DEVELOPING A MULTI-VARIABLE FOREST FIRE RISK MODEL AND FIRE RISK ZONE MAPPING

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KEY WORDS: Forest fire risk, multi-variable, DEM, spatial data analysis.

ABSTRACT:

Forest steppe and taiga regions with a dry climate, small fires occur frequently between large fires, and therefore groups of trees of various ages and structures are formed in these forests, which has the effect of increasing fire exposure and "fuel reserves". The main goal of this research is to develop a multi-variable forest fire risk model and to mapping forest fire risk. The study area is the forest community in Bulgan province. Forest cover maps are essential for current research of community. We used in this research Landsat OLI and Digital Elevation Model (DEM) data. Soil moisture index and land surface temperature data from Landsat satellite data and elevation data (DEM) were used to determine slope and aspect. A multi-variable forest fire risk model was developed in this research. The final output delineated fire risk zones in the study area in four categories that include high-risk, moderate-risk, low-risk, and non-fire risk zones. Accuracy assessments on the two Landsat scenes indicates that forest/non-forest maps derived using the forest index (FI) have high accuracy.

1. INTRODUCTION

Forests are playing an important role in maintaining the balance of ecosystems and mitigating climate change. For Mongolia, which is warming faster than the global and regional climate, it is one of the pressing issues to calculate the depletion and degradation of forest resources and implement a proper management policy (Amarsaikhan 2004, Augusto and Boča 2022). Mongolia is located in the transitional zone between Central Asian deserts and the Siberian Boreal Taiga Forest, and it is divided into six primary biogeoclimatic zones, with more than half of the total land elevation exceeding 1,400 meters above sea level (Batkhuu, Lee and Tsogtbaatar 2011). Mongolian forests are defined as mountain forests that grow in the extreme climate of Central Asia, have limited natural regeneration capacity, and are easily affected by fire-damaging insects and human activities. 8.1% or 12.7 million ha of Mongolia's land area is covered by forests, and due to the negative impact of human activities, forest resources are decreasing, and the quality and rank of forests continue to decrease (Yangiv, 2008). In the last 40 years, Mongolian forests have been affected by fires and harmful insects, 1.4 million ha have been lost due to inappropriate human activities, 30% of the forest ecosystem has been affected by human side effects, and it is believed that the quality of forests has deteriorated. Forest reserve areas in Mongolia include forest cover, forest gaps, logging areas, areas affected by fires, pests, and diseases, areas up to 100 meters from the edge of the forest, areas where seedlings and saplings are grown, and tree nurseries. Forest area is divided into two categories: forest area and non-forest area (Nyamjav, Goldammer and Uibrig 2007, Chuluunbaatar 2001).

Forest fire (wildfire) is a vital issue of environment for creating natural disaster and socioeconomic damage to affect in ecosystem and human lives. Fires usually occur in dry ecosystems, typically in steppe and grassland area, when are uncontrolled wildfires outbreak due to the physical or natural events and human actions. Fire is a natural factor in many climates with high levels of vegetation stress (Zhao, et al. 2021, Sivrikaya and Küçük 2021). In forest steppe and taiga regions with a dry climate, small fires occur frequently between large fires, and therefore groups of trees of various ages and structures are formed in these forests, which has the effect of increasing fire exposure and "fuel reserves". The wildfire for Mongolia, especially the northern and eastern part of area has been frequented the wildfire occurrence in every dry season of the last years. It was caused by increasing accumulation of the fire impact to the environment and natural resources (Nasanbat, et al. 2020). According to the Forest Research and Development Center (FRDC), the total area burnt is 1.7 million hectares or 13 percent of Mongolia's total forest area. 10 Burned areas account for approximately 88 percent of the degraded forest and are more vulnerable to insect pests and increased grazing pressure (FRDC 2017).

