National Fire Risk Map for Continental USA: Creation and Validation

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Abstract. A nation-wide fire risk map for the continental USA has been created based on a hybrid fire risk model, incorporating a combination of static risk indicators which change very slowly over time, and dynamic risk indicators that may vary significantly from week-to-week. Static risk indicators include: terrain elevation, terrain slope, terrain aspect, and distance from roads and settlements. Each of the static risk indicators are derived from Intermap’s high-accuracy NEXTMap® USA database. The dynamic risk indicators are derived from satellite-based multi-spectral imagery and provide a snapshot of the fuel-moisture conditions during fire seasons. Each of these risk indicators are combined to produce a map provided at 5m posting and normalized to the range of 0 (very low risk) and 255 (very high risk). The map has been validated in two selected areas using historical fire information.

1. Introduction
Fires can have catastrophic effects on human lives and resources, particularly when severe fire seasons arise [1], as was the case in many western states in the USA in the past two years. Numerous models for assessing fire risk have been developed throughout the world [1-4] and remote sensing and geographic information systems (GIS) have been increasingly used in the development of these models. It has been a common practice to include variables that account for fuel, topography, and weather in fire risk assessments. More sophisticated models add variables for assets at risk, housing density, and impediments to fire suppression such as the width, curviness and steepness of roads [5]. Ultimately, a comprehensive risk assessment will take into account all of these variables. Such a map will help forest management, property insurance, and fire mitigation and prevention.

To date, most research has focused on model development at the regional or local scale. There is no nation-wide, high spatial resolution (30m or better) fire risk map available for the contiguous USA. This work will integrate both structural fire risk and weather-related fire risk. It uses the basic fire risk model presented in [6] with improvements in two major areas: 1) Topographic variables will be derived from NEXTMap® USA 5m DTM; 2) Normalized Difference Moisture Index (NDMI) will be derived from MODIS data but averaged over a period of three months during the summer.

2. Fire risk model
In this section we discuss how to model fire risk by combining both structural and dynamic variables. Our model is adapted from the hybrid fire index (HFI) detailed in [6]. The basic idea was first introduced by Chuvieco and Congalton in 1989 [2]. A similar model was also used by Erten et al (2002) for a study area in Turkey [7] and by Caetano et al for their study area in Portugal [4]. In this
first phase of model development, the goal is not to predict forest fires in a dynamic real time sense. Rather, the focus is to provide a map that indicates the wildland fire potential for a given location based on slowly varying indicators.

2.1. Vegetation Moisture
In this research, we use the Normalized Difference Moisture Index (NDMI) derived from MODIS spectral bands 2 and 6 and calculated using the following equation:

\[ \text{NDMI} = \frac{\text{Band 2} - \text{Band 6}}{\text{Band 2} + \text{Band 6}} \]

This index contrasts the near-infrared (NIR) band 2, which is sensitive to the reflectance of leaf chlorophyll content to the mid-infrared (MIR) band 6, which is sensitive to the absorbance of leaf moisture. NDMI provides an indication of the moisture of an area and thus indicates flammability and spreadability of fire. By nature, NDMI is dynamic because it can change daily.

The MODIS’s Surface Reflectance 8-Day L3 product (MOD09A1) has been used in this work. It records the best observations during an 8-day period as determined by the overall pixel quality and observational coverage and is provided as 500m raster grids. The data were downloaded and integrated in two ways: 1) spatially, so that we get a full coverage of the entire continental USA; 2) temporally, so that we get an overall dryness index for each location for a given fire season. The latter was done by averaging the NDMI values obtained from all 12 observations in the months of June, July and August. The intention of this averaging is to produce a typical dryness map in the fire season for the entire area. The averaged NDMI values for the conterminous USA are shown in Figure 1. The values are in the range of \([-1, 1]\) with -1 being very dry and 1 being very wet.

