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RESEARCH ARTICLE

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Improved forest fire spread mapping by developing custom fire fuel models in replanted forests in Hyrcanian forests, Iran

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Abstract

Aim of study: Forest fuel classification and characterization is a critical factor in wildfire management. The main purpose of this study was to develop custom fuel models for accurately mapping wildfire spread compared to standard models.

Area of study: The study was conducted at a replanted forest dominated by coniferous species, in the Arabdagh region, Golestan Province, northern Iran.

Materials and methods: Six custom fuel models were developed to characterize the main vegetation types in the study area. Fuel samples were collected from 49 randomly selected plots. In each plot, the fuel load of 1-hr, 10-hr, 100-hr, 1000-hr, live herbs, live woody plants, surface area volume ratio, and fuel depth were estimated using the Fuel Load (FL) sampling method along three transects. Canopy fuel load was calculated for each fuel model. The performance of the custom fuel models versus standard fuel models on wildfire behavior simulations was compared using the FlamMap MTT simulator.

Main results: The results showed that, despite the similarity in the burned area between observed and modeled fires, the custom fuel models produced an increase in simulation accuracy. Compared to the observed fire, simulation results did not give realistic results to the crown fire. The simulation using standard fuel models did not result in crown fire, while the simulation using custom fuel models showed a moderate rate of crown fire with a Kappa coefficient of 0.54.

Research highlights: The results demonstrated the importance of developing custom fuel models to simulate wildfire maps with higher accuracy for wildfire risk management.

Keywords: custom fuel model; FlamMap; replantation; vegetation type; wildfire behavior.

Authors' contributions: Conceived, designed and performed the experiments: MWAK, SSJ and RJ. Analyzed the data: MWAK, SSJ and RJ. Contributed reagents/materials/analysis tools: MWAK, SSJ, RJ and VB. Wrote the paper: MWAK, SSJ, RJ and VB.

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Introduction

Globally, millions of hectares of forests are burned annually, affecting all major biomes in terms of ecosystem structure, biogeochemical cycles, and atmospheric composition (Andela *et al.*, 2019). Although wildfires are integral parts of many of these ecosystems, lacking the capacity for integrated fire management can lead to severe economic, social, and environmental damages. Therefore, predicting the spread and behavior of wildfires is essential for a better understanding of fire processes and to inform fire and land management decision-makers (Taylor *et al.*, 2013). Fire behavior is commonly defined by the manner the fuel ignites, the rate of spread, energy release and associated flame front dimensions, perimeter and burned area, and other phenomena such as crowning, spotting, and fire whirl activity (Alexander & Cruz, 2013). Therefore, the use of advanced modeling tools to predict fire spread and behavior is widely recognized as an effective method to support wildland management (Keeley *et al.*, 2004). For example, fire prediction tools provide land and forest managers the opportunity to better evaluate appropriate fuel management methods for wildfire risk mitigation (Salis *et al.*, 2018) or potential fire control practices for more efficient and cost-effective wildfire management (Jahdi *et al.*, 2014).

The main factors that influence wildfire occurrence and behavior are landscape fuels, weather, and topography conditions (Carlson & Burgan, 2003; Pierce *et al.*, 2009; Cai *et al.*, 2014). Fuel is the third side of the fire behavior triangle and, as the only factor that can be changed or controlled by humans, the most important one for managers (Fernandes, 2001; Bennett *et al.*, 2010). Thus, describing wildland fuel, as well as vegetation conditions, is essential for accurately predicting wildfire behavior, designing and planning fuel management tactics, prioritizing treatment areas, designing protection of ecosystem services, and reducing the growing financial and ecological losses from catastrophic wildfires (Sexton, 2006; Calkin *et al.*, 2011; Ager *et al.*, 2011).

Fuel can be divided into three layers, based on their positions in the vegetation profile, including ground (duff), surface, and canopy fuel (Keane *et al.*, 2015). Surface fuels are all biomass within 2 m above the ground, which are comprised of leaf and needle litter, dead branch material, downed logs, bark, tree cones, shrubs, and herbaceous. Generally, surface fuels contribute the most to the fuel load or quantity (Reich *et al.*, 2004; Hines *et al.*, 2010). Canopy fuel includes foliage, 0-3 mm diameter live branches, and 0-6 mm diameter dead branches (Scott & Reinhardt, 2005). The fundamental properties of the fuel, which are affecting fire behavior are size, loading, bulk density, moisture content, chemical content, continuity, and vertical arrangement (Anderson, 1981; Reich *et al.*, 2004; Ottmar *et al.*, 2007).