Remote sensing is one of the most significant instruments for studying and detecting forest fires (Payra, Sharma and Verma 2023). Using remote sensing imagery to monitor forest fires over broad areas has become both cost and time effective. As a result, forest fire assessment and mapping are critical for reducing the impact and frequency of fire episodes (Lin, et al. 2023, Qadir, et al. 2021). Forest fire prediction analyses and predicts the combustion hazards of combustible things in the forest by combining weather parameters, geography, dryness and categories of flammable items, and ignition sources. Although it is hard to control forest (wild) fires, a forest fire danger map helps identify and minimize high-risk locations (Ghali and Akhloufi 2023, Payra, Sharma and Verma 2023).

Forest cover change analysis Researchers Chengquan Huang and Kuan Song (Chengquan Huang, 2008) Landsat 1990 and 2000 forest cover change maps by region. It investigated the possibility of automatically identifying forest area in satellite data using forest peak threshold values for each channel. Also, in 2014, researchers such as Wentoa Ye, Xi Li, and Guo Zhang studied boreal forests in the temperate zone by determining the forest index FI for forest cover mapping (Ye, Li, Chen, & Zhang, 2014). Based on the results of the study, the forest index was formulated so that pixels with forests have a positive high value, while pixels without forests have a low value. Also, Grabska's colleagues (Grabska, Hostert, Pflugmacher, & Ostapowicz, 2019) used the short time frequency of high-resolution Sentinel-2 data to study

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forest types and species, and it is widely used in monitoring studies.

There is need to identify a method of forest fire risk model and hazard to enable the sustainability of the natural resources. The aim of this study is to investigate research is to develop a multi-variable forest fire risk model and to mapping forest fire risk. To achieve this goal, the following objectives were set:

I. To determine the variables of the forest fire risk and to create maps for each of the factors influencing forest fires,
II. Calculate the impact of multiple factors by mapping each of the influencing factors into risk levels.
III. To map forest fire risk in Khanbuyan community of Bulgan province.

Further research will focus on forest fire risk assessment will be studied in the study area.

2. STUDY AREA AND DATA SETS

2.1 Study area

The study area is KhanBuyan community, Khangal soum, Bulgan province, which located in Northern part of Mongolia (Figure 1). Bulgan province is situated in the northern part of Mongolia. The north of the province is characterized by alpine forests, gradually blending in the arid steppe plains of the central Mongolian highland. According to the Holdridge life zones system of bioclimatic classification Bulgan is situated in the boreal dry scrub biome (larch, birch, and shrub) where larch is 86.12% and birch is 13.88% (Report 2016). This area has a subarctic climate where the annual average temperature is -1.3 degrees Celsius (29.7 degrees Fahrenheit) and total annual precipitation averages is 278.4 mm (11 inches). According to our survey, the forest in Khanbuyan community covers an area of 11750 hectare and its elevation is between 1260m and 1570m. The research region is part of Mongolia with humid cool summers and cold winters. Average annual rainfall is 310-360 mm, the thickness of the snow cover is not much, and the average air temperature is 29.70C° (Norovsuren B., 2019).

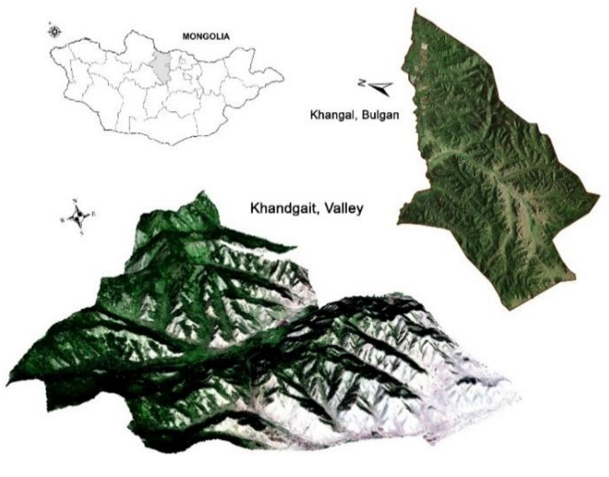

Figure 1. Study area Khangal soum (49°15′ to 49°10′ N and 104°05′ to 104°15′ E).