![Figure 1. NDMI map for the continental USA without masking the water bodies.](image)

2.2. Topography
Both the elevation itself and slope are crucial physiographic variables that have impacts on fire behaviours. Elevation is a physiographic variable that is associated with wind behaviour (affecting fire spreading capability), vegetation structure, fuel moisture, and air humidity. Slope is a variable that is associated with the speed of fire spreading: fires move most quickly up slopes and move least quickly down slopes. In addition, in steeper slopes, the rate of fire spread is increased. Aspect is a physiographic variable that is associated with sun exposure (affecting fuel moisture), temperature, wind direction, and air humidity.

In this work, the NEXTMap® USA DTM is used for deriving both slopes and aspects. The DTMs are posted at 5m spacing and are derived from Interferometric Synthetic Aperture Radar (IFSAR or InSAR) Digital Surface Models (DSM) [8]. This data has a 1.0 meter LE90 vertical accuracy in low-
sloped unobstructed terrain and is seamlessly available for the continental USA. It thus provides an ideal data source for this type of application.

2.3. Proximity to human activities
Forest regions are more prone to fire if they are located near roads and settlements [2]. Roads and paths allow easier access for local people and tourists to enter the fuel-rich region and cause fire [6]. Intermap’s AccuTerra road product in the USA was used to derive distance from roads. It is one of the GPS Map layers that have been used on many outdoor / recreational GPS devices. Intermap’s 5m land cover characterization mask product was used to derive distance from dense and sparse urban areas (settlements). This mask product combines existing land classification maps and a DEM editing mask which provides very accurate water boundary information and some additional high resolution classification information.

2.4. Fire risk model
The Hybrid Fire Index (HFI) is calculated based on the six parameters using the same equation as in [6].

\[
HFI = 20v + 10s + 5a + 2r + 2c + e
\]

where \(v\), \(s\), \(a\), \(r\), \(c\), and \(e\) are the intermediate fire risk values from vegetation moisture, slope, aspect, distance from roads, distance from settlements, and elevation respectively. This HFI value is normalized to the range of 0–255, with 0 as the lowest risk and 255 as the highest risk. The normalized HFI value can also be classified into descriptive classes, such as “Low Risk”, “Moderate Risk”, and “High Risk”.

3. Validation
Validation of a fire risk model is important, but also difficult. Both hot spot data derived from MODIS and historical fires have been used by some earlier work (e.g., [4,6]). In this work, we use historical fire data as “reference” data in the sense that they were “realizations” of fire risk. There are two nation-wide fire datasets available for the continental USA. The first one is the Federal Fire Occurrence data that are available from the USGS wildfire website (http://wildfire.cr.usgs.gov/firehistory/data.html). At the time this paper was written, the data available through this website contains over 677,000 fire records collected by Federal land management agencies for fires that occurred from 1980 through 2012 in the United States, with attributes such as: start date, size, fire type, cause, statistical cause, specific cause, etc. The data are provided as point features in a vector GIS layer. The second nation-wide fire dataset is the perimeter data produced by the Geospatial Multi-Agency Coordination Group (GeoMAC). It gives fire managers and users near real-time information about active fires. The fire perimeter dataset is updated daily based upon incident intelligence sources, GPS data, and infrared imagery. Archived data is also available for the major fires since 2000. These data are provided as polygons.

In this validation effort, we combined the perimeter data and the fire occurrence data to produce a more complete reference dataset. The historic fire perimeters (polygons) from GeoMAC for 2000–2012 are used first, which are suitable for large fires. The historic fire records (points) for 2000–2012 that are outside the GeoMAC polygons are buffered based on the indicated fire sizes, assuming the burnt area is circular and centered at the given location. The GeoMAC polygons and the buffered points are used to create a validation mask. The fire risk indices within the validation mask are used for statistical evaluation of the fire risk model.

Figure 2 depicts the hybrid fire index model for the Stevenson Ranch area located to the north of Los Angeles, California. It is one of the most fire prone areas in the USA. The perimeters of all large historic fires that occurred from 2000 to 2012 are shown as magenta polygons in Figure 2, while all other small fires are shown as black circles. Figure 3 is the normalized HFI map overlaid with the same historical fire layers. It shows clearly that most of historical fires are within an area having very
high normalized HFI value. The corresponding histogram of the normalized HFI values of all burnt
areas is shown in Figure 6.

