. The data has been recorded in this research regarding the duration and presence of the disease as among the categories of 3-5 years 81 (21.6%), 5-10 years 129 (34.4%), 11-15 years (128 (34.1%), 16-20 years 30 (8.0%), and more than 20 years 07 (1.9%). The highest ratio among the group 11-15 years was 34% among the population under observation during the study conducted in this study. Meta-analysis established in a survey declared that the duration of DM is evident due to glycemic conditions among the diabetic population (Stolar, 2010; Hemmelgarn, 2011).

The data regarding behavior among the study population has been recorded to control the diabetic condition as very strict control 4.26%, strict control 129 (34.4%), and not strict control 230 (61.3%), and as in the low-income population, the control of DM type 2 is behavior dependent, so knowledge and practices to overcome diabetes and its complications are significant among diabetic population (Papatheodorou, Banach, 2018). A study established that general health awareness, lifestyle changes, and following the right treatment plan remained good to control diabetes (Gruss & Nhim, 2019). The findings of this study also showed the situation of practice and behavior of the participants regarding control of DM type 2. Our research expressed that only a small group controls the condition, and 61% of individuals were not serious regarding their disease due to lack of knowledge. A larger group was on oral medication, taking medication by mouth 65%, insulin 18.93%, and 16% were not taking any treatment.

The study also witnessed that 11 (2.9%) participants did not visit a general physician, 267 (71.2%) visited but not regularly, while only a small group 92(25.9%) visited regularly for medical advice or treatment. Lack of knowledge and awareness hinders the perception of taking advice on medical care about diabetic control (Nagelkerk, Reick & Meengs, 2006). his is also stated by data that practitioners face difficulties in treating a patient of DM due to a lack of knowledge about the disease. Healthcare providers make decisions while considering DM to treat the patient, so decision-making is very important for the treatment with pills, insulin, or both (Chimoriya & MacMillan, 2024)Furthermore, medical advice acceptance is very crucial for diabetic control as the treatment plan or strategy prescribed by the health care practitioner leads to better control and prevents complications in advanced age if the disease remains untreated or uncontrolled (Najafipour & Farjami, 2021).

The control and prevention of diabetes is a public health concern for the community all over the world as well as regional situations. The practice and perception of controlling the disease is not ideal, and the presence of the undiagnosed or untreated disease is the cause of many complications (Hamid, Akash & Rehman, 2021). Our study strongly overlooked the status regarding complications as a result of untreated or uncontrolled DM type 2 and found a very crucial scenario in which only 15% of participants visited a specialist doctor to take advice regarding any complication introduced as a result of diabetes. This is also evidence of a lack of knowledge regarding diabetes and its complications. The group of participants who did not visit a specialist for an expert opinion regarding complications was as crucial as other groups. This group is also at risk of diabetic complications.

Recommendations

- Establishing a public health issue, specifically among the diabetic community, needs to be considered as a public health disaster due to the increasing mortality rate and compromising quality of life among the diabetic population.
- Lack of awareness is a barrier to controlling and managing the scenario regarding behavior, perception, and practices among the community.
- Further studies may lead to follow-up guidelines to address the issue on a larger scale and benefit the population of other areas.

Limitations of the study

Lack of awareness and socio-economic factors remained the limitations, while follow-up visits. A small sample size was considered for the study, but further research may be continued in the future involving a large sample size, expanding the scope of study at the community level. Due to its significance and severity, this public health issue must be treated as a disaster.

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Analyzing the Impact of Covid-19 on Climatic Condition in Pakistan Using Geospatial Approach

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Abstract

Coronavirus affected the usual trends of environmental factors, globally. This study is an attempt to assess the impacts of COVID-19 on climatic conditions in Pakistan using a geospatial approach. The secondary data is used in this study. For analysis of climatic conditions satellite data of selected climatic factors (wind speed and LST) was collected from openly available websites. The climatic data were downloaded from the MODIS MERRA-2 sensor from EOSDIS Worldview NASA in NC4 File format of wind speed and data of LST from USGS Earth Explorer. The data were processed by using geospatial approaches, such as interpolation (IDW), zonal statistics, and weighted sum. By doing statistical analysis the variations in climatic conditions are assessed. The findings revealed that during the lockdown period variations were observed in climatic conditions due to limitations on anthropogenic and industrial activities. During the lockdown period of the COVID-19 pandemic not only the cases were under control but positive changes in climatic conditions were also observed. During the lockdown period of the pandemic, negative standardized anomalies in LST and wind speed were observed compared to prior years 2018 and 2019. Restriction on anthropogenic activities produces positive changes in environmental conditions.

Keywords: climatic conditions, covid-19, LST, wind speed, lockdown and geospatial approaches.

Introduction

A little cluster of cases of the disease now known as COVID-19 or coronavirus was first detected when a few patients with early symptoms of pneumonia were admitted to hospitals in the Chinese city of Wuhan on December 29, 2019 (Price et al., 2020). Globally WHO (World Health Organization) reported 28,276 confirmed cases with 565 deaths as of February 6, 2020, including at least 25 countries (Wu et al., 2020). Coronavirus was announced as a general public health emergency of International Concern in January 2020 (Bhatnagar et al., 2021) and coronavirus had turned into a global health concern of prime significance, influenced more than

400 million people with 5.7 million confirmed deaths by January 10, 2022 (Praharaj et al., 2022). Coronavirus is a positive single-stranded RNA genome encompassed by an envelope and its diameter ranges from 60nm to 140nm (Singhal, 2020). This disease has expanded expeditiously to the world and poses huge economic, environmental, health, and social challenges to the whole human population (Chakraborty and Maity, 2020).

In Pakistan first case of COVID-19 was reported on February 26, 2020, due to entry of infected pilgrims from Iran (Raza et al., 2021). A constant increase was observed in total cases of coronavirus until 12th June. 273,113 total confirmed cases were reported until 25th July 2020 (Ahsan-ul-Haq et al., 2022). The mortality rate was low in Pakistan as compared to other countries like Italy, Iran, Spain, and the USA (Amin et al., 2020). The spread of this pandemic can only be controlled by taking preventive measures. Pakistan imposed its first lockdown after three weeks since the first case reported when the total number of cases was greater than 880 (Farooq et al., 2020). The government of Pakistan did not impose a complete lockdown precipitously around the country but instead imposed it systematically (Khan et al., 2021). In Pakistan, the first lockdown was imposed on 23rd of March 2020, within the province of Sind, accompanied by a nationwide lockdown from 25th March, 2020. However, the lockdown policy varied from sector to sector such as the residential and industrial sectors. Therefore, divided the lockdown period into different stages, P1 the earlier stage from January to February, P2 before the lockdown period from the 1st of March to the 22nd of March 2020, P3 lockdown period from the 23rd of March to the 15th of April 2020, P4 loosed lockdown period from 16th of April to 30th of April 2020 and P5 selected lockdown period from 1st of May to 15th of May 2020. P4 refers to a partial or loose lockdown period when industries were not operating (Ali et al., 2021).

The association between coronavirus and climatic factors was ambiguous, which was demonstrated by both positive and negative impacts (Amnuaylojaroen et al., 2021). The positive environmental variations were reported because of the lockdown period during the COVID-19 pandemic (Evangeliou et al., 2021). COVID-19 had many positive impacts on air pollution and climatic conditions. A decrease in anthropogenic activities led to a significant decline in air pollution (Khan et al., 2021). The lockdowns during the COVID-19 pandemic brought larger changes in land surface temperature between rural and urban areas due to a reduction in anthropogenic activities (Sahani et al., 2021). The anomalies in land surface temperature during the lockdown period of COVID-19 were first studied over the worst virus-affected areas of North America and Europe. The studies discovered huge negative changes in night-time land surface temperature in Europe (0.11°C to -2.6°C) also significant changes were observed in both day and night time LST across North America from March to May in the pandemic year 2020 contrasted to the average of years before pandemic from 2015 to 2019, which can be partly due to the effects of lockdown period during COVID-19. The reduction in LST was associated with a negative change in air temperature (-0.46°C to -0.96°C). On the other side, the increase in daytime LST was observed throughout most regions of Europe due to a decrease in solar radiation by barometrical aerosols. The negative changes in LST at night time may be associated with reduced anthropogenic activities. In North America, studies discovered a significant negative change in LST of both day and night time during the lockdown period (Parida et al., 2021).

The changes in wind speed are mainly due to land use and land cover changes (Navinya et al., 2020). An increasing trend was observed in wind speed during the pandemic between 10^{th} March 2020 and 21^{st} July 2020. After that time period, a decline was observed in wind speed. In Pakistan, fluctuations were observed in wind speed from 10^{th} March 2020 to 04^{th} October 2020 (Ali et al., 2021). The overarching goals of this research are to analyze changes in LST and wind speed during the lockdowns of the pandemic by using satellite data. However, the present study is based on previous literature and elucidates the impact of COVID-19 on climatic factors across the Pakistan and also helps to interpret the significant changes in climatic factors during the lockdown period and the reasons behind these significant changes in the study area by using geospatial approaches.

Study Area

The study area named Pakistan is located in the western zone of South Asia geographically extends from 30°22'31.2" N latitudes. It denotes Pakistan's location in the Northern Hemisphere and ranges from 69°20.707' E longitudes which represent the eastern location of Pakistan (Salma et al., 2012). Pakistan is comprised of four provinces Punjab, Sindh, Baluchistan, and KPK, and Islamabad Capital Territory. Additionally, there are two other administrative states Azad Jammu Kashmir (AJK) and Gilgit Baltistan as shown in Figure **1**. Pakistan is a land of mountains, plains, deserts, and coastal belt. The area of Pakistan is 796,095 square kilometers (Mohsin, 2020). Pakistan enjoys a wide range of seasons. Pakistan lies in the temperate zone, above the tropic of cancer. Pakistan has a bimodal distribution of rainfall. Pakistan is a developing country with a fragile health system and the financial condition of

Pakistan is also not better, the impacts of the virus were more in Pakistan as compared to developed countries. The potential risk of COVID-19 risk was more in Pakistan because of Pakistan's Population dynamics and demographics (Noreen et al., 2020). This study also analyzes the impacts of the COVID-19 pandemic on the climatic factors of Pakistan and helps to create a pandemic overview in Pakistan.

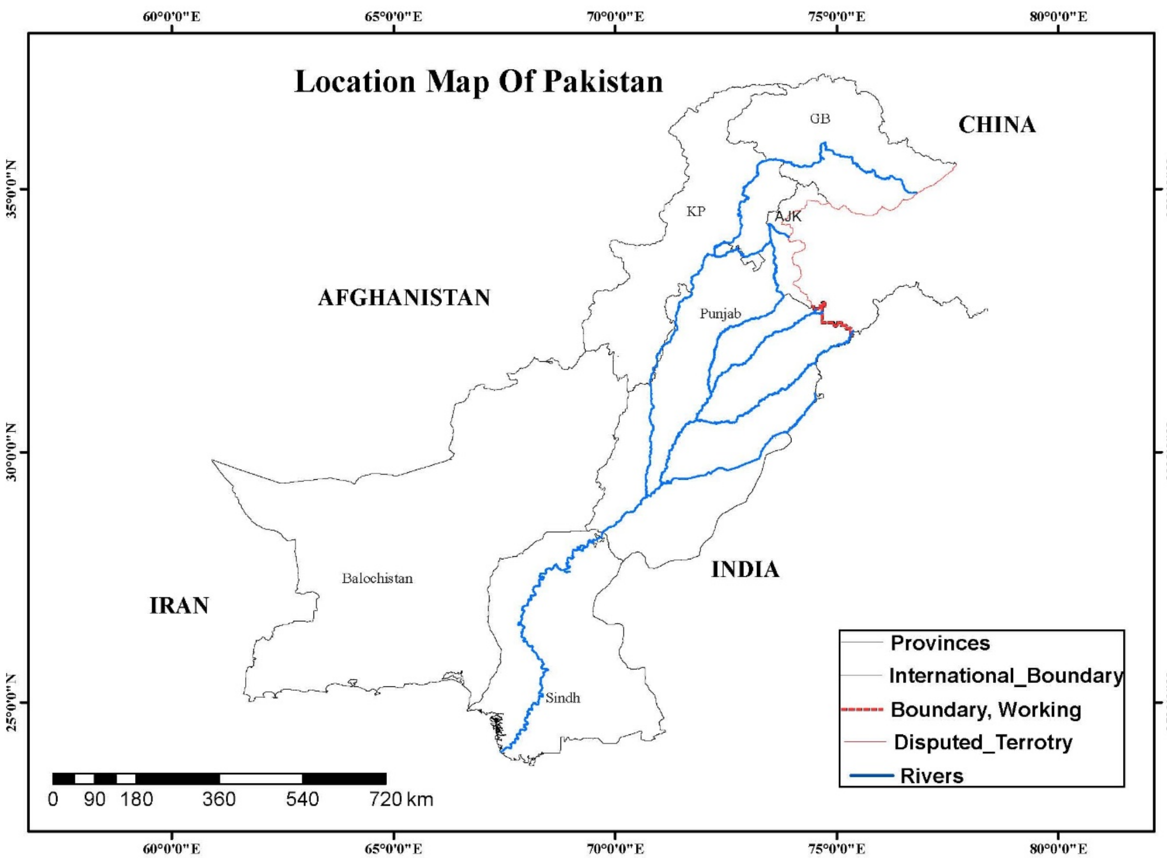

Figure 1: Study Area Map of Pakistan

Datasets used

To achieve the objectives of this study secondary data sources were exploited. For this study, satellite data and COVID-19 data were used. The data was collected through remote sources. Data has been downloaded manually from different websites. The monthly data of selected environmental factors (LST and wind speed) was downloaded from January 2018 to March 2022 and of preceding years 2018 and 2019 of pandemic and during COVID-19 pandemic. This data was collected from satellites images namely MODIS MERRA-2 sensor from EOSDIS Worldview NASA in NC4 file format of wind speed and data of LST from USGS

Earth Explorer to analyze the changes in environmental condition. In this study, the satellites images of climatic data of Pakistan were downloaded of preceding years 2018 and 2019 as a proxy for conditions and compared them with data for the period 2020, 2021 and 2022 under lockdown conditions. And province wise COVID-19 monthly data set of total cases assembled from open source website covid.gov.pk from March 2020 to March 2022 of COVID-19 this time period was considered for statistical data analysis because the first case of COVID-19 in Pakistan was reported on 26th February 2020. Table **1, 2 and 3** summarized the COVID-19 data which was used in this research and collected from open source website covid.gov.pk.