2.2 Data sets

In this research, we applied Digital elevation model, Landsat satellite images for the forest fire regime mapping in Khangal soum. The research was carried out in August, 2020.

Used data	Accuracy	Year	Source
Digital Elevation Map (DEM) • Slope • Aspect	30м	2020	SRTM data (http://gdem.ersdac.jspacesystems.or.jp/)
Landsat satellite images • Soil moisture index (SMI) • Forest index (FI) • Land surface temperature (LST)	30м	2020	Landsat data (http://glovis.usgs.gov/)

Table 1. Applied data

Landsat OLI8 satellite data - The Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) images consist of 9 spectral bands with a spatial resolution of 30 meters for the Bands 1 to 7 and 9. The resolution for Band 8 (panchromatic) is 15 meters. The thermal bands 10 and 11 are handy to provide more accurate surface temperatures and are collected at 100 m. The approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi) (U.S. Geological Survey 2018). The thermal bands 10 and 11 were used for the land surface temperature (LST). Landsat 8 Operational Land Imager (OLI) image (September 2020, path 133, row 26) was downloaded from the USGS earth resource observation and science center (EROS) (http://glovis.usgs.gov/).

ASTER satellite data - The advanced spaceborne thermal emission and reflection radiometer (ASTER) satellite was applied in this research, global digital elevation model (GDEM) data with a 30-meter resolution in order to develop the aspects and slope. The ASTER GDEM is shaped into a GeoTIFF format with geographic lat/long coordinates and a one arc-second (30 m) grid of elevation postings. It is referenced to the WGS 84/EGM 96 geoids (http://gdem.ersdac.jspacesystems.or.jp/).

3. METHODOLOGY

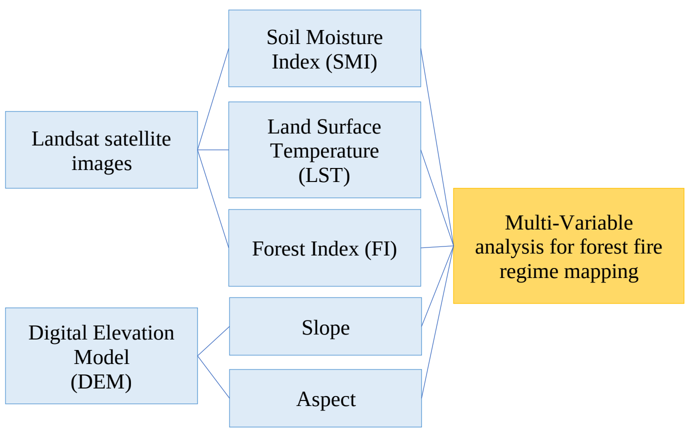

Figure 2. Methodology schema.

In order to estimate each variable based on remote sensing data, Landsat images were applied for estimation of soil moisture index, forest index and land surface temperature. ASTER satellite was utilized for the slope and aspect in the study area (Figure 2).

Forest index (FI): To make the process of forest cover mapping simple and rapid, a simple spectral index called forest index (FI) was proposed to highlight the forest land cover by a threshold in Landsat scenes. (Ye et al., 2014).

Where L = 0.01; C1 = 1; C2 = 0.1

The parameter L is a very small value and the introduction of which can effectively lower the normalized difference vegetation (NDVI) of water while has little impact on the NDVI of vegetation. C1 and C2 are empirical parameters used to scale the function. Thus, the range of the FI is from minus infinity to 7. FI gives a positive value on forested area and vice versa negative value on the non-forested area.

The *soil moisture index (SMI)* was calculated using the Landsat 8 OLI/TIRS bands (2 and 5) (Dupigny-Giroux and Lewis 1999). The equation (2) for the study area in the Khanbuyan community is calculated as equation (2):

$$SMI = \frac{NIR}{VisBlue} \tag{2}$$

where NIR is the near-infrared channel (0.851 ~ 0.879 µm); VisBlue represents the visible blue channels (0.452-0.512 µm).