The most widely used fire spread and behavior models (*e.g.* BehavePlus, FARSITE, FlamMap) require as input so called “fire behavior fuel models”, consisting of a number of surface fuel parameters, or fuel bed characteristics (*e.g.* load and surface-area-to volume-ratio by size class, heat content, and fuel bed depth). There are several classifications used to describe fire behavior fuel models. Based on the 13 standard fuel models established by Albini (1976), Anderson (1981) provided aids for describing and selecting the fuel models, characterizing their fuel loads by size classes, fuel bed depth, and dead fuel extinction moisture. Continuing, Burgan (1988) described a new version of the NFDRS (The National Fire Danger Rating System) fuel models, and a further 40 standard fuel models were developed by Scott & Burgan (2005). These models represent expected fire behavior more than actual fuel characteristics (Keane, 2015), and they are site-specific and cannot be easily generalized to other regions or landscape contexts, thus leading to significant errors when applied in different environments (Reich *et al.*, 2004; Elia *et al.*, 2015).

Several wildfire behavior software-based systems, such as FlamMap (Finney, 2006), allow the input of custom fuel models for predicting wildfire behavior (Wu *et al.*, 2011). Custom fuel models can be created from a fuel data collection and inventory or by adjusting one of the standard fuel models (Burgan & Rothermel, 1984). Numerous studies and organizations have tried to define custom fuel models for specific regions, such as the FBP system (Forestry Canada Fire Danger Group, 1992). Several site-specific or custom fuel models have been developed to represent fuel characteristics of Mediterranean vegetation in southern Europe (Arca *et al.*, 2007, 2009; Cruz & Fernandes, 2008; Sağlam *et al.*, 2008; Fernandes, 2009; Santoni *et al.*, 2011; Silva & Molina-Martínez, 2012; Vega-Garcia *et al.*, 2014; Elia *et al.*, 2015). Furthermore, in other regions, Dymond *et al.* (2004) developed a template of fuel characteristics from temperate fuel classification systems for Malaysia and Western Indonesia. Cheyette *et al.*, (2008) created custom fuel models for Anchorage, Alaska using forest inventory data from 13 cover types. Also, Wu *et al.* (2011) developed four fuel models using hierarchical cluster analysis based on fuel data collected across a boreal forest landscape in Northeastern China.

Many studies have also focused on the development of canopy fuel models to predict crown fire behavior. These studies showed that crown fire occurrence and subsequent crown fire behavior are strongly dependent on canopy fuel characteristics, especially canopy fuel load (CFL), canopy base height (CBH), stand height (SH), canopy bulk density (CBD), and canopy cover (CC) (Scott & Reinhardt, 2001; Keane *et al.*, 2005; Güngöroglu *et al.*, 2018; Cobian-Iñiguez *et al.*, 2019). The most common method for estimating canopy bulk density uses measurements of tree diameter, height, and crown base height for all trees in a stand to estimate crown biomass distribution from allometric crown biomass equations (Keane *et al.*, 2005). However, crown biomass equations are not available for all tree species and different ecosystems, so this method is not suitable for many ecosystems (Keane *et al.*, 2005). Therefore, it is imperative to estimate canopy fuel load based on vegetation types for predicting wildfire behavior.

In the Hyrcanian forests of northern Iran, most fires occur from August until the end of December when there is a decrease in humidity and an increase in winds (Allard, 2001), when wildfires have caused substantial losses in forests and other natural resources (Jahdi *et al.*, 2014). Several studies have highlighted the pressing need for rigorous validation of fire spread simulations in the area (Jahdi *et al.*, 2015, 2016, 2020; Adab *et al.*, 2018). However, this area lacks an appropriate fuel characterization that will help in accurately predicting wildfire behavior, prioritizing the treatment areas, and designing treatments to reduce crown fire risk. The aim of the study is twofold. The first objective is to develop custom fuel models for surface and canopy fuels in replanted forest areas in northern Iran and to estimate the canopy fuel characteristics using fuel data that have been collected from the study area. The second objective is to compare the results of wildfire behavior simulation using custom fuel models versus the standard fuel models of Scott & Burgan (2005).

Materials and Methods

Study area

This study was conducted in the Arabdagh plantation, which is located on the east of Golestan Province, in northern Iran (55° 37' to 55° 47' N, 37° 32' to 37° 36' E). It covers about 5000 ha, ranging in elevation from 250 to 850 m above mean sea level. The region's climate is cold semi-arid, and it has a five-month dry period (May-September). The mean annual temperature for the study area is 16.9 °C, and the mean annual precipitation is 536.7 mm. The area which was a degraded forest contains thorny shrubs and broadleaf trees, replanted between 1986-1990 with softwood species including *Cupressus sempervirens* L., *Cupressus arizonica* Greene, *Pinus brutia* Tenore, *Pinus pinea* L., and it also contains some areas of natural broadleaf trees and shrubs such as *Zelkova carpinifolia* (Pall.) Dippel., *Platanus orientalis* L., and Acer velutinum Boiss., *Acer monspessulanum* L., *Paliurus spina-christi* Mill., *Punica granatum* L., *Rubus caesius* L., and agricultural lands (Fig. 1).