Figure 2. GeoMAC polygons (magenta) and buffered fire points (black) on Landsat imagery for the Stevenson Ranch area.

Figure 4 shows the Colorado Springs area located to the south of Denver, Colorado. It is less fire prone than Stevenson Ranch, but had a large forest fire event in 2012. The Waldo Canyon fire destroyed approximately 346 homes. The perimeters of the Waldo Canyon fires are shown as magenta polygons in the centre of Figure 4. Similarly other small fires are shown as black circles. Figure 5 is the final normalized HFI map overlaid with the same historical fire layers. It shows clearly that most of historical fires are within an area having very high normalized HFI value. The actual histogram of the normalized HFI values of all burnt areas is shown in Figure 7.

4. Conclusions
A national fire risk map has been created for the continental USA with the NEXTMap® USA data being an enabling layer. The map has been partially validated using historical fires extracted from GeoMAC and Federal Wild Fire Occurrence datasets. Based on two study areas, more than 90% of the burnt areas have a normalized HFI value larger than 150.

This research is ongoing and the fire risk map will continue to evolve as more layers and fire indicators are incorporated, such as fuel layers, moisture index derived from Landsat imagery and historical weather information. A wider validation will also be conducted to include less fire prone areas. Finally, the model will made more dynamic by including variables such as current weather conditions and by increasing the frequency of the updates with the most recently available multispectral imagery.
Figure 3. GeoMAC polygons (magenta) and buffered fire points (black) on the normalized HFI map for the Stevenson Ranch area.

Figure 4. GeoMAC polygons (magenta) and buffered fire points (black) on Landsat imagery for Colorado Springs AOI.

Figure 5. GeoMAC polygons (magenta) and buffered fire points (black) on normalized HFI map for Colorado Springs AOI.
Figure 6. Histogram of normalized HFI of all burnt areas for the Stevenson Ranch area.

Figure 7. Histogram of normalized HFI of all burnt areas for the Colorado Springs area.

References

[1] Chuvieco E, Aguado I, Jurdao S, Pettinari M L, Yebra M, Salas J, Hantson S, De La Riva J, Ibarra P, Rodrigues M, Echeverria M, Azqueta D, Román M V, Bastarrika A, Martinez S, Recondo C, Zapico E Y and Martínez-Vega F J 2012 Integrating geospatial information into fire risk assessment, International Journal of Wildland Fire, 2012, http://dx.doi.org/10.1071/WF12052

[2] Chuvieco E and Congalton R G 1989 Application of remote sensing and geographic information systems to forest fire hazard mapping. Remote Sensing of the Environment 29, pp.147-159

[3] Schoning R, Bachmann A and Allgower B 1997. GIS-Based framework for wildfire risk assessment. Final Report for MINERVE 2, Zurich, Switzerland

[4] Caetano M R, Freire S, Carrão H 2004 Fire Risk Mapping by Integration of Dynamic and Structural Variables, Remote Sensing in Transition (R. Goossens, editor), Millpress, Rotterdam, 2004. 1 pp 319-326.

[5] Brenner J, Green K, Coen J, McLellan S 2001 Assessing Fire Risk in Florida Using Integrated GIS and Remote Sensing Applications, Proc. ESRI 2001 User Conference (San Diego, USA, 9-13 July 2001)

[6] Adab H, Kanniah K D and Solaimani K 2011 GIS-based Probability Assessment of Fire Risk in Grassland and Forested Landscapes of Golestan Province, Iran, Proc. of International Conference on Environmental and Computer Science(Singapore, 16-18 September 2011)

[7] Ertena E, Kurgun V and Musaoglu N 2004 Forest Fire Risk Zone Mapping from Satellite Imagery and GIS: a Case Study, Proc. ISPRS Archives – Volume XXXV Part B8, 2004 (Istanbul, Turkey, 12-23 July, 2004)

[8] Mercer B and Zhang Q 2008 Recent advances in airborne InSAR for 3D applications, Proc. of the ISPRS XXIIth Congress (Beijing, China, 3-11 July 2008)