Table 1: Monthly COVID-19 data of Total Cases

COVID-19 Total Cases 2020							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK
March	54	708	0	253	158	184	6
April	343	6340	6053	2627	1049	339	66
May	2589	26240	28245	10027	4393	711	255
June	12912	76262	84640	26598	10476	1489	1093
July	150333	93057	121039	34056	11743	2134	2084
August	15649	96832	129469	36118	12879	2903	2299
September	16611	99479	137106	37811	15281	3787	2731
October	19970	104271	145851	39564	15920	4261	4133
November	30406	119578	174350	47370	17187	4658	6933
December	37888	138608	215679	58701	18168	4857	8277

Table 2: Monthly COVID-19 Total Cases of 2021

COVID-19 Total Cases 2021							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK
January	41418	157796	247249	67214	18823	4909	9019
February	44373	172054	258266	72424	19049	4956	10243
March	58557	223181	265680	88099	19576	5033	12805
April	75498	303182	283560	118413	22369	5310	17187
May	81257	340110	318579	132822	25218	5588	19250
June	82706	346301	337674	138068	27178	6138	20343
July	87699	356920	382865	144264	30432	8156	24501
August	99516	394738	432637	162402	32248	9919	32228
September	105516	431666	457928	174017	32926	10328	34157
October	106921	440259	470175	178074	33263	10390	34478
November	107722	443185	475820	180075	33484	10412	34556
December	108666	445107	482029	181402	33638	10429	34662

Table 3: Monthly COVID-19 Total Cases of 2022

COVID-19 Total Cases 2022							
Months	ICT	Punjab	Sindh	KPK	Baluchistan	Gilgit Baltistan	AJK
January	128429	480421	543170	194887	34417	10703	38339
February	134404	501544	568277	216174	35345	11499	42978
March	135072	505003	575257	219026	35472	11702	43261

The data of wind speed (m/s) was extracted from MEERA-2 2d_lfo_Nx which is monthly mean data collection and for Land Surface Temperature (Kelvin) (LST) data collected from USGS Earth Explorer in HDF format. For the conversion of radiance Kelvin values to LST, first digital number (DN) obtained from USGS of the image were calculated and their average was taken out and multiplied with 0.02 and then radiance was subtracted from 273.15 (Javid et al., 2019). The data has been prepared by using the ArcGIS 10.3.1 software and MS Excel. The COVID-19 data was analyzed by using Microsoft Excel Spreadsheet and presented in the form of tables. The COVID-19 and climatic data both were processed by using Arc GIS. After that Inverse Distance Weighted (IDW) was used for visualization and to show the trends of COVID-19 data and variations of climatic factors. IDW is type of deterministic method of interpolation that estimates cell values by averaging the value of given sample data points in the neighborhood of each processing cell. Finally, zonal statistic implemented to show districts wise visualization of both COVID-19 and climatic data. Furthermore, maps were produced to show spatial distribution across Pakistan by using Arc Map Tools. The weighted sum analysis approach provides the ability to weight and combine series of raster inputs to create an integrated analysis. The weighted sum multiplies all the input raster values by specified weight. Statistical Analysis was performed to show changes in environmental factors at district level of Pakistan. By using this method, a generalized visualization of variation in climatic conditions in areas of Pakistan due to COVID-19 is shown.

Results

In this research impacts of the COVID-19 pandemic on climatic conditions are assessed and also how the lockdown period during the pandemic caused variations in environmental conditions. In this study it has already been mentioned cause of this pandemic, preventive measures were taken such as wearing masks, social distancing, limiting transport, closure of industries, and lockdowns were imposed to control the spread of COVID-19, lockdowns not only minimized the spread of COVID-19 but also brought positive changes in environmental conditions. In this study analysis are performed at both level district and province level. Tables represent impacts of lockdown on environmental conditions at district-level and images across the country. In Pakistan the first lockdown was imposed in the month of March 2020 to June 2020 known as strict lockdown. In the month of July 2020, the government again imposed a partial lockdown. In May 2021 the government again imposed a lockdown known as Eid lockdown. By June 2021 COVID-19 had hit Pakistan hard. Until March 2022 the most affected province by coronavirus was Sindh with 575257 total reported cases. And the least affected was GB with 11702 total cases. The total cases in March 2022 were 251334. The lockdown not only controlled the spread of COVID-19 cases but also caused changes in climatic conditions. Figure 2 depicts how during strict lockdown the cases of COVID-19 were under control. When the government loosened the lockdown, an increasing trend was observed in total cases in different parts of the country. Figure 3 **Error! Reference source not found.**shows how COVID-19 during the partial lockdown affected the country. Figure 4 depicts how COVID-19 affected Pakistan after the month of October 2020. Similarly, Figure 6 and 7 show the terrible increase in COVID-19 cases. And Figure 8 presents how pitifully coronavirus affected the Pakistan till March 2022.

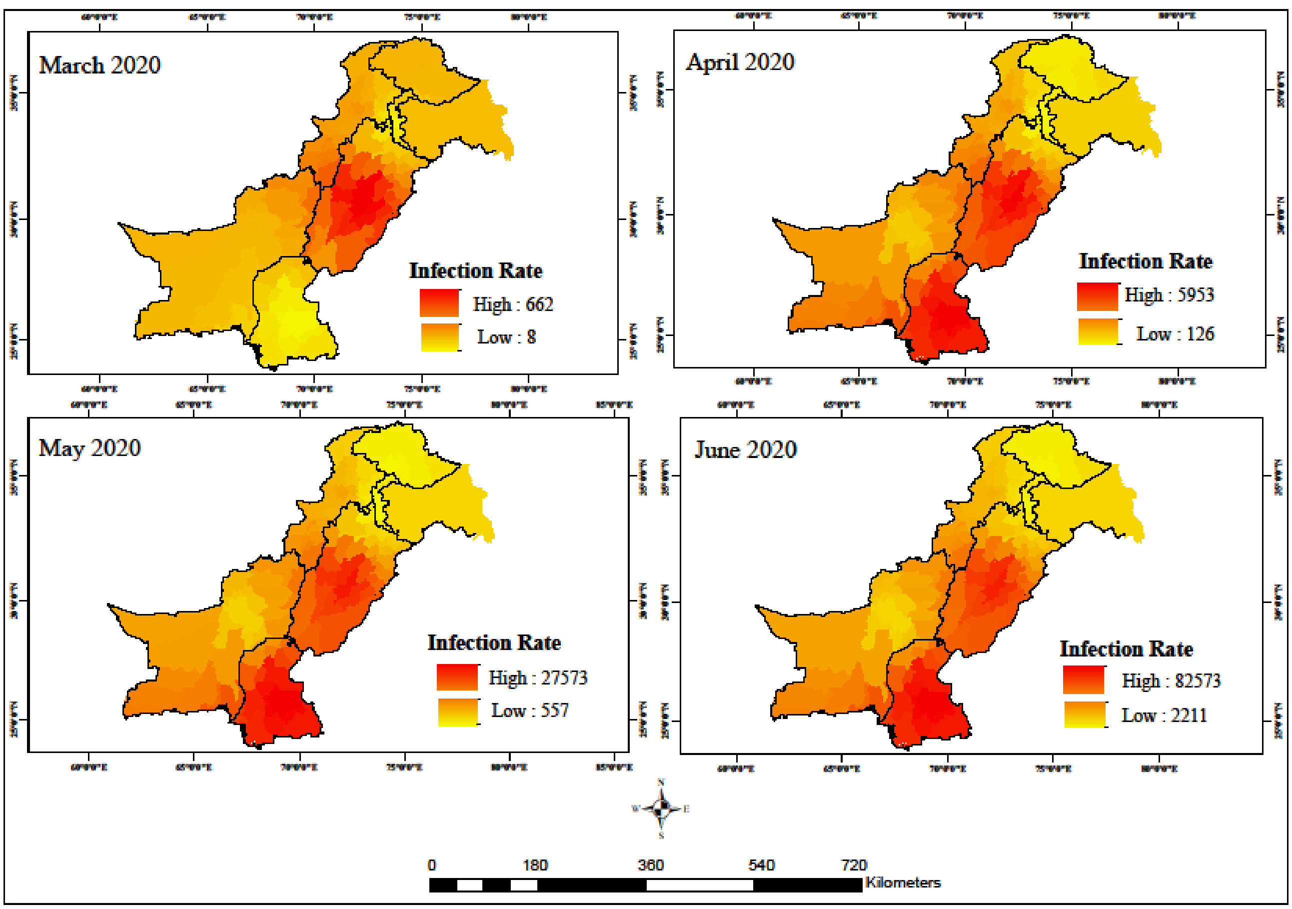

Figure 2: Spatial Distribution of Total Cases of Covid-19 during Strict Lockdown Period

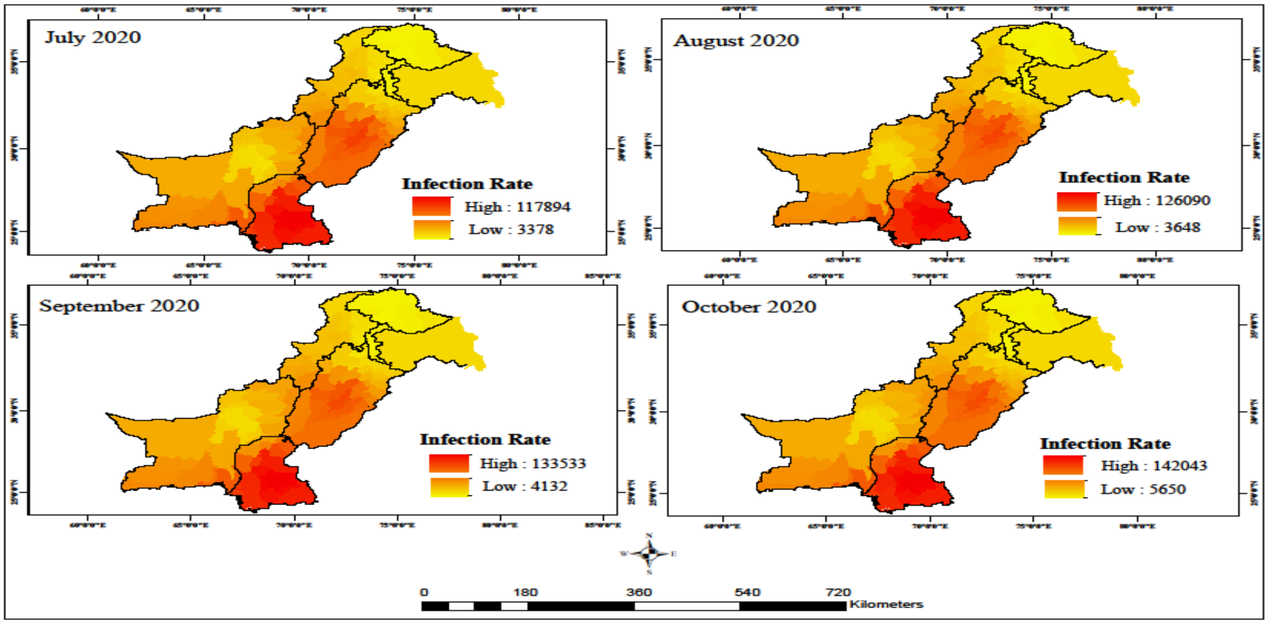

Figure 3: Spatial Distribution of Total Cases of Covid-19 during Partial Lockdown Period