Field Data sampling

Forest fuel loads were determined using field surveys through the transect sampling method. Firstly, the study area was stratified on the vegetation map according to the land use type (such as forest stands, shrubs, etc.). The area was surveyed on-site and 49 representative sampling plots (Table S1 [suppl.]) with similar fuel conditions based on vegetation types found in the study area (Fig. 1) were randomly selected. Fuel sampling was conducted according to the method developed by Lutes & Keane (2006), where the area of the circular plot was 1962.5 m^2. Within each plot, we established three fuel transects with three directions (0, 120, and 240 degrees) from the centers of plots, each 25 m long (thus a total of 75 transects for each sampling plot). In this method, the samples have taken from 20 m only, but in the FL method, sampling had suggested over a 20-m distance with additional 5 m of the buffer provided to keep from disturbing fuels around the plot center (Lutes & Keane, 2006). Each transect was divided into three parts, the first part was from 5 to 7 m, the second part was from 5 to 10 m, and the third part was from 5 to 25 m. 1-hr and 10-hr fuels were sampled from the first part, the 100-hr fuels are sampled from the second part, and the 1000-hr fuels are sampled from the third part, respectively. Litter/Duff measurements were done in 2 m diameter circular subplots at the 15 m and 25 m marks on the transect. Live and dead vegetation covers of shrubs and herbaceous were estimated in a box plot with 2 m by 2 m by 2 m high at the 15 m and 25 m point marks. All fuel

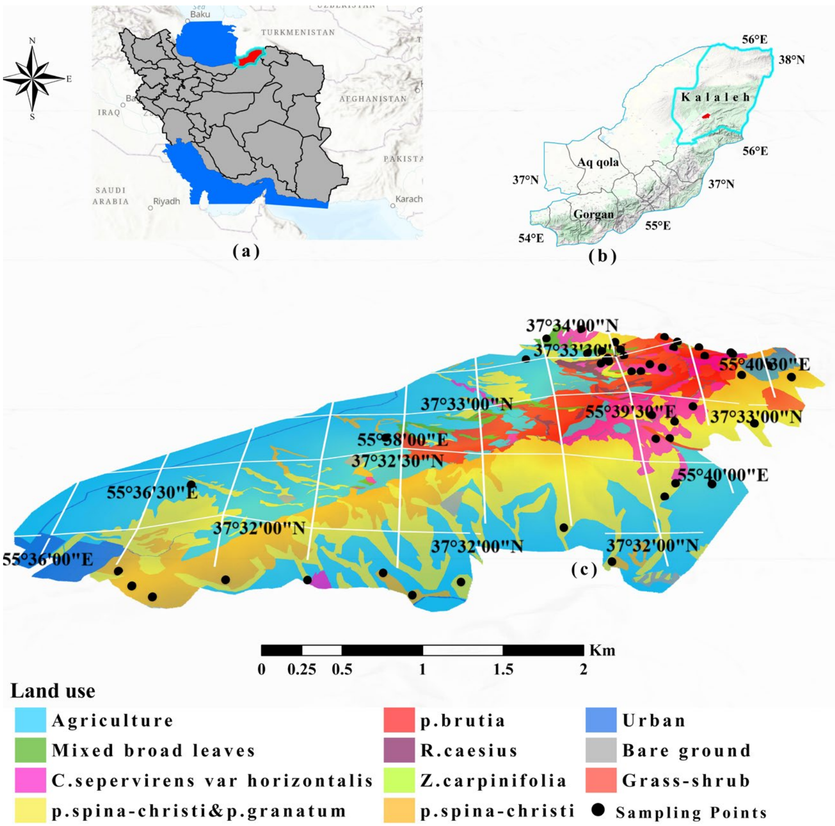

Figure 1. (a) Location of the study area in Iran (b) Golestan province (c) Land use map and sampling centers plots locations in the study area.

data were collected during the time fires occurred (June and July) in 2019.

According to the aim of the study, and for getting more accurate results, the samples were taken from the nearest boundary to wildfire with 500 m buffer around burned area (to avoid differences of fuel loads with burned stands) so that these samples were similar points to accrued fires.