Land surface temperature (LST) - Single channel is a commonly used approach to estimate LST from the Landsat thermal infrared observations (Ndossi & Avdan, 2016). Among Landsat 5, 7 and 8, only Landsat 8 carries two thermal bands (Parastatidis et al., 2017), therefore the single channel approach is used in this study for consistency. The LST was calculated using Equation (3) by (Natsagdorj et al., 2019).

$$LST = \left(BT + w * \frac{BT}{p}\right) * \ln(e) \tag{3}$$

where BT is the satellite brightness temperature (K); w is the wavelength of emitted radiance (11.5µm); p = h*c/s (1.438*10^–2 m K), h is the Plank's constant (6.626*10^–34 Js); s is the Boltzman constant (1.38*10^–23 J/K), c is the velocity of light (2.998*10^8m/s); e = 0.004*Pv + 0.986, Pv = (NDVI–NDVImin/NDVImax–NDVImin)2 is the proportion of vegetation.

Aspect and Slope - For the aspect and slope we used the ASTER satellite, GDEM data for a 30 m resolution. Figure 7 and 8 illustrates the aspect and slope from a 30 m ASTER resolution in the Khanbuyan community, Khangal soum.

3.1 Multi-variable forest fire risk model

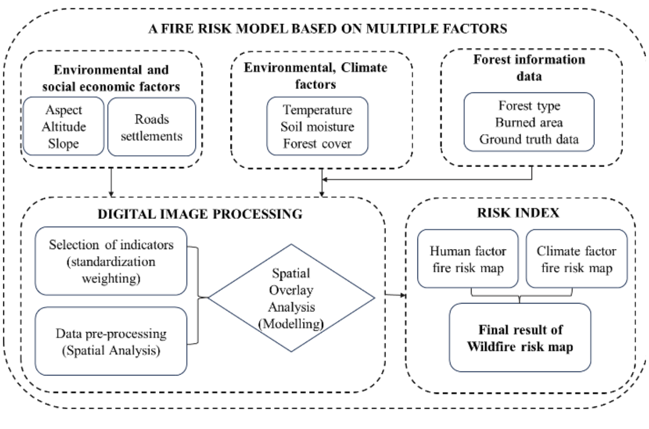

Figure 3. Workflow of the model

$$FI = \left(\frac{P_{nir} - P_{red} - L}{P_{nir} + P_{red}}\right) + \left(\frac{C_1 - P_{nir}}{C_2 + P_{green}}\right) \tag{1}$$

The multi-variable analysis (based on GIS) was applied to determine the forest fire risk model. This research determines the multi-variable methodology for forest fire risk model (using multispectral data) by means of the predicted forest fire map. The innovative part of the research is to consider the FI, SMI and LST with other environmental drivers in mountainous and forested regions for the forest fire risk estimation. The forest index which is able to calculate fast and image forest index simply divides forest into two groups called forested and non-forested area through permanent meaning.

$$FFR = FI + SMI + LST + ASP + SLP \tag{4}$$

Where: FI – forest index; SMI – soil moisture index; LST - Land surface temperature.
ASP - Aspect; SLP - Slope.

4. ANALYSIS AND RESULTS

In this study, the Landsat and ASTER satellite images were combined for the estimation of forest fire risk model. Soil moisture index, Forest index and land surface temperature indexes were calculated from the spectral bands of the Landsat images in August of 2020. ASTER satellite was applied for the calculation of slope and aspect in the study area.

Once we have each variable then classified into risk level in the study area. Four classes were defined from the geospatial analysis. The value 1 indicates that non-risk, 2 indicates low risk, 3 indicates moderate risk and 4 indicates high risk area.

The classes of each variable are different values based on each condition which are soil moisture index and forest indices are defined by index. Land surface temperature was defined by Celsius. Slope and aspects are defined by degrees. The classes of values with higher level represents the forest fire risk is high, low level is displays non risky for forest fire. All variables thematic maps (soil moisture index, forest index, land surface temperature, slope, aspect) were reclassified (Table 2).