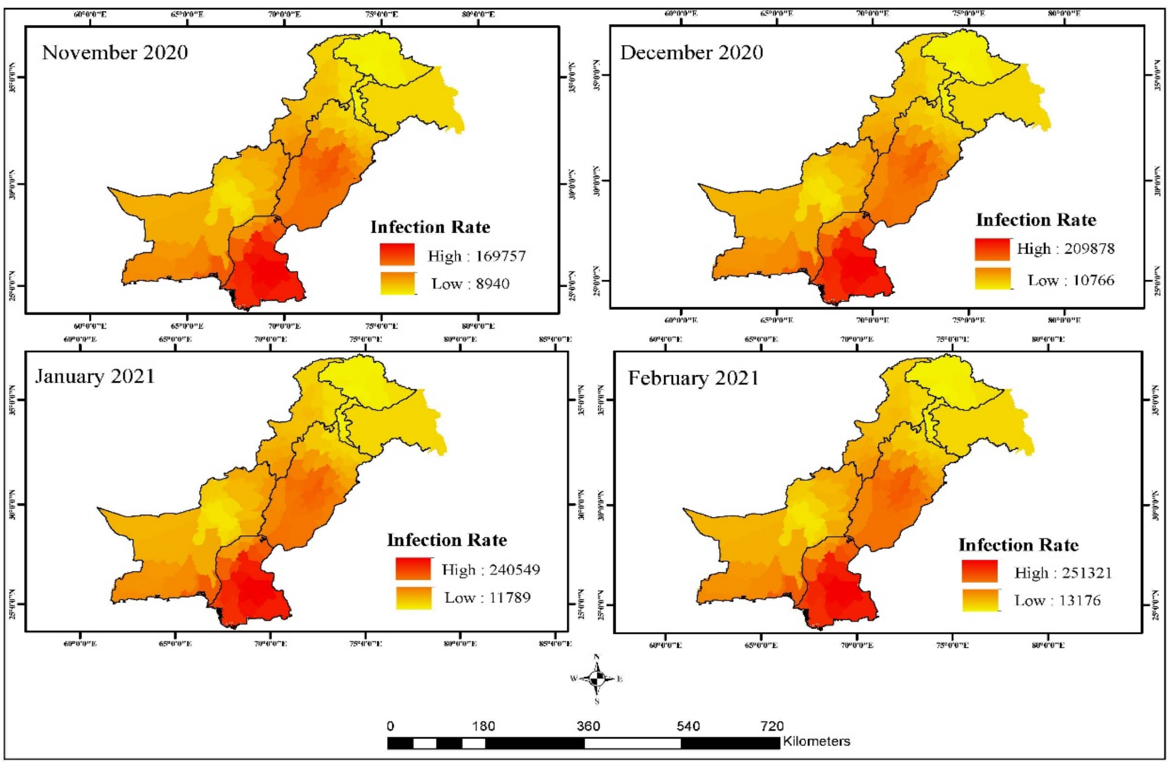

Figure 4: Spatial Distributions of Total Cases of Covid-19 after Lockdown Period

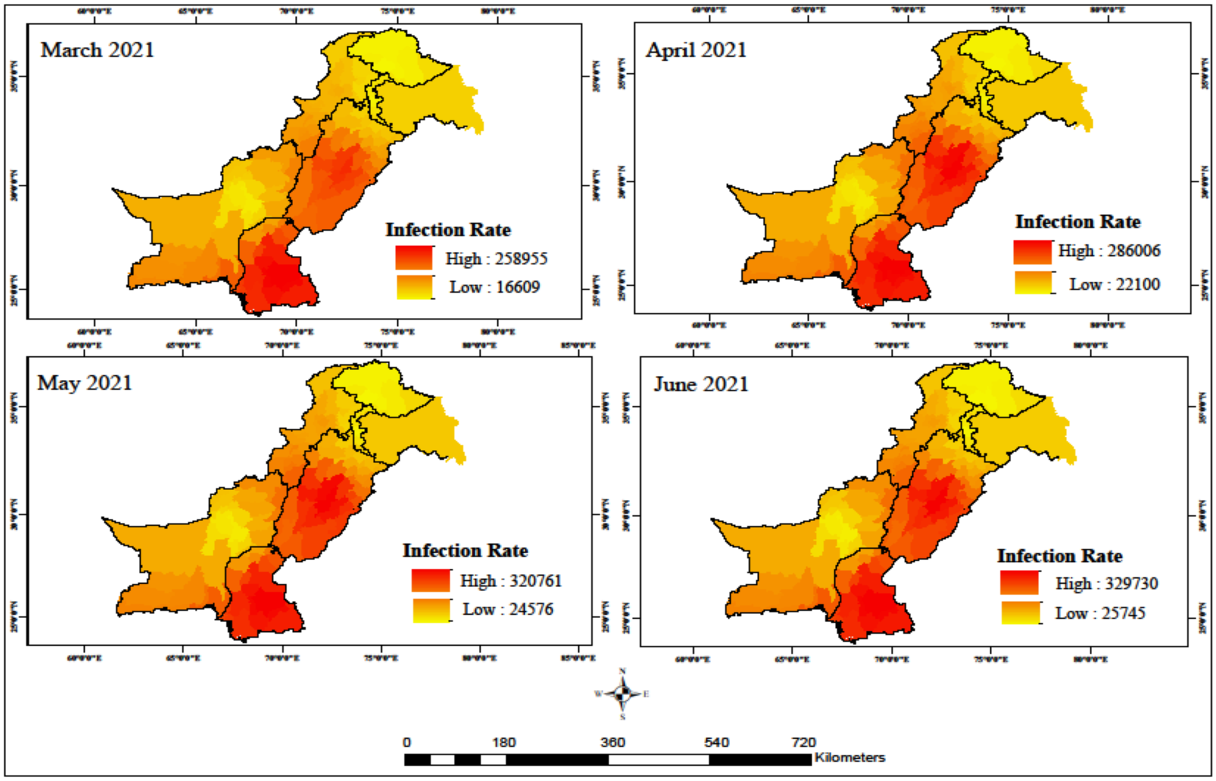

Figure 5: Spatial Distribution of Total Cases of Covid-19

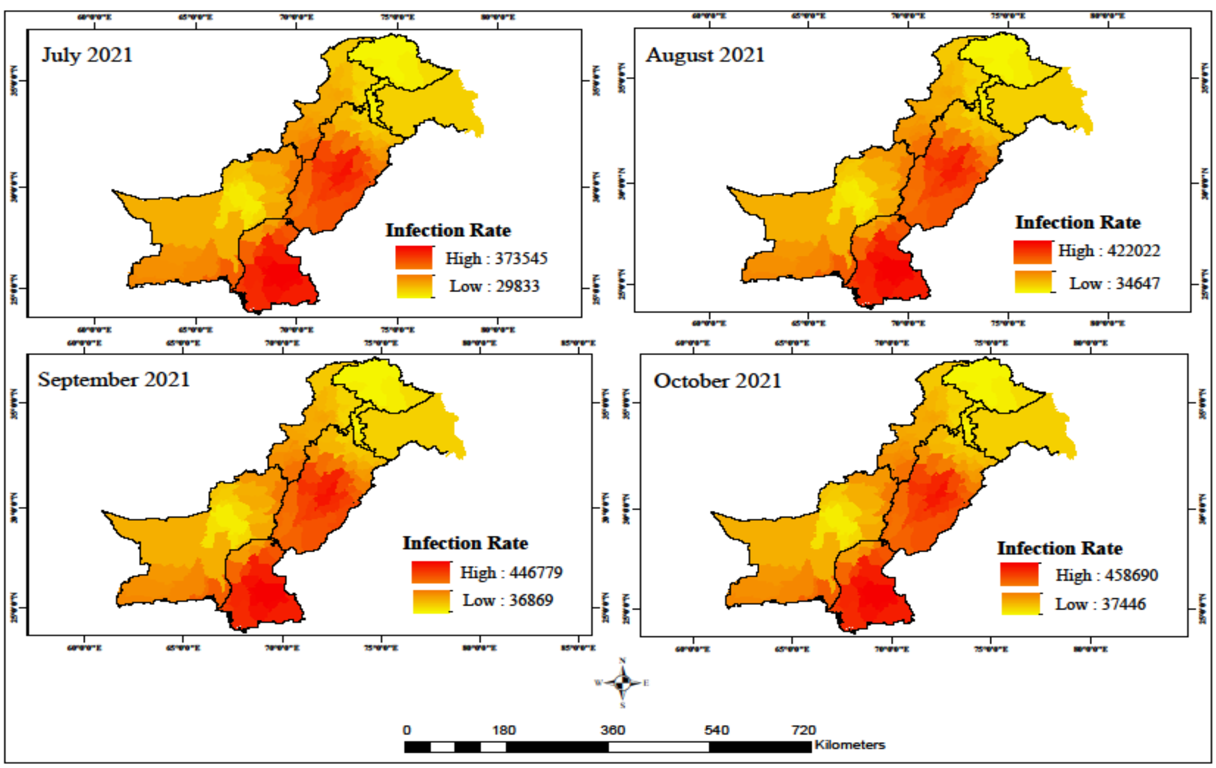

Figure 6: Spatial Distribution of Total Cases of Covid-19

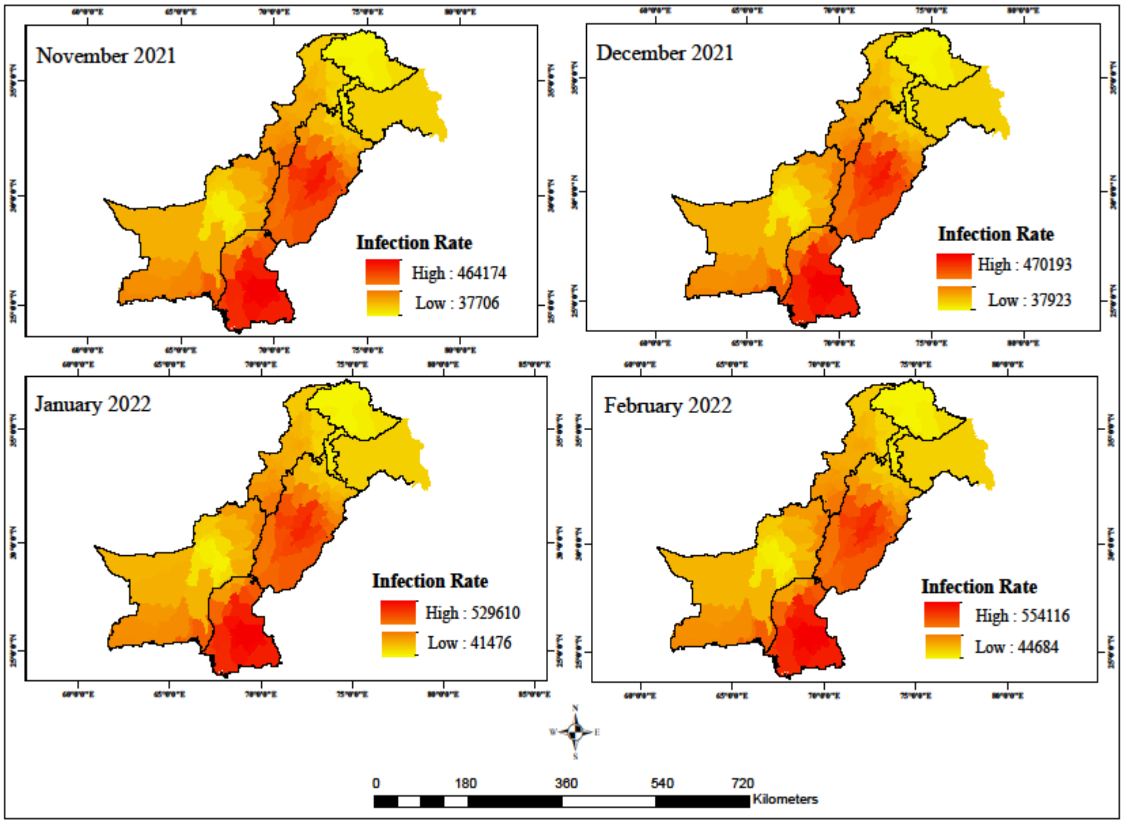

Figure 7: Spatial Distribution of Total Cases of Covid-19

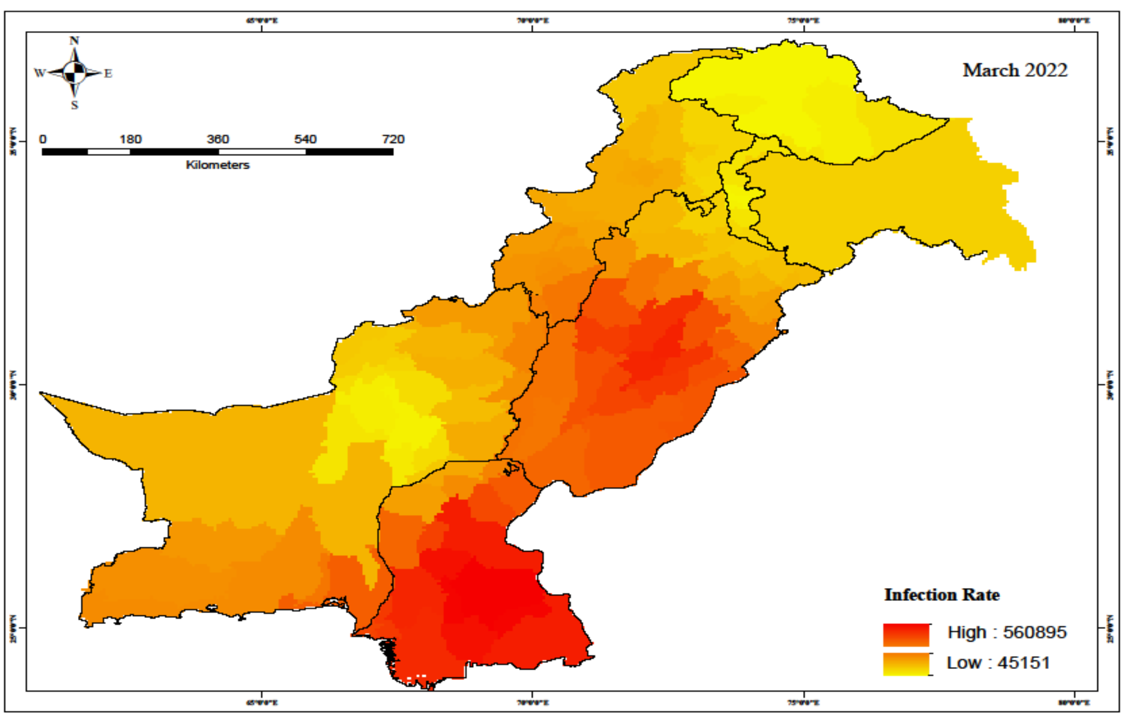

Figure 8: Spatial Distribution of Total Cases of Covid-19

A substantial variation in climatic factors was observed over Pakistan during the lockdown period. The results show a clear distinction between climatic factors before and after the lockdown period over the country. In the COVID-19 pandemic during the lockdown period decreasing trend was observed in the monthly district-wise mean of wind speed. In March 2020, the monthly average wind speed decreased to 4.23m/s from 4.38m/s and 4.36m/s compared to March 2018 and March 2019 respectively. A similar trend was also observed during the lockdown period of April 2020. There was a decline in the monthly district-wise average wind speed from 4.66m/s in April 2018 and 4.55m/s in April 2019 to 4.28m/s in April 2020. Figure 9 and 10 represent the spatial distribution of wind speed before the lockdown in March and April 2018 and 2019. Figure 11 shows the spatial distribution of wind speed during the lockdown period of March and April 2020. The monthly district-wise mean wind speed decreased. In May 2020 wind speed was 4.85m/s which decreased from 4.97m/s and 4.91m/s respectively prior to the years 2018 and 2019. Figure 16 shows the spatial distribution of wind speed during the lockdown period of May 2020 and Figure 14 and15 portray the spatial distribution of wind speed before the lockdown period of May 2018 and 2019. In June 2020, the wind speed also decreased due to lockdown from 5.26m/s in June 2018 and 5.14m/s in June 2019 to 4.58 m/s in June 2020. A similar trend was also observed during the 2021 lockdown in the month of May 2021.