Custom Fuel Model Development

Surface Fuel

The fire model input requirement defined the fuel characteristics to be collected: fuel loads (Mgha^{-1}) of 1-hr, 10-hr, 100-hr, 1000-hr fuels, live herb and live woody fuels, surface area volume ratio (Cm^{-1}), fuel bed depth (cm), heat content (KJ kg^{-1}), and moisture of extinction (%). The fuel loading is calculated as the weight per unit area of dry fuel, expressed in Mg per hectare (Paysen *et al.*, 2000). All collected plant samples were dried in an oven to calculate the dry weight. The moisture of samples was calculated using Equation 1 (Norum & Miller, 1984) and the bulk density using Equation 2 (Keane, 2015) and then the fuel loading for the downed woody debris was obtained based on the number of branches on each transect and time-lag class (Nalder & Wein, 1999), using Equations 3 and 4 (Brown *et al.*, 1982), respectively.

$$\mathrm{FMC} = \frac{w_0 - w_{dry}}{w_{dry}} * 100 \quad (1)$$

Where, is fuel moisture content, w_{dry} is the dry fuel mass, and w_0 is the wet fuel mass.

$$P_b = \frac{W}{S} \quad (2)$$

Where, is bulk density, W is the oven-dry mass (kg m^{-2}), and S surface fuel depth (m).

$$W_j = \frac{\pi^2 * s * n * c * \bar{d}^2}{8 * l} \quad (3)$$

Where, Wj is mass per unit area or fuel load (Mg ha^{-1}), s is specific gravity (kg m–3), n is the number of intercepts over the length of a transect, d is the quadratic mean diameter (cm), l is the length of the transect (m), and c is the slope correction factor, which is calculated according to Equation 4.

$$C = \sqrt{1 + \left(\frac{\text{percent slope}}{100}\right)^2} \quad (4)$$

Besides, the specific gravity was calculated based on the Archimedes rule. Percent cover and mean height of shrubs and herbaceous in each plot were estimated to calculate shrubs and herbaceous load using Equation 5 (Fernandes, 2009).

$$B = H * C * P_b \quad (5)$$

Where B is fuel loading (kg m^{-2}), H is the height (m), C is percent cover/100, and P_b = bulk density (kg m^{-3}).

The litter and duff loadings are also calculated by multiplying the average depth by the bulk density of litter and duff. The surface area/volume ratio for 1-hr time-lag class, live herb and live woody was calculated based on Equation 6 (Keane, 2015).

$$\mathrm{SAVr} = \frac{S}{V} \quad (6)$$

Where SAVr is the surface area volume ratio, S is the surface area, and V is the volume.To calculate SAVr, 20% of fuel was collected from each sampling plot then the surface area and the volume were calculated depending on the geometric shape of fuels (length and diameter of branches, surface area and thickness of leaves).

Furthermore, dead fuel extinction moisture content was estimated based on the fuelbed bulk density by Equation 7 (Rebain *et al.*, 2010). The heat content was identified as the standard value for all fuel models, which equal to 18608 (KJ kg^{-1}) (Scott & Burgan, 2005).

$$MX_{dead} = 12 + 480 * \left(\frac{0.0624 * Pb_{FuelBed}}{32}\right) \quad (7)$$

Crown Fuel

Canopy characteristics including canopy base height (CBH), stand height (SH for each tree in plots), mean diameter of trees, percent canopy cover, and bulk density (CBD), were calculated for each plot. To calculate canopy bulk density, 42 trees were randomly cut from species found in the study area, and the dry-oven mass of less than 0.6 cm diameter branches and needle calculated using Equation 8.

$$\mathrm{CBD} = \frac{\mathrm{CFL}}{\mathrm{CBH}} \quad (8)$$

Where CBD is Canopy bulk density, CFL is the mean canopy fuel load (kg m^{-2}) calculated for each tree and CBH is the mean crown base height (m).

To determine bulk density in each fuel model after calculating the canopy bulk density for each tree, the mean canopy bulk density was estimated for each species. Then canopy bulk density for the fuel load model was estimated using canopy cover percentage (Finney, 1998).

Custom fuel model development

All fuel data collected (surface and crown fuel parameters) in the study area were analyzed to develop custom fuel models by Hierarchical cluster analysis with relative Squared Euclidean distances and Ward's method (Poulos *et al.*, 2007, 2009; Wu *et al.*, 2011; Elia *et al.*, 2015). The clustering approach has many advantages but it could be sensitive to outliers, thus all fuel parameters were standardized to Z score before cluster analysis to account for differences in means and variances (Poulos, 2009; Wu *et al.*, 2011; Elia *et al.*, 2015). The number of clusters was determined using the Silhouette method (Fig. S1 [suppl.]), performed with R software and the NbClust cluster package (Charrad *et al.*, 2014). Fuel model parameters were assigned by the average values of all the plots that were classified into the same cluster. Significant differences in the forest fuel parameters among fuel models were tested by non-parametric Kruskal–Wallis tests (Wu *et al.*, 2011; Elia *et al.*, 2015).