Variables	High risk	Medium risk	Low risk	Non-fire risk
Risk level	4	3	2	1
Soil moisture index (SMI)	0.5 >	0.5 – 1.0	1.0 – 1.5	1.5 <
Land surface temperature (C°)	28 <	22 - 28	15 - 21	15 >
Forest index (FI)	Forested area		Non forested area	
Slope (degrees)	25 <	10 - 25	5 - 10	5 <
Aspect (degrees)	North	East	South	West

Table 2. Forest fire risk model's variables in Khangal soum

SMI was classified into 4 classes. The green color shows the low and non-risky area. Orange and dark orange shows the moderate and high risky area for soil moisture index (Figure 4 and Table 3).

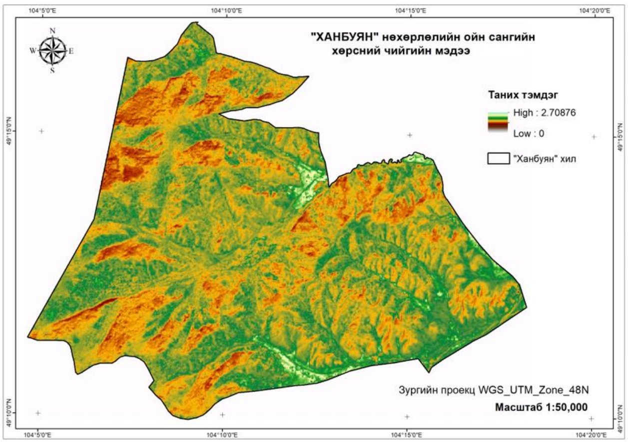

Figure 4. Soil moisture classification map

Soil moisture index (SMI)	Classification code	Risk level
1.5<	1	Non risk
1.0 - 1.5	2	Low
0.5 - 1.0	3	Moderate
0.5>	4	High

Table 3. Soil moisture classification in Khangal soum

Land surface temperature was calculated from the thermal bands of Landsat OLI8 and defined by Celsius. It is classified into four classes as shown in figure 5 and Table 4.

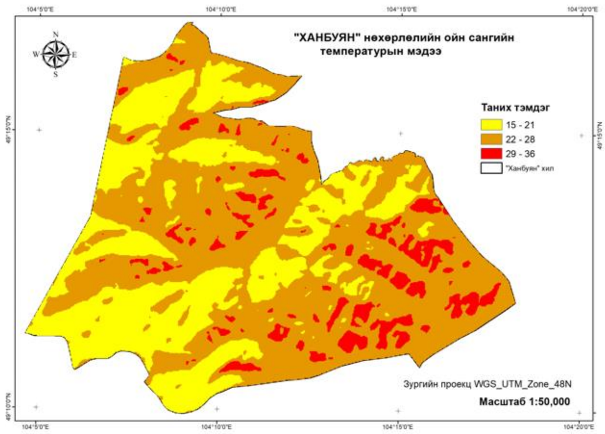

Figure 5. Land surface temperature classification map

Surface temperature (°C)	Classification code	Risk level
15>	1	Very risk
15 - 21	2	Low
22 - 28	3	Moderate
28<	4	High

Table 4. Land surface temperature classification

The forest index (FI) is derived from three green, red and near-infrared (NIR) bands and an FI image can be classified into forest and non-forest map with a threshold (Ye, Li, Chen, & Zhang, 2014). We were calculated Forest Index (FI) from Landsat satellite data performed using ENVI 5.3 program (Figure 6).