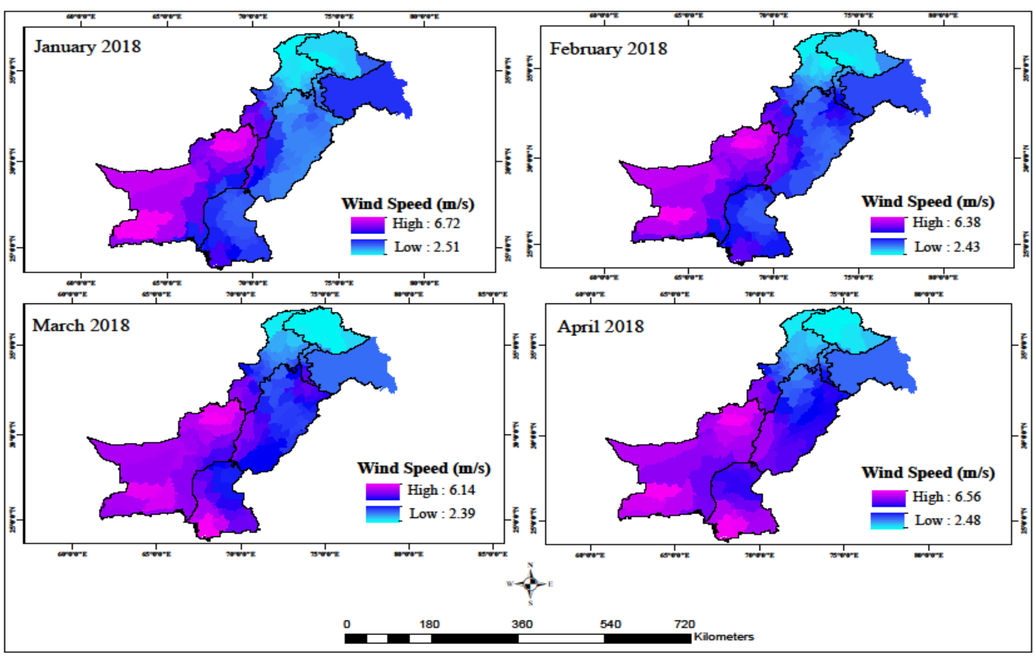

Figure 9: Spatial Distribution of Wind Speed in 2018 before Covid-19 Pandemic

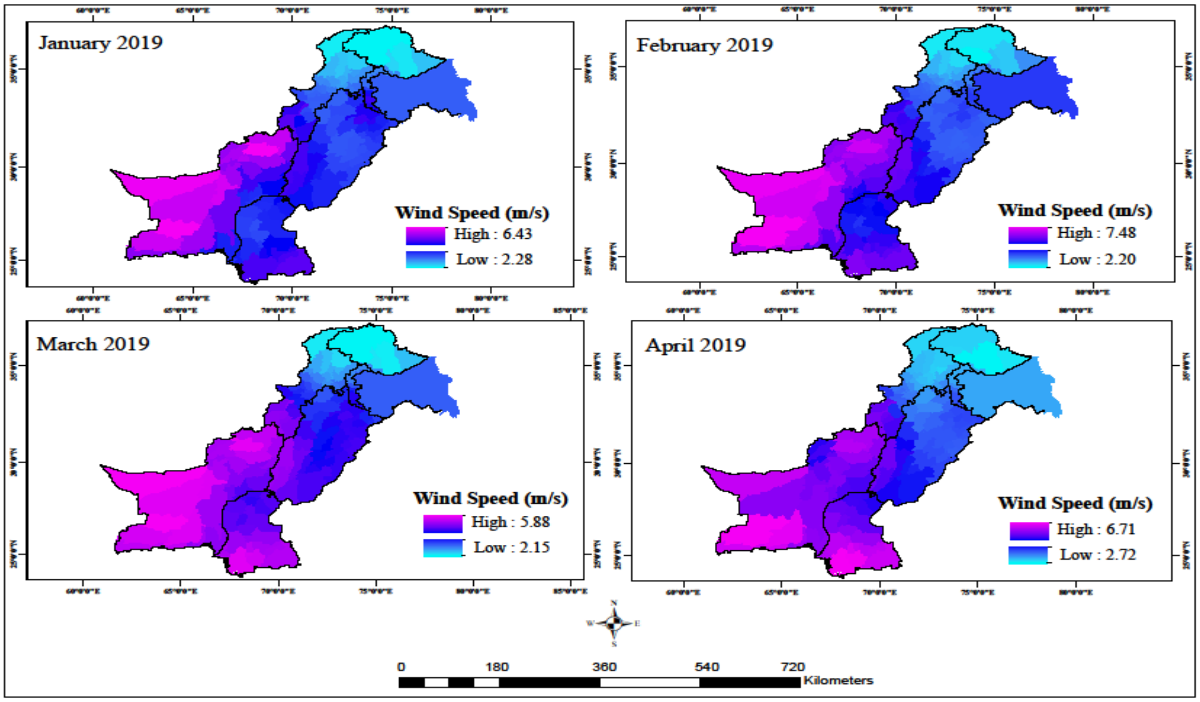

Figure 10: Spatial Distribution of Wind Speed in 2019 before Covid-19 Pandemic

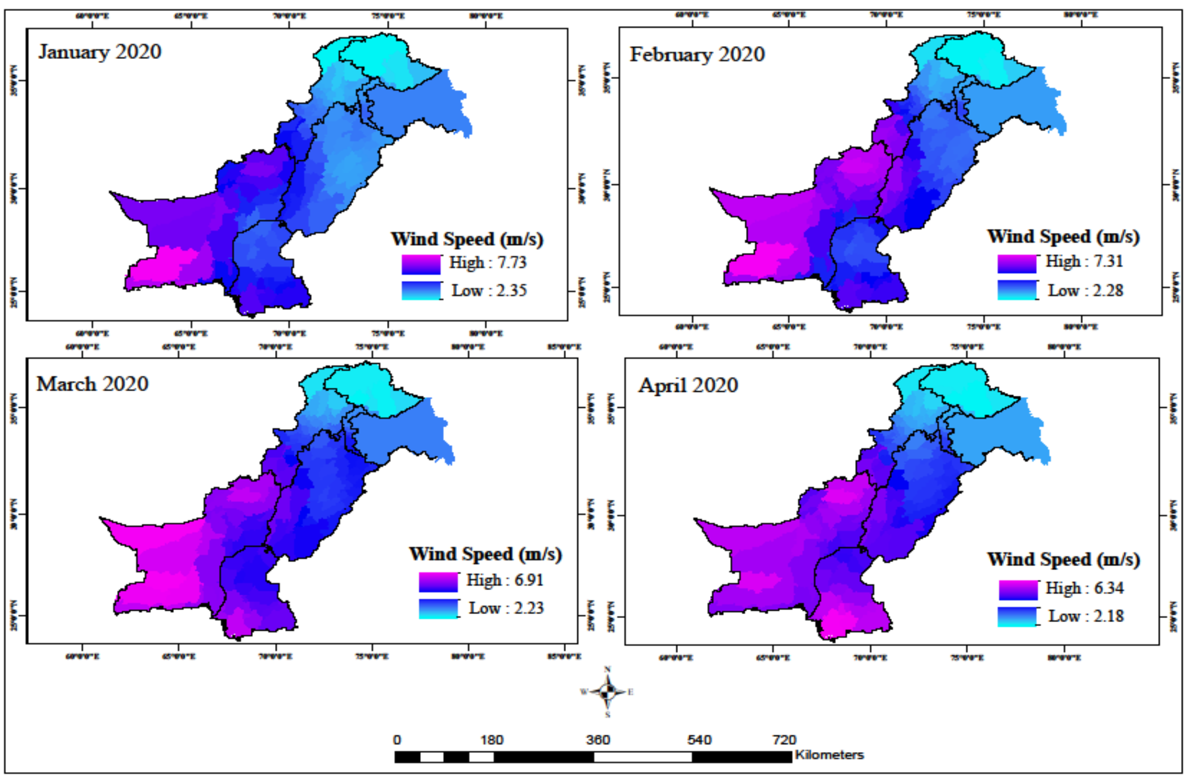

Figure 11: Spatial Distribution of Wind Speed during Pandemic 2020

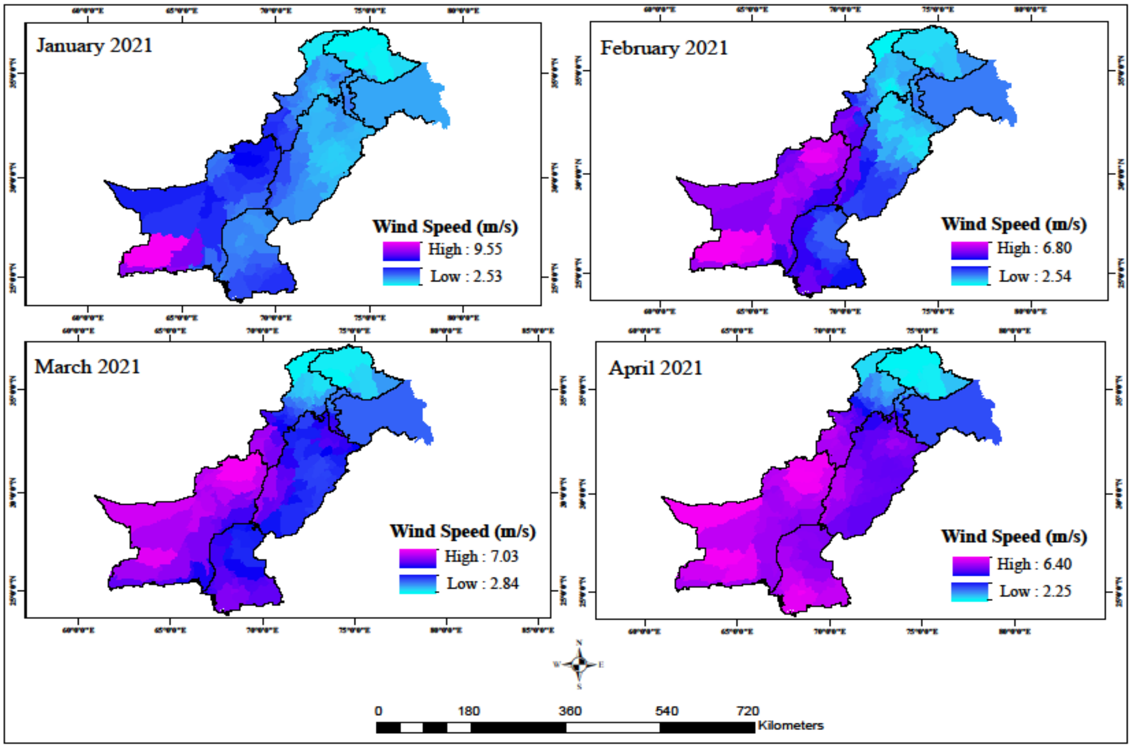

Figure 12: Spatial Distribution of Wind Speed during Pandemic 2021

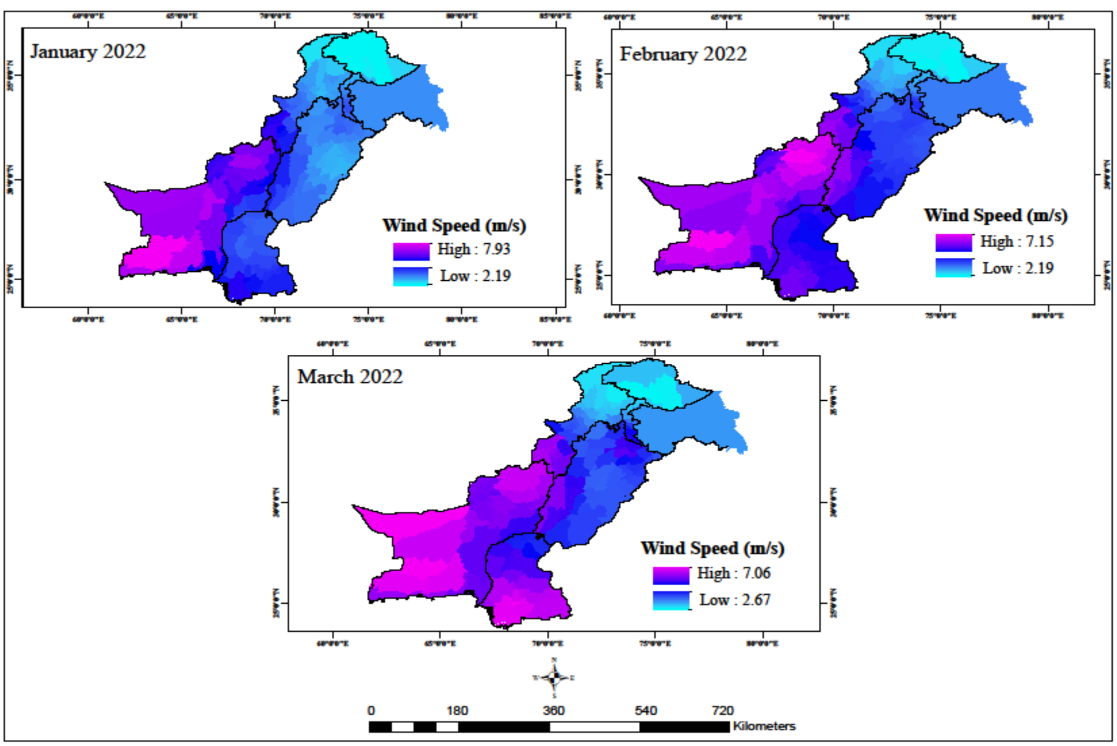

Figure 13: Spatial Distribution of Wind Speed during Covid-19 Pandemic 2022

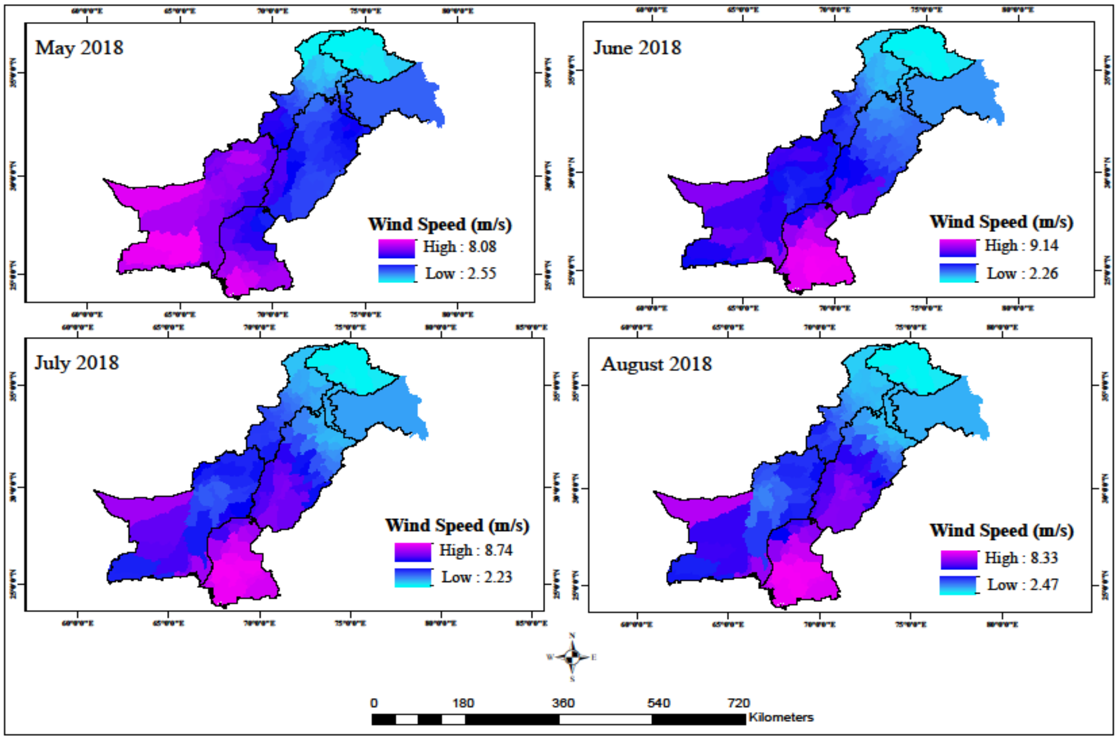

Figure 14: Spatial Distribution of Wind Speed 2018 before Covid-19 Pandemic

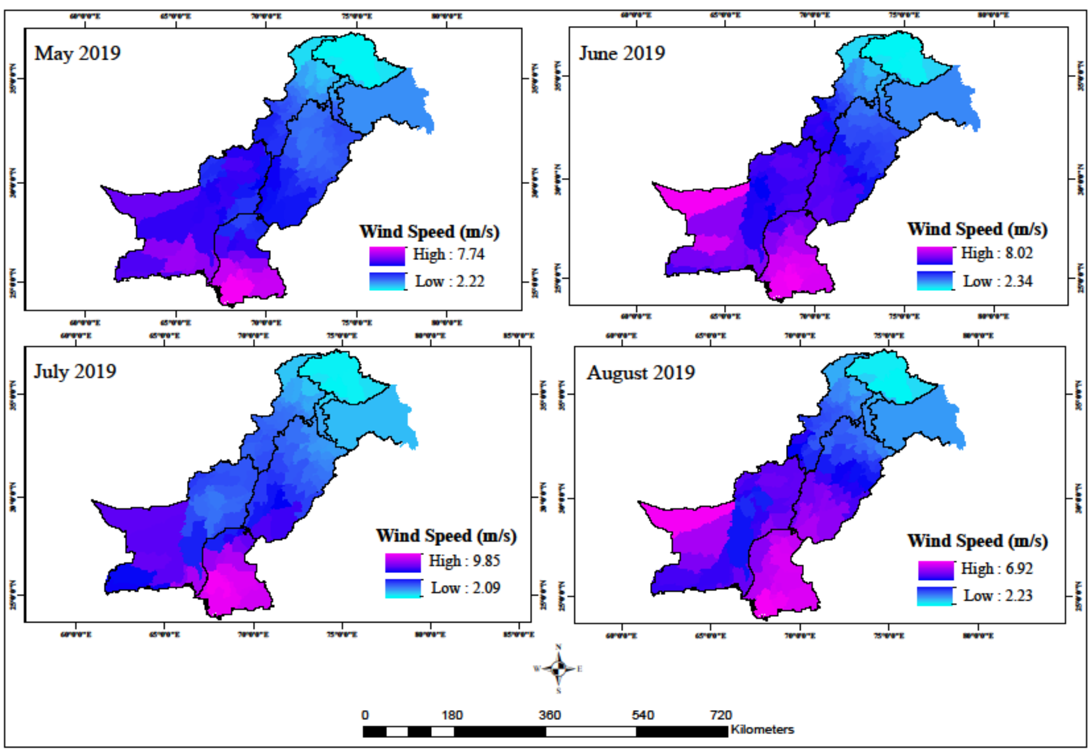

Figure 15: Spatial Distribution of Wind Speed 2019 before Covid-19 Pandemic

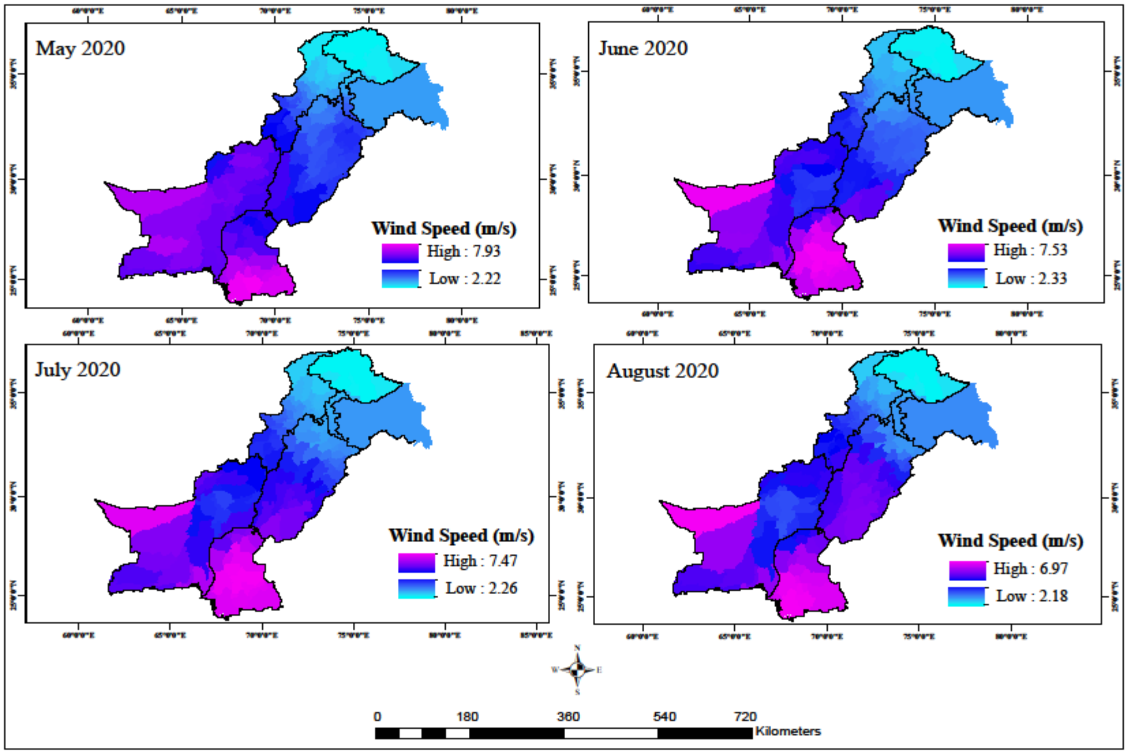

Figure 16 Spatial Distribution of Wind Speed 2020 During Covid-19 Pandemic

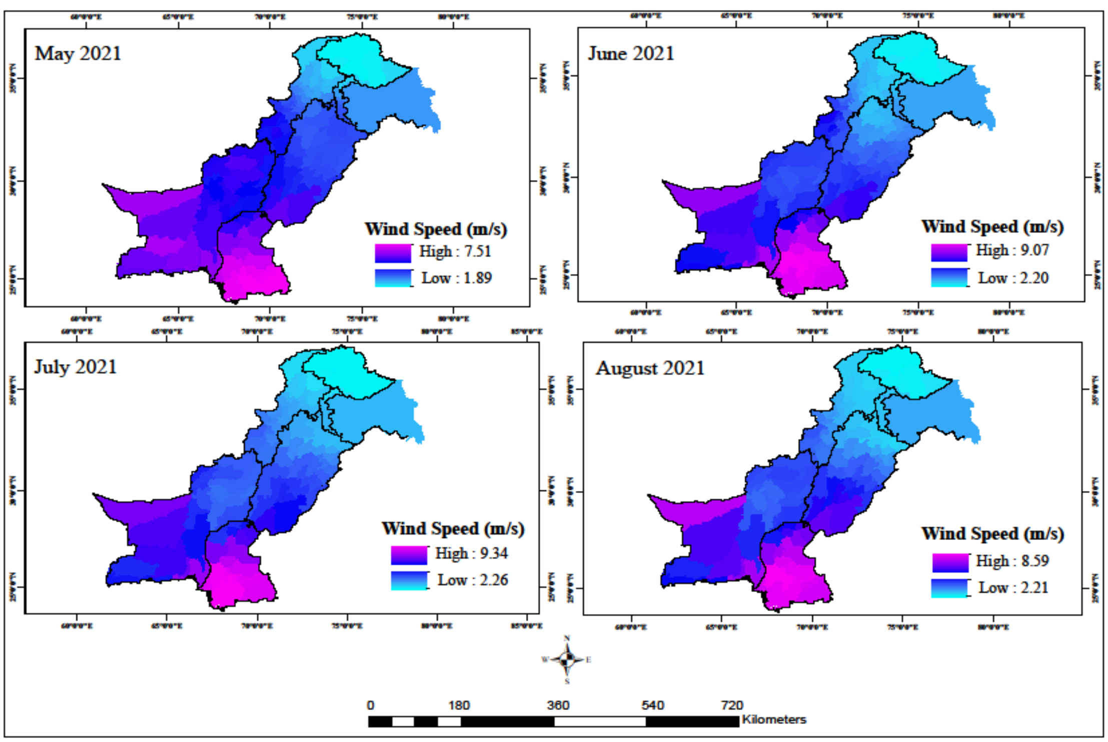

Figure 17: Spatial Distribution of Wind Speed 2021 during Covid-19 Pandemic

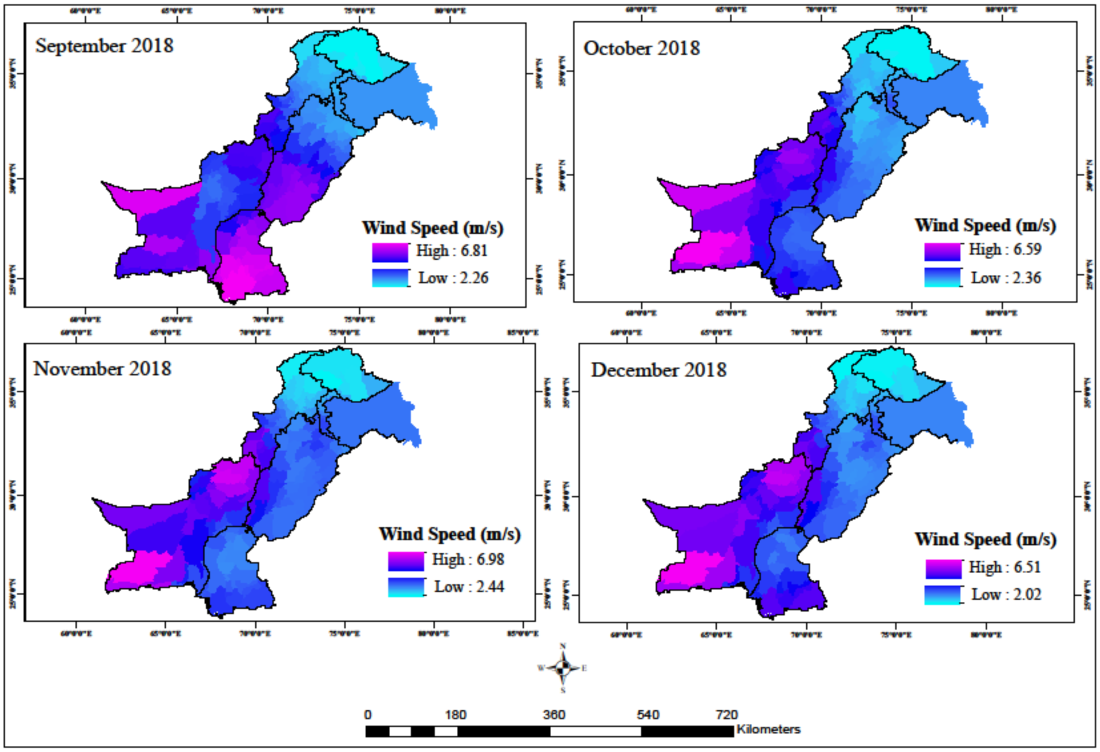

Figure 18: Spatial Distribution of Wind Speed 2018 Before Covid-19 Pandemic

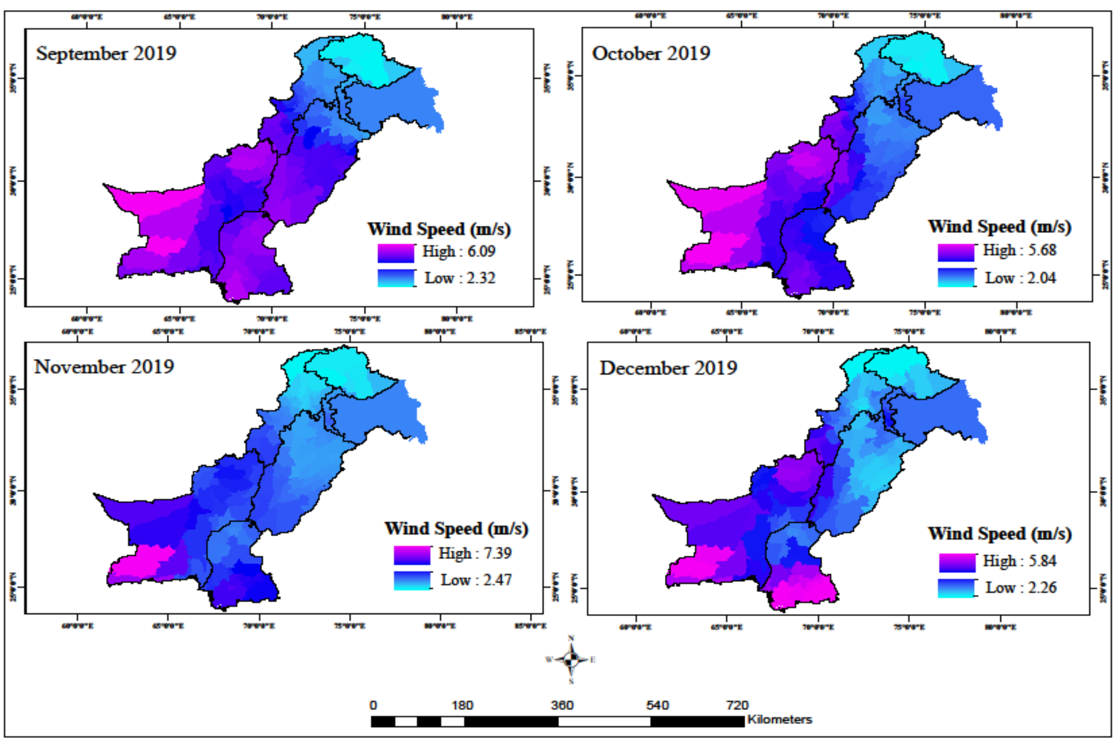

Figure 19: Spatial Distribution of Wind Speed 2019 before Covid-19 Pandemic

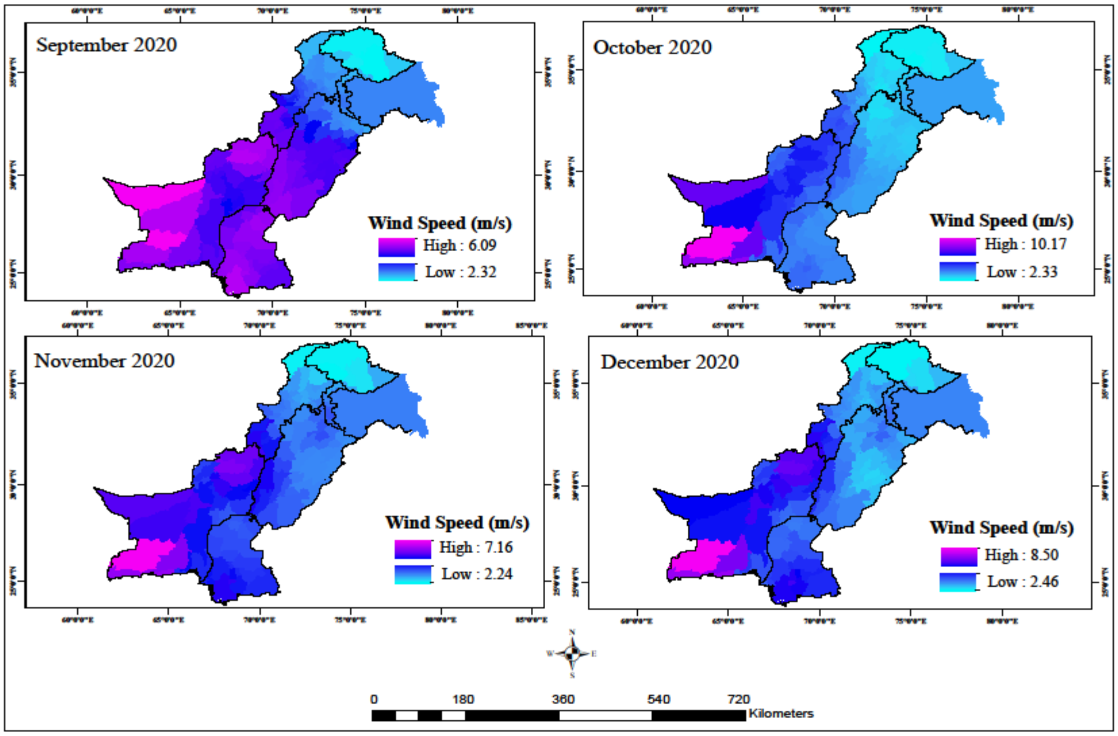

Figure 20: Spatial Distribution of Wind Speed 2020 during Covid-19 Pandemic

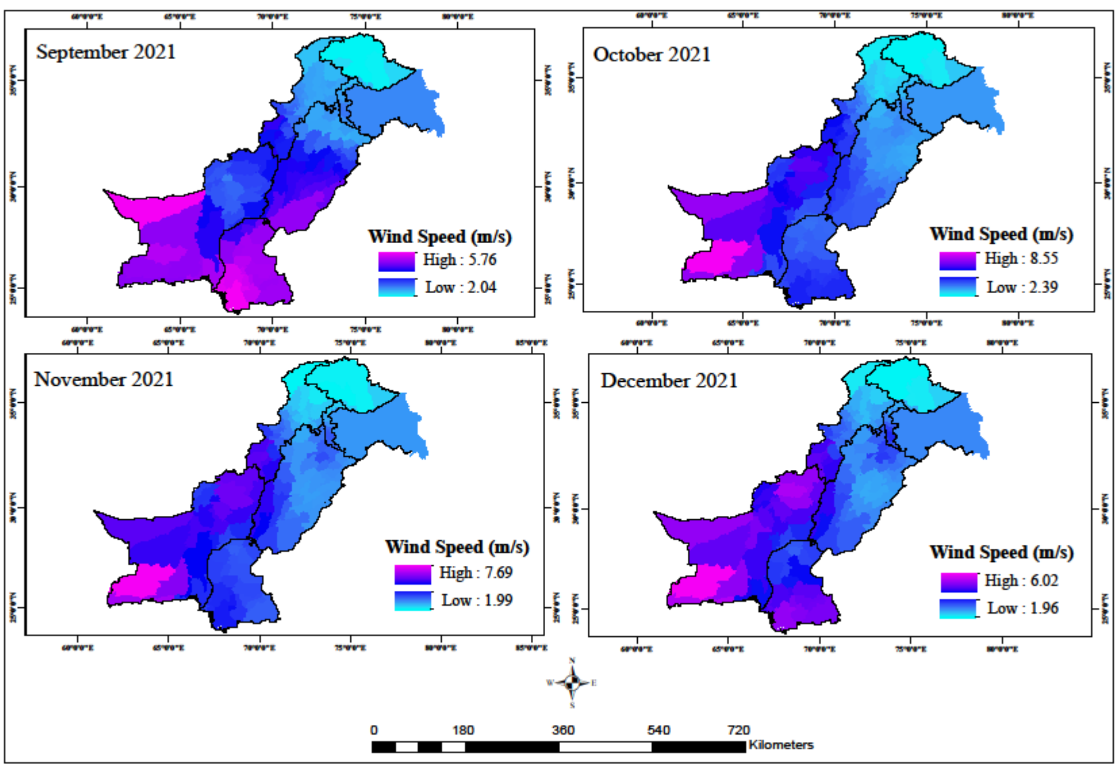

Figure 21: Spatial Distribution of Wind Speed 2021 during Covid-19 Pandemic

Table 4 : Statistics of Wind Speed During Lockdown

Wind Speed (m/s)	2018	2019	2020	2021
March	4.38	4.36	4.23	4.86
April	4.66	4.55	4.28	4.76
May	4.97	4.91	4.85	4.52
June	5.26	5.14	4.58	4.91

Figure 14 and 15 show wind speed distribution before the lockdown period of May 2018 and 2019. The monthly district-wise mean wind speed decreased in May 2021 (decreased to 4.52m/s May 2021 from 4.97m/s in May 2018 and 4.91m/s in May 2019. Figure 17 depicts the spatial variation of wind speed during the lockdown period of May 2021. After June 2020 again contrasting variation was observed in the values of wind speed this was because of the loosening of the lockdown. From the obtained results variations in wind speed were very clear during the lockdown period. Figure 9, 10, 14, 15 18 and 19 depict the spatial distribution of wind speed before the COVID-19 pandemic of 2018 and 2019 respectively. Figure 11, 12 16, 17, 20 and 21 show the spatial distribution of wind speed during the COVID-19 pandemic 2020 and 2021, sequentially. Similarly, Figure 13 shows wind speed district-wise distribution during the COVID-19 pandemic from January to March 2022. During the pandemic years 2020 and 2021 the annual average wind speed increased compared to the previous year 2019. Table 4 represents district–wise average of wind speed during the lockdown period of the pandemic.

The reduction in LST during the lockdown period was observed over Pakistan. The results of this study revealed that a 5°C reduction in the district-wise average of LST over Pakistan was observed in the month of March 2020 against the month of March 2018 (from 28°C in 2018 to 23°C in 2020) and as compared to the March 2019 the decline was 1°C (from 24°C in 2019 to 23°C in 2020). Figure shows the spatial distribution of LST over the country during the lockdown of March 2020 compared to 2018 and 2019 March before the lockdown period in Figure 22 and 23 respectively. The decline in LST was also observed in the month of April 2020. Figure 24 portrays the distribution of LST during the lockdown period of April 2020. The month of April 2020 showed a 2°C negative anomaly in LST against April 2018 (from 33°C in 2018 to 31°C in 2020) and as compared to the 2019 the decline was 1°C (from 32°C in 2019 to 31°C in 2020). Figure 22 and 23 depict the spatial distribution of LST before lockdown in April 2018 and 2019 sequentially. The decline in LST was also noticed in the month of May 2020 and LST had shown a negative anomaly of 1°C compared to the May of 2018 and 2019 (from 38°C to 37°C in both years 2018 and 2019). Figure 29 depicts the spatial distribution of LST during the lockdown period of May and June 2020. Figure 27 and 28 depict the distribution of LST before the lockdown period of May and June of 2018 and 2019 respectively. A decrease in the month of June 2020 was also noticed. The LST decreased 1°C in June 2020 compared to previous years 2018 and 2019 (from 38°C in June 2018 to 37°C in June 2020 and similarly in June 2019 from 38°C to 37°C). The same pattern was also remarked for LST in the month of May 2021 because of the lockdown and LST had shown a negative anomaly of 1°C as compared to 2018 and 2019 (from 38°C to 37°C in both years 2018 and 2019). Figure 30 shows the spatial distribution of LST during the lockdown period of May 2021. The drop in LST could be associated with lockdown or generally cooler weather. After the month of June 2020, we again started to observe the increase in LST because of the loosening of the lockdown that increased the anthropogenic activities. Figure 22, 23, 27, 28 31 and 32 depict the spatial distribution of LST before the COVID-19 pandemic period.