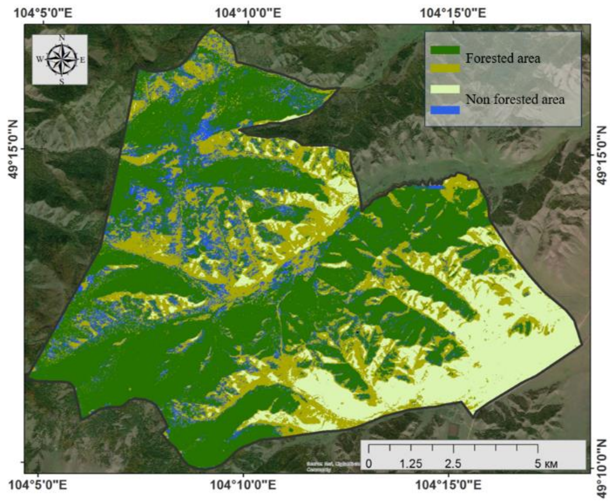

Figure 6. Forest index classification map

Forest fire index (FI)	Classification code	Risk level
Non forested area	1	Very risk
	2	Low
Forested area	3	Moderate
	4	High

Table 5. Forest index classification

Slope was calculated from the ASTER GDEM data and classified into four classes which is shown figure 7 and Table 6. Aspect was estimated from the ASTER GDEM data and classified into four classes which is shown figure 8 and Table 7.

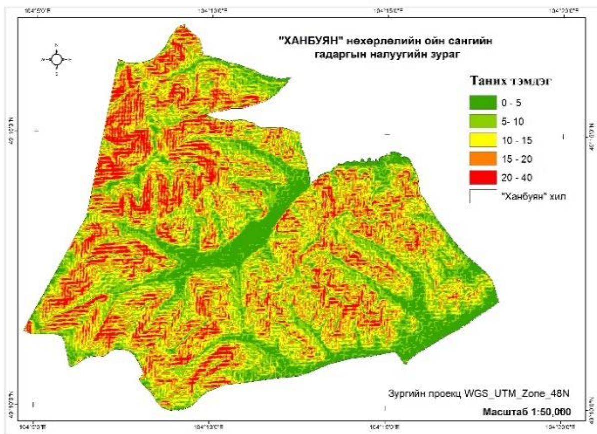

Figure 7. Slope classification map

Slope (%)	Classification code	Risk level
0 - 5	1	Very risk
5 - 10	2	Low
10 - 15	3	Moderate
15<	4	High

Table 6. Slope classification

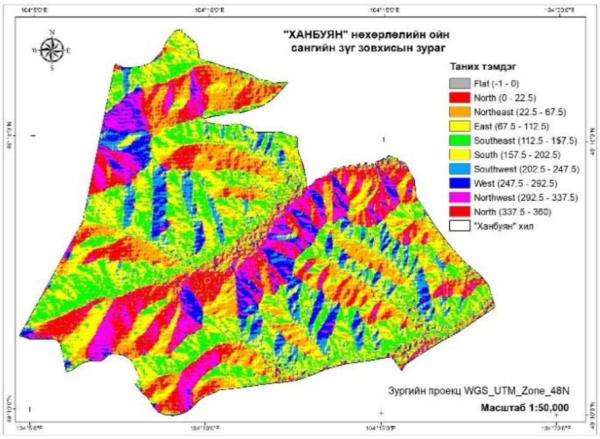

Figure 8. Aspect classification map

Aspect (°)	Classification code	Risk level
North (15 – 45)	1	Very risk
East (45 – 135)	2	Low
South (135 – 225)	3	Moderate
West (225 – 315)	4	High

Table 7. Aspect classification

Forest fire map was displayed in Figure 9, forest fire risk map is shown in Figure 10. Forest fire was occurred in the red coloured area (Figure 9).