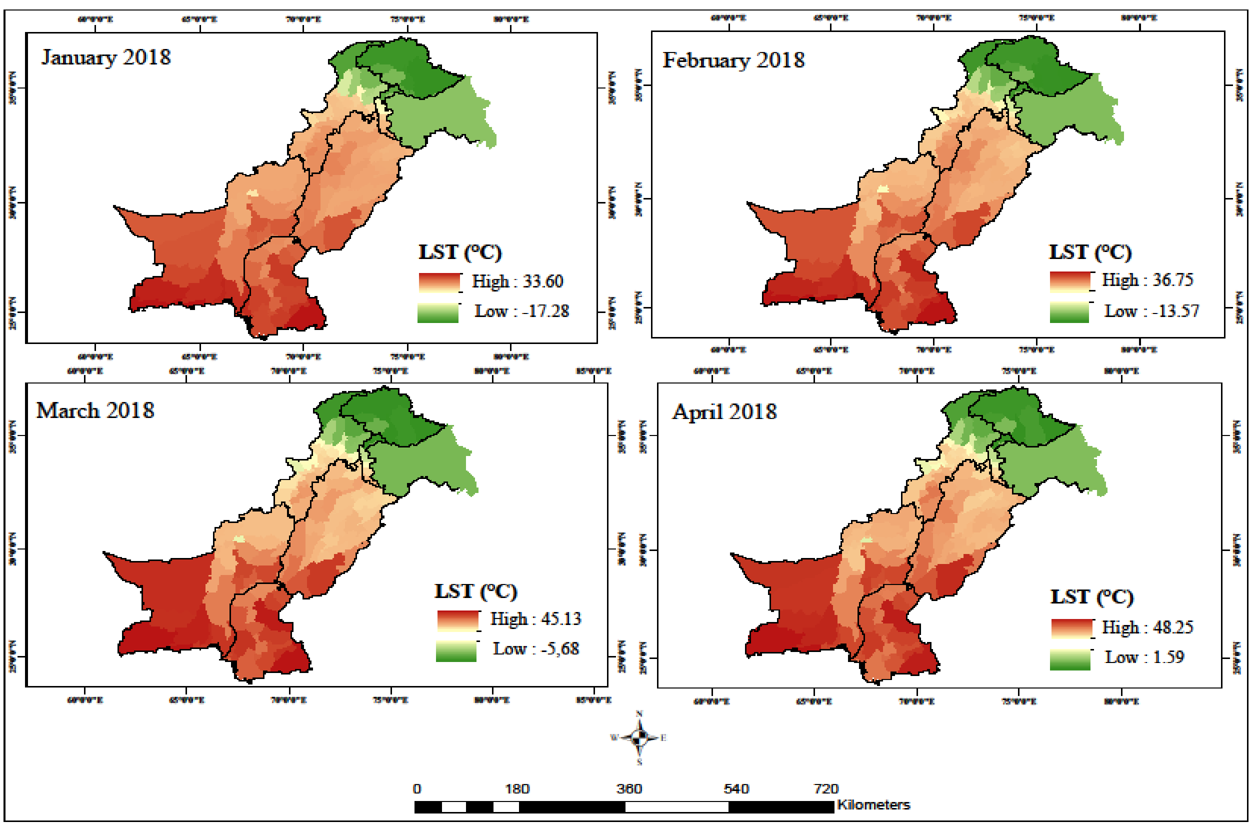

Figure 22: Spatial Distribution of LST before Covid-19 Pandemic 2018

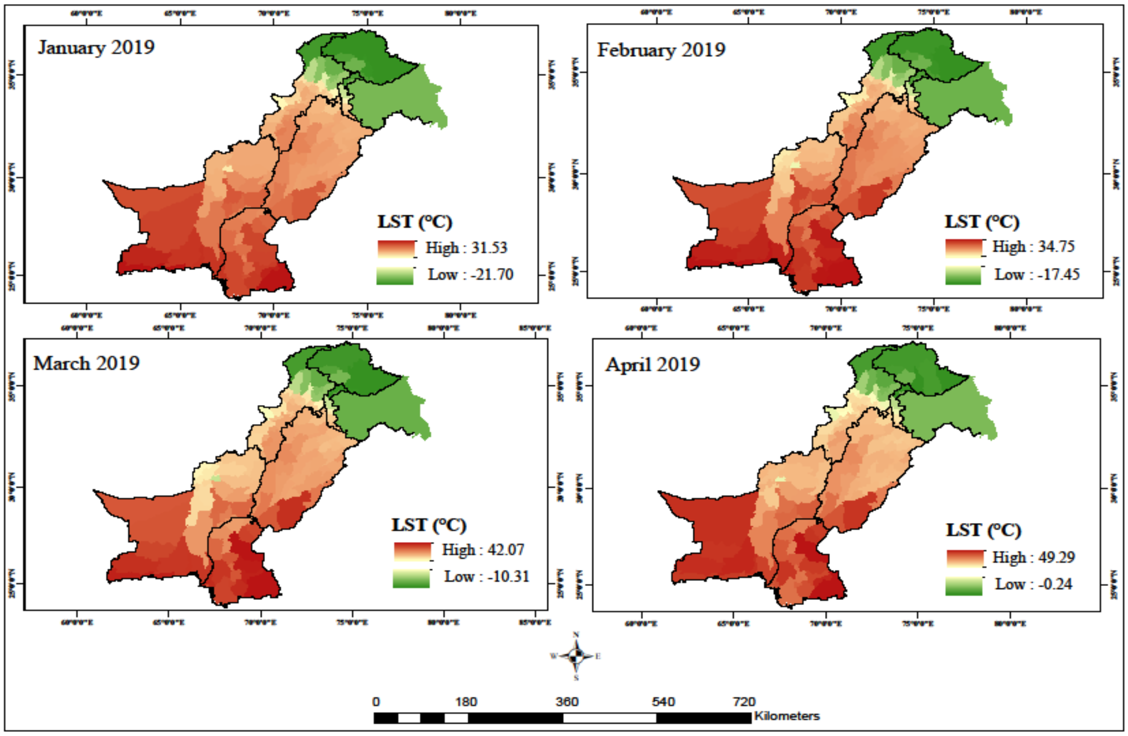

Figure 23: Spatial Distribution of LST Before Covid-19 Pandemic 2019

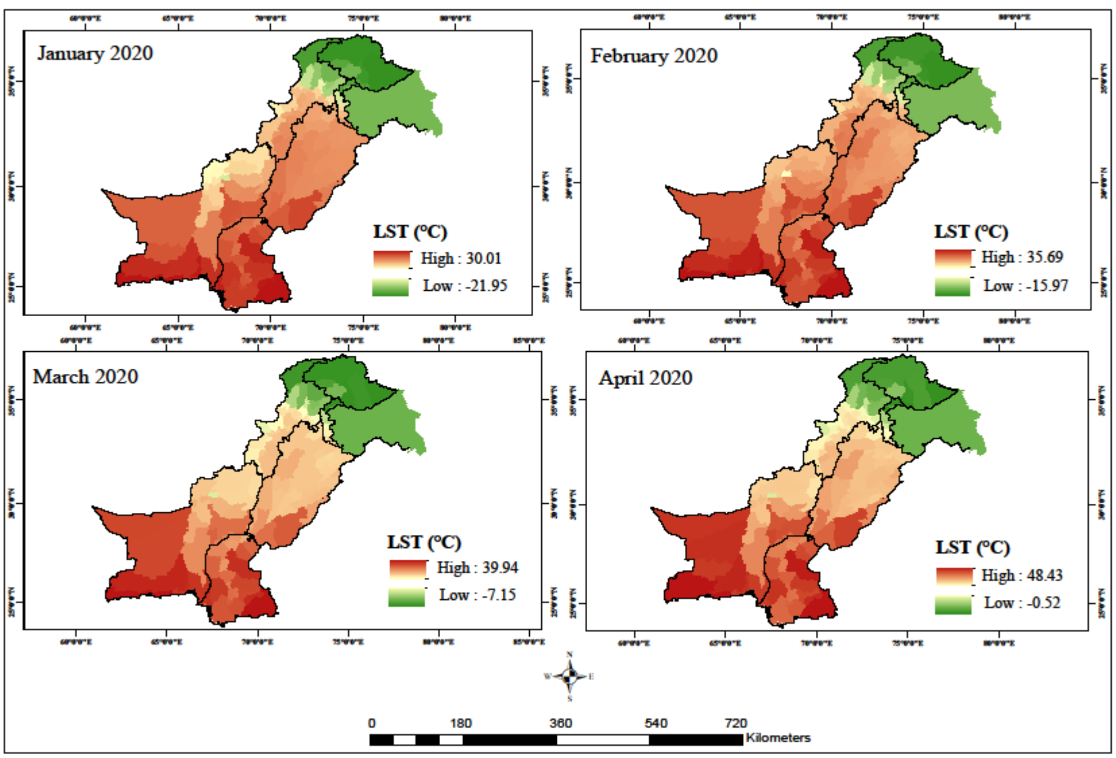

Figure 24: Spatial Distribution of LST During Covid-19 Pandemic 2020

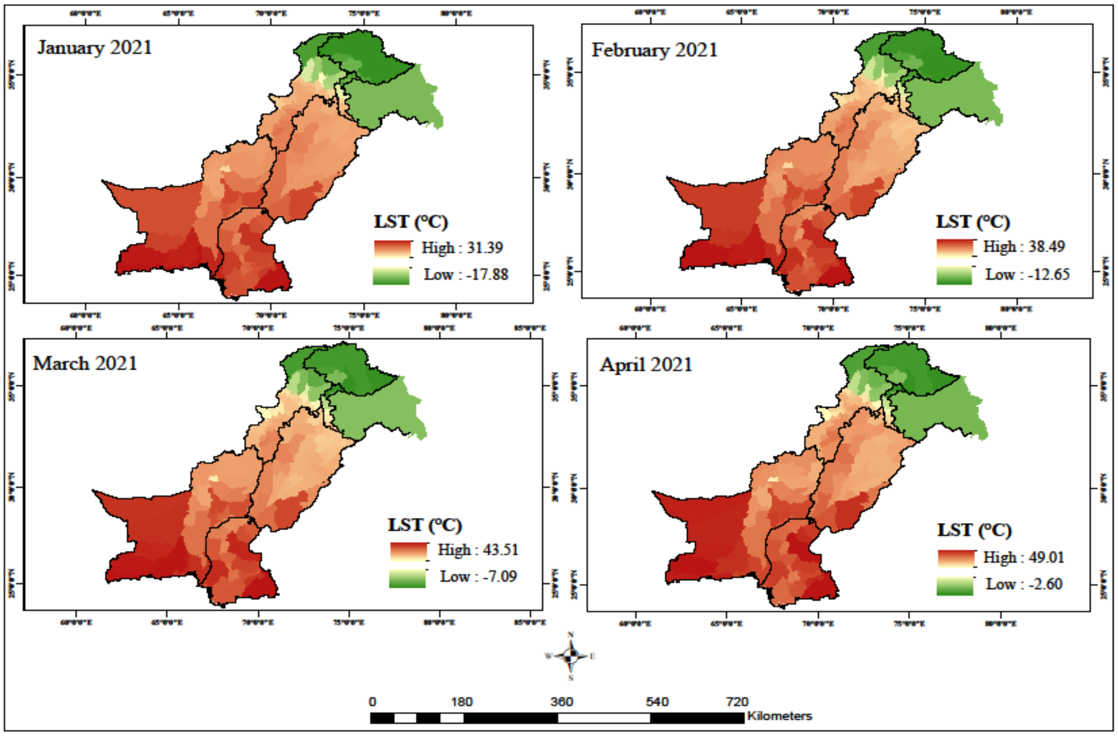

Figure 25: Spatial Distribution of LST During Covid-19 Pandemic 2021

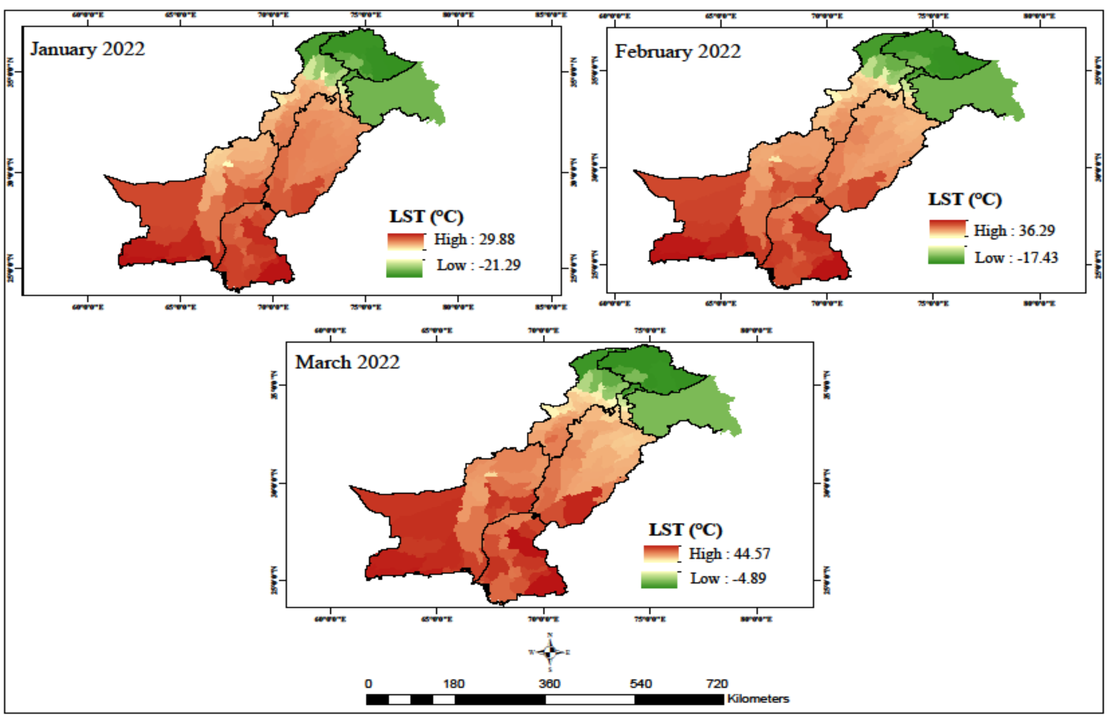

Figure 26: Spatial Distribution of LST During Covid-19 Pandemic 2022

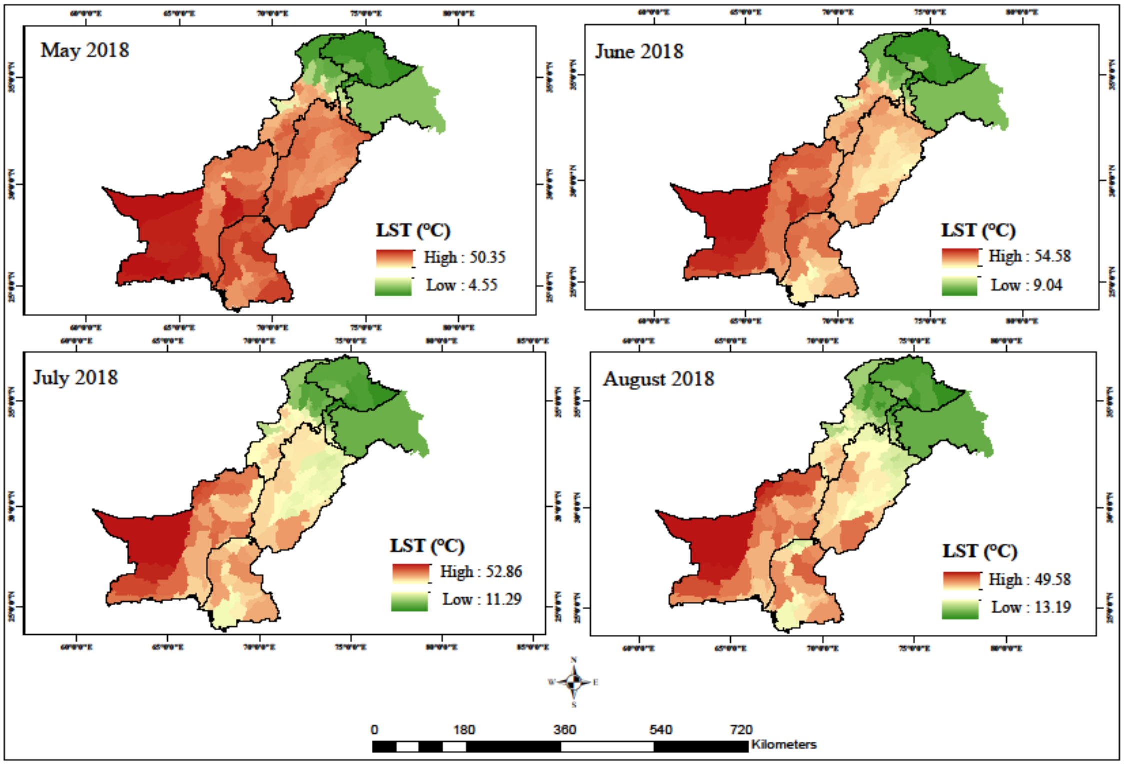

Figure 27: Spatial Distribution of LST Before Covid-19 Pandemic 2018

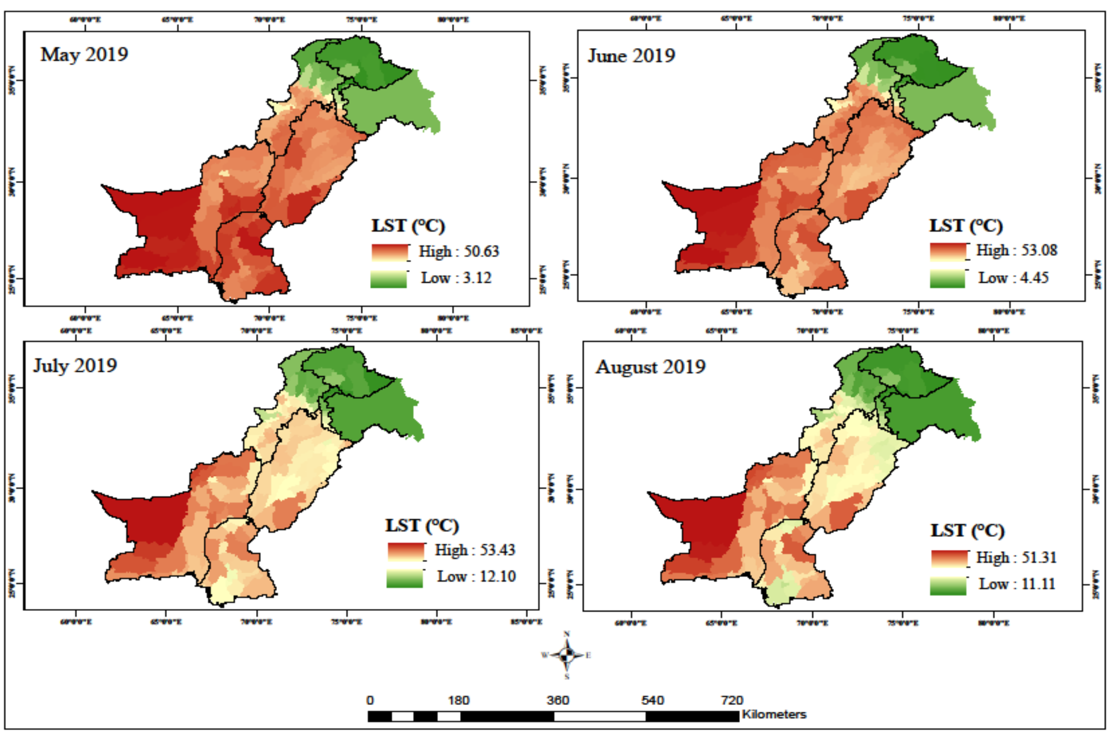

Figure 28: Spatial Distribution of LST Before Covid-19 Pandemic 2019

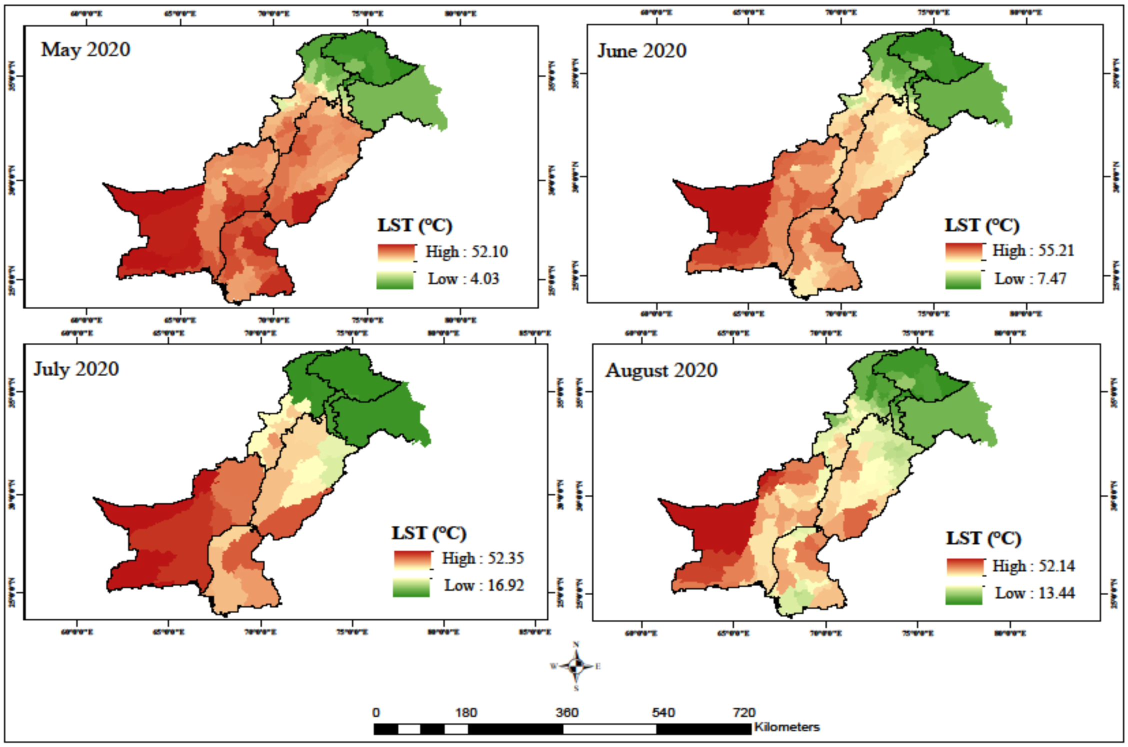

Figure 29: Spatial Distribution of LST During Covid-19 Pandemic 2020

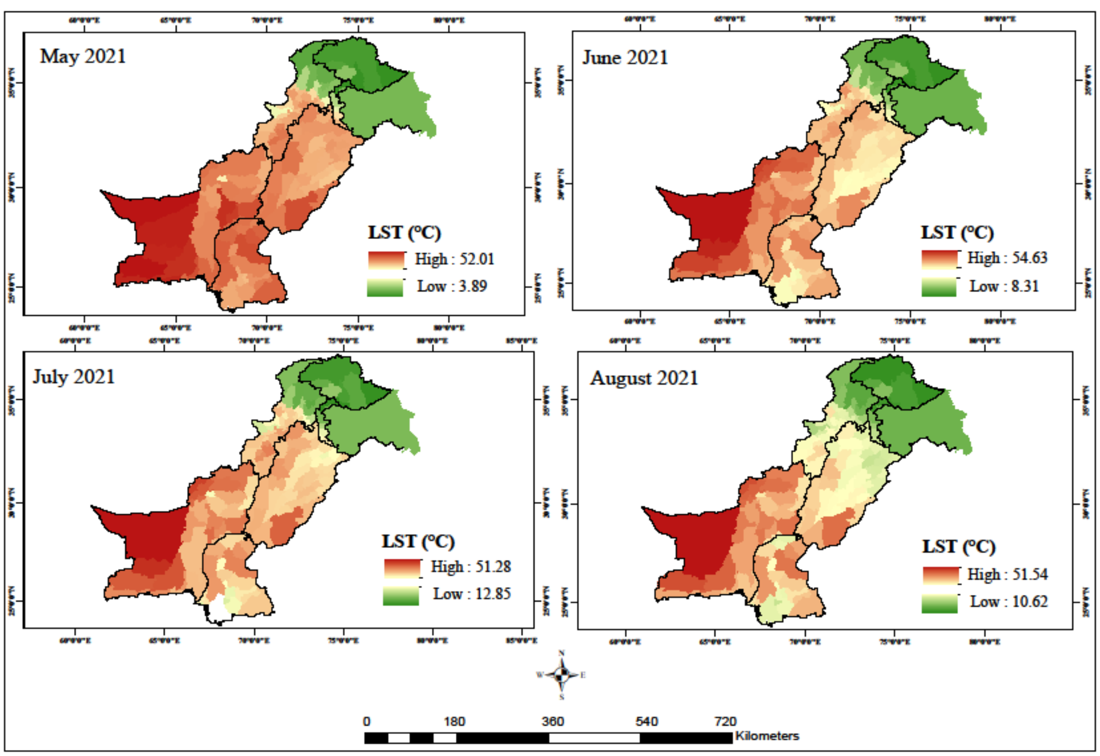

Figure 30: Spatial Distribution of LST During Covid-19 Pandemic 2021

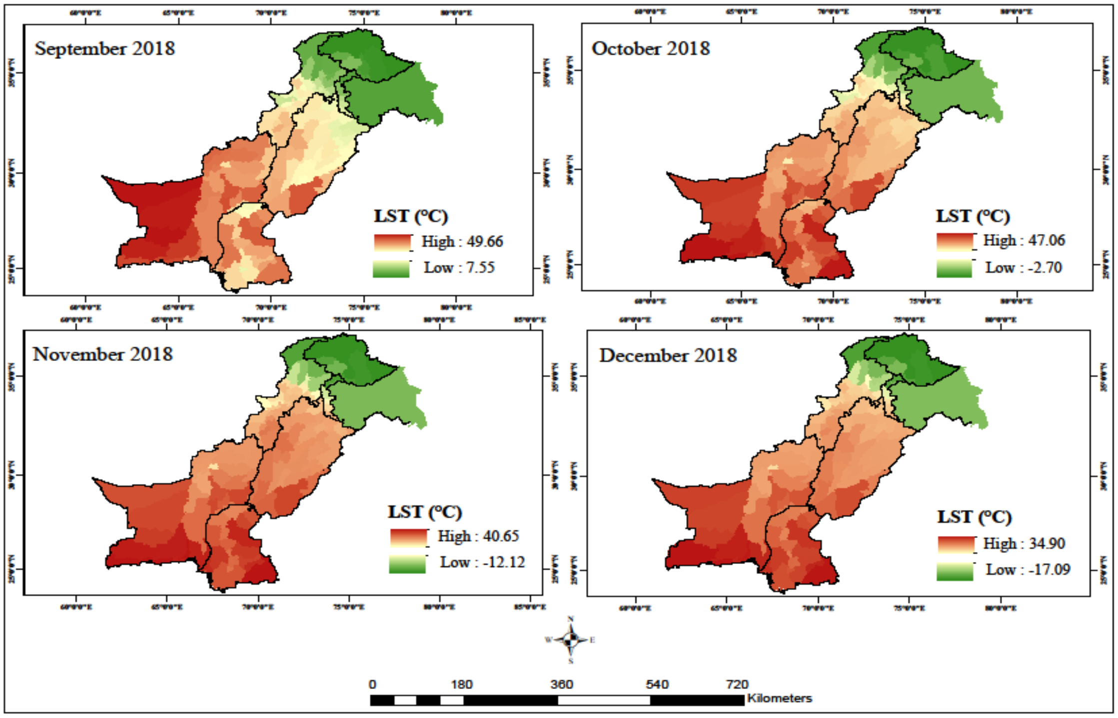

Figure 31 Spatial Distribution of LST Before Covid-19 Pandemic 2018

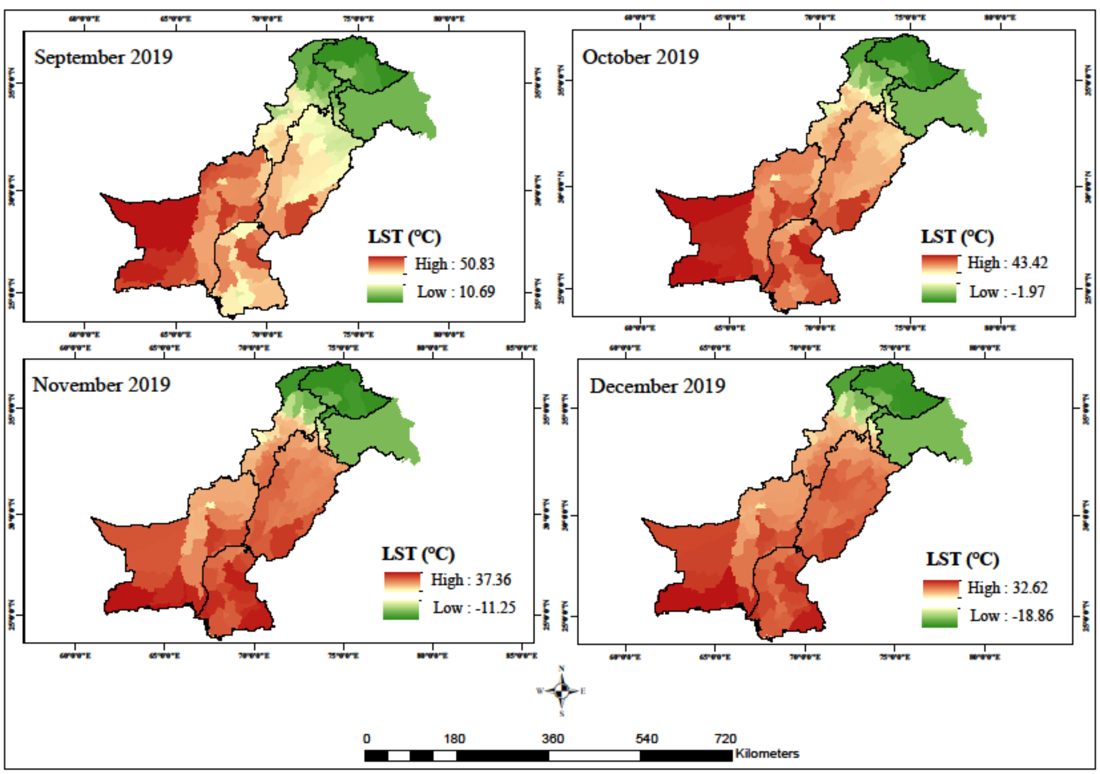

Figure 32: Spatial Distribution of LST During Covid-19 Pandemic 2019

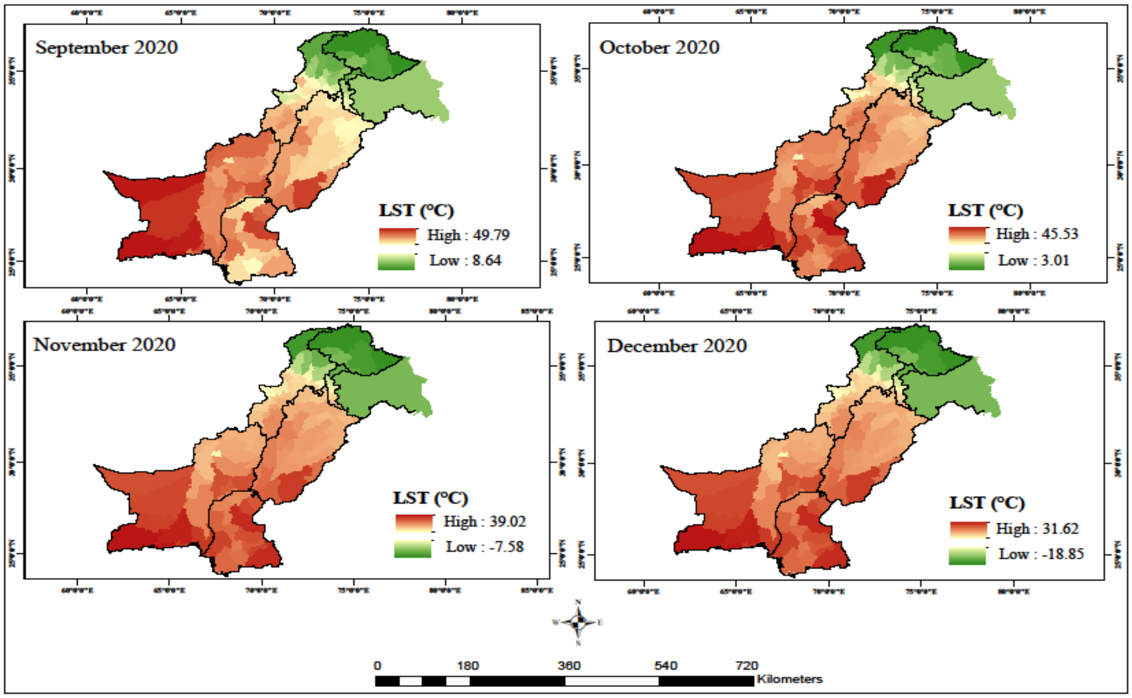

Figure 33: Spatial Distribution of LST During Covid-19 Pandemic 2020

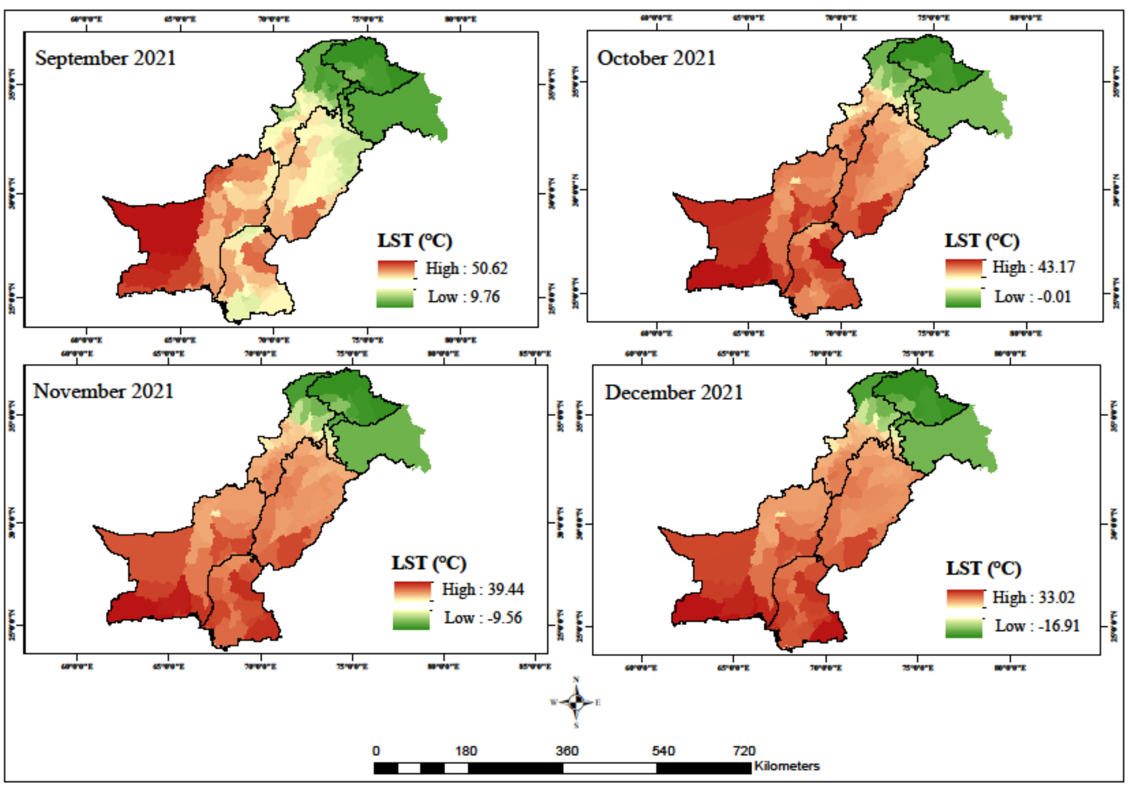

Figure 34: Spatial Distribution of LST During Covid-19 Pandemic 2021

Table 5: Statistics of LST during lockdown

LST(°C)	2018	2019	2020	2021
March	28	24	23	27
April	33	32	31	33
May	38	38	37	37
June	38	38	37	37

The main variations due to the lockdown period were observed during the 2020 pandemic year. Figure 24 and 29 and Figure 33 show the distribution of LST during the pandemic year 2020. The decrease in 2021 was basically due to a generally cooler weather pattern. Figure 25 and 30 and 34 portray spatial distribution during the COVID-19 pandemic of 2021. Figure 26 shows the distribution of LST during COVID-19 from January to March 2022. The variations in climatic conditions are very clear from the obtained results. A decreasing trend was observed during the lockdown period in wind speed and LST. Figure 35 shows the overall condition of selected environmental factors (wind speed and LST of prior years of the pandemic 2018 and 2019. Table 5 represents the district-wise average of LST during the lockdown period.

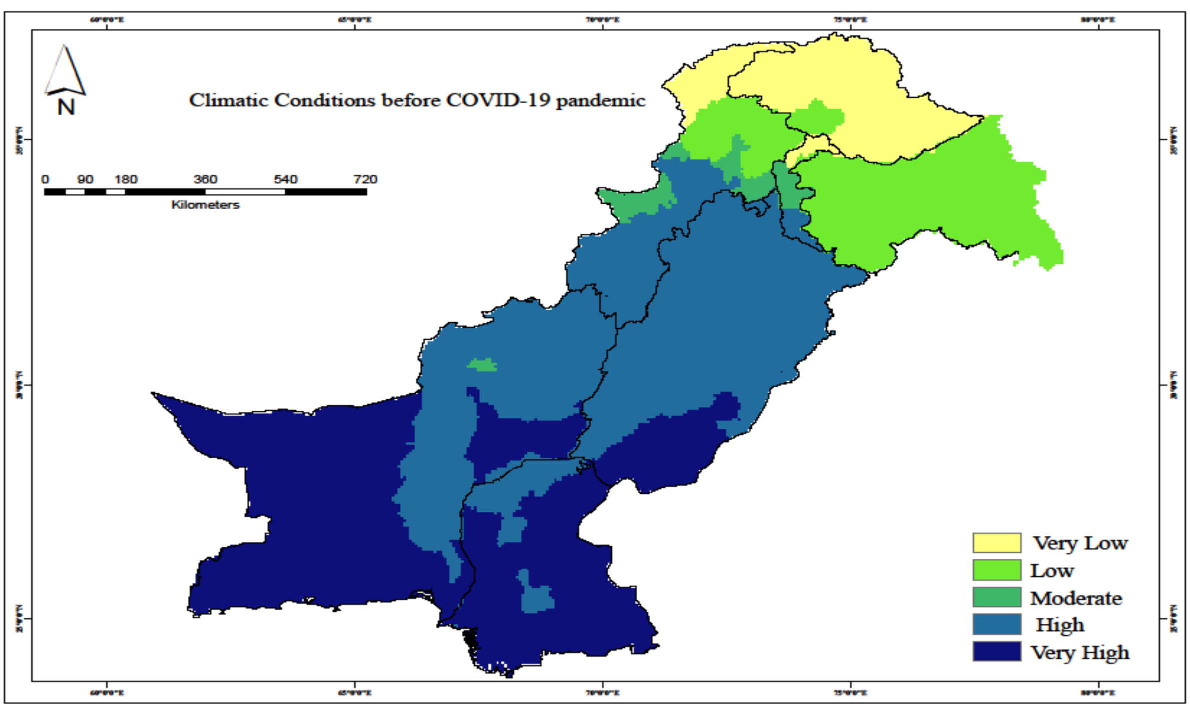