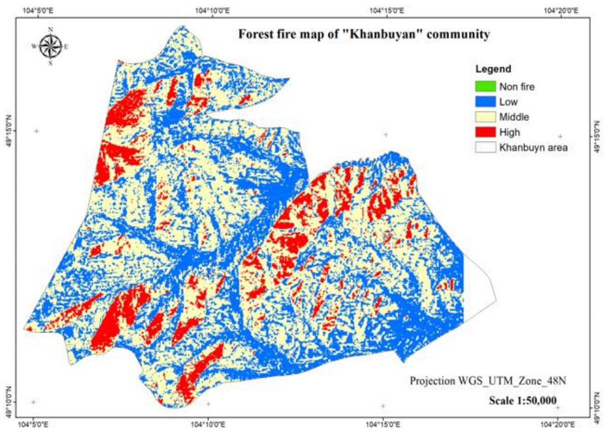

Figure 9. Forest fire map

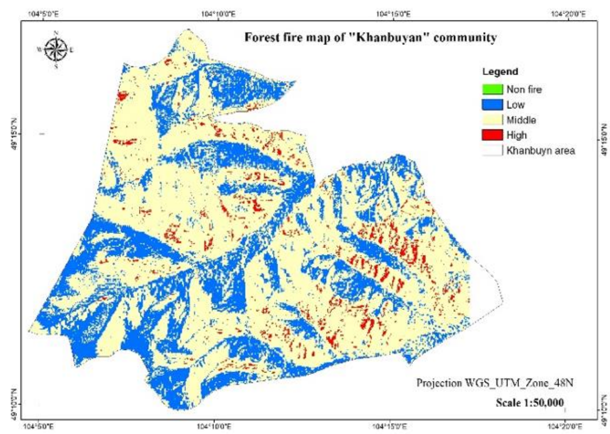

Figure 10. Forest fire map

The human impact of forest fire map was displayed in Figure 11.

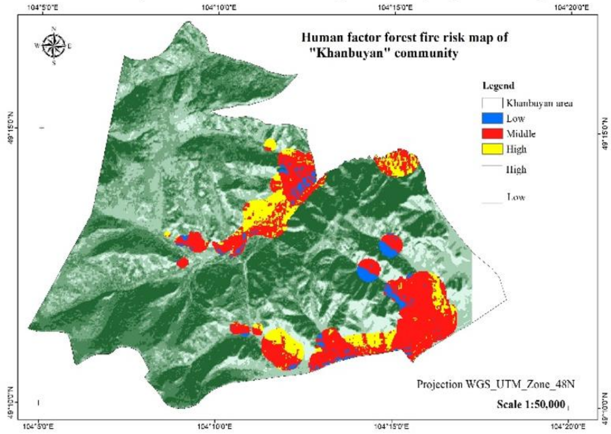

Figure 11. Human factor forest fire risk map

Forest fire is affected by human impact. Forest fire represented in red colour (Figure 9); high risky area was shown in red colour (Figure 10) and moderate human impacted on forest fire area in red colour (Figure 11). Blue colour shows the low forest fire area (Figure 9) and low risky of forest fire (figure 10). Highly human impacted forest fire area was in yellow colour (Figure 11). Most human impacted fire was presented by close to the rural area.

5. CONCLUSION

Remote sensing technologies aid in the analysis of broad scenarios and elements influencing forest fires. Using remote sensing satellite data to create a map of forest distribution in a sparsely populated country like in Mongolia is very important in terms of economic and timely. There are many possibilities to have remote sensing data for free accessible and doing our selected research such as Landsat and ASTER satellite images.
In this study, we have tried to develop forest fire risk model based on multi-variable analysis using geographic information system. Forest is more distinctive on any forest index during growing season. Community partnerships of forested area are possible to analyse on forest pest, fire, deforestation, shortage area and long-term monitoring through Landsat satellite data. Coaching community partnerships is important to identify for fire risk based on above methodology. Forest fire risk map should be used for forest management. The overall objective of this study is to apply a model, to mapping forest fire risk.
The following results were obtained from this study.

- The forest fire risk map showed a moderate concordance between the fire-prone areas and the fire-exposed areas.
- The main topic of this research is that some natural factors were taken into account to determine the forest fire risk map. The forest fire risk map was obtained by processing soil moisture map, land surface slope, direction map, land surface temperature and forest index map.

In the future, we will carry out detailed research and continue our research by considering human factors and some factors that may affect forest fires.

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