Figure 35: Spatial Distributions of Overall Environmental Conditions before Pandemic (LST, Wind Speed)

Figure 36 depicts how COVID-19 caused changes in climatic conditions during the COVID-19 pandemic in 2020, 2021 and 2022. The changes in climatic conditions were associated with lockdown period during the COVID-19 pandemic and also with a reduction in air pollutants resulting in changes in the trend of climatic conditions.

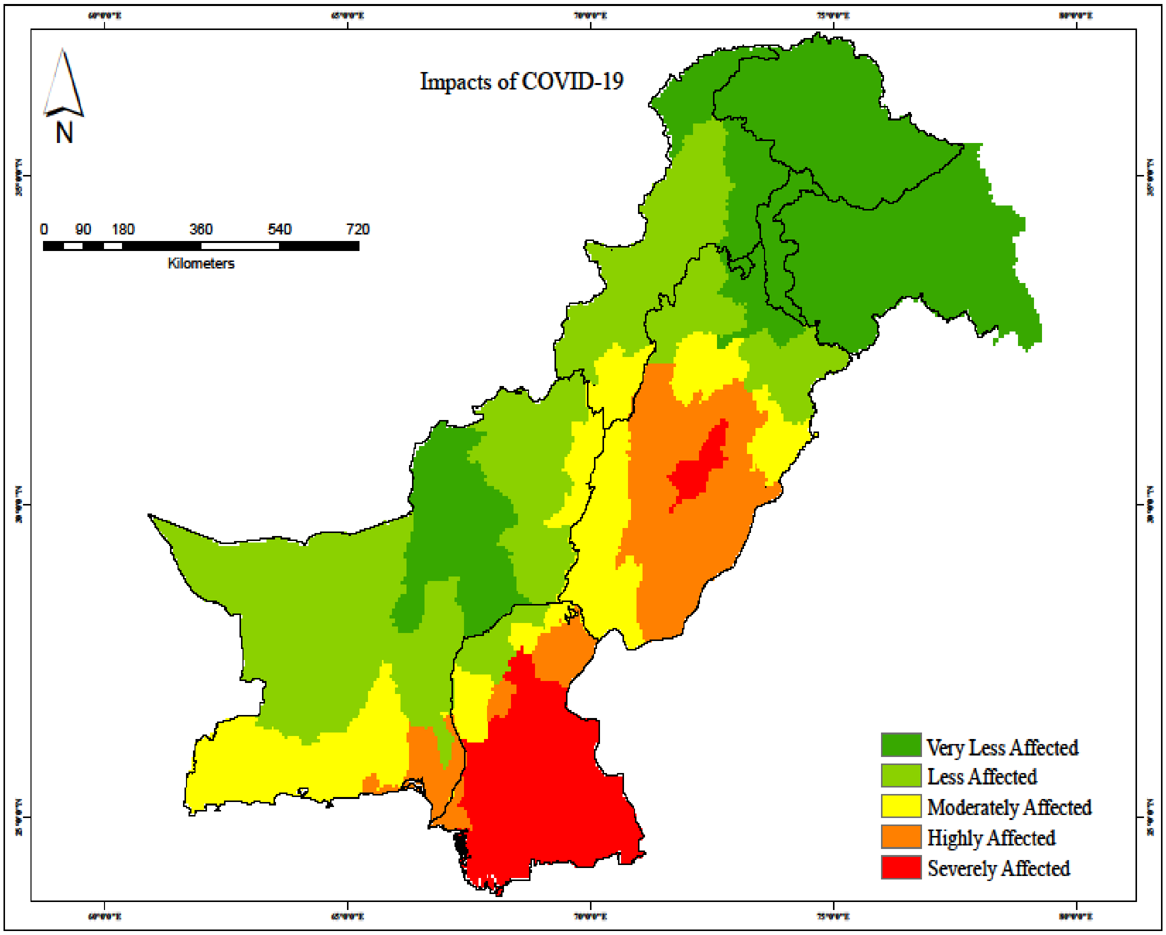

Figure 36: Impacts of Covid-19 on Climatic Conditions

Discussion

In this study the impacts of COVID-19 on environmental conditions and how preventive measures such as lockdown helped to control the spread of coronavirus and caused variations in climatic conditions were assessed over the country. From the obtained results of this research, it could be observed that the most affected province by COVID-19 was Sindh. To limit the spread of COVID-19 the government of Pakistan imposed the lockdown that not only controlled the spread of coronavirus cases but also caused variations in the climatic conditions over the country. The decreasing trend was observed in LST and wind speed in the study domain during the strict lockdown period of 2020 and 2021. These variations in climatic conditions were mainly due to a decrease in anthropogenic activities, restricted transport and closure of industries during the lockdown period of the pandemic. A similar decreasing trend in LST was also observed over different parts of Europe during the lockdown period (Parida et al., 2021). The similar decreasing trend in wind speed was also observed over the different cities of India (Navinya et al., 2020). Lockdown policies during this pandemic around the world had led a way to explain human effects on the environment. This research is of great help to understanding the variation that occurred during the COVID-19 pandemic because this study is based on long-term data analysis and discussed all lockdown periods during the COVID-19 pandemic. And in this study, only secondary data is used and only statistical analysis is performed to understand the impacts of COVID-19 on environmental conditions at district level. In the future more, advanced satellite data can improve the results and ground-based data on metrological factors can be more useful to compare variations for this kind of research paper.

Conclusion

This study provides the impacts of COVID-19 on climatic conditions in Pakistan. The COVID-19 epidemic had improved temporarily climatic conditions around the world, owing to the large-scale reduction in human activities, transport, and industrial activities which caused positive changes in environmental conditions. The results of the present study showed a generally decreasing trend in LST and wind speed around the country during the lockdown period of the pandemic was observed. The variations were mainly due to lockdowns, limited transport and reduction in industrial production. These climatic factors and anthropogenic emissions returned to their standard levels as the government removed the preventive measure such as lockdown and restrictions on transport and also resumed industrial activities. However, this study provides improvements in climatic conditions can be achieved by adopting sustainable usage of transport and industrial production. Furthermore, only secondary data of climatic factors is used in this research to understand the impacts of COVID-19 on climatic conditions over the country. By using ground-based data for comparison the obtained results could be more accurate.

Recommendations

• The officials of government should make policies such as a brief lockdown and sustainable production of industries to control the concentration of atmospheric pollutants resulting in improvements in environmental conditions.

• The officials should take preventive measures to reduce fossils fuel usage resulting reduction in aerosol concentrations. This will cause positive changes in environmental conditions.

• The most significant outcome of this study is to suggest to policymakers and officials that such purposeful actions to reduce atmospheric pollution and even population density in cities can have serious consequences for human life.

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Authors' contributions

The authors declared that this research was done by the both authors named in this manuscript and all liabilities pertaining to claim relating to the content of this article will be borne by both of them. Hazeema Mumtaz conceived the research and drafted the manuscript. Kanwal Javid revised the manuscript. Both authors performed a review of the manuscript before approving its publication in this journal.

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Competing Interests

The authors declare that they have no competing interests.

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