Standard fuel models selection

To compare custom and standard fuel models, standard fuel models (Scott & Burgan, 2005) were selected according to their similarity to available custom fuels in terms of general fire-carrying fuel type, fuel properties (*e.g.* depth, live fuel load, compactness), photo-guides and expected fire behavior (Salis *et al.*, 2016). All fuel models with herbaceous components with moisture above 30% are considered dynamic, meaning that their herbaceous load shifts between live and dead depending on the specified live herbaceous moisture content, in contrast, static fuel models do not contain live herbaceous fuel. In addition, the fuel models were numbered differently from Scott & Burgan's standard fuel models (2005). Furthermore, we used the initials of vegetation types and numbers from 15-20 to number and code the custom fuel models.

Fire Behavior Simulation

To evaluate the custom fuel models, we tested them by comparing predicted fire behavior to observed fire behavior from the fire that occurred in the study area on June 30, 2018. With this aim, the FlamMap version 6.0 (Finney, 2002, 2006), a spatial fire behavior mapping and analysis software, was used to compute potential fire behavior characteristics (rate of spread, flame length, fire line intensity, etc.) over a landscape for constant weather and fuel moisture conditions. FlamMap makes independent fire behavior calculations for each pixel of the raster landscape and incorporates the Rothermel surface fire model (1972) and the crown fire initiation model described in Finney (2004). Topographic variables (elevation, slope, and aspect) were extracted from the Digital Elevation Model (DEM; 10-m resolution), and surface fuel and canopy cover maps were derived from site-specific mapping (Table S2 [suppl.]). These geospatial input layers, describing the landscape of the study area, were analyzed and assembled into the landscape file (LCP) within a Geographic Information Systems (GIS) environment (ArcMap 10; ArcFuels 10, Ager *et al.*, 2011). In addition, the weather data including wind speed and direction, humidity, and temperature, were taken from the closest synoptic weather station (Qhappan 37°37'N, 55°42'''E, 10 Km from the study area; Table 1), are acquired and prepared as text format. The WindNinja mass-consistent model (Forthofer, 2007; Forthofer & Butler, 2007) was used to generate raster grids of wind speed and direction depending on weather parameters (speed, direction, cloud cover, and air temperature) taken from the synoptic weather station during fire time to be used in FlamMap MTT simulations.

The occurred fire in the study area burned about 1370 hectares, comprising conifer plantations, broad-leaved

Table 1. Values of fuel models obtained from the K means cluster analysis with Ward's method (mean ±SD)

Forest fuel characteristic parameters	Custom fuel model					
	FM15 (AG1)	FM16 (BR1)	FM17 (CO1)	FM18 (RC1)	FM19 (CO2)	FM20 (RA1)
1-h loading (Mg ha^{-1})**	2.207±0.121	3.753±1.459	7.899±0.134	1.071±0.147	4.971±0.464	1.257±0.04
10-h loading (Mg ha^{-1})**	0±0	3.636±0.524	0.886±0.49	0.209±0.267	1.206±0.371	0±0
100-h loading (Mg ha^{-1})**	0±0	0.118±0.108	1.237±0.149	0±0	0.978±0.233	0±0
Live herb loading (Mg ha^{-1})**	0±0	1.801±1.307	0±0	0.592±0.254	2.223±0.348	0±0
Live wood loading (Mg ha^{-1})**	0±0	1.025±0.475	0.064±0.023	4.598±0.447	1.454±0.383	4.154±0.044
Litter depth (cm)**	0±0	0.374±0.029	2.386±0.674	0.299±0.139	1.682±0.477	0.367±0.153
Tree height (m)**	0±0	1.9±0.652	9.45±1.35	3.5±1.24	9.75±1.12	1.633±0.153
Crown height (m)**	0±0	7.14±0.611	5.5±0.75	0±0	3.3±1.1	0±0
Canopy cover (%) **	0±0	2.9±0.265	54.35±20.69	0±0	52.50±23.96	0±0
Crown diameter (m)**	0±0	2.95±0.585	4.203±0.359	0±0	4.78±0.51	0±0
Elevation (m)	439.5±165.471	484.4±134.693	649.714±38.339	451.176±122.02	616.364±59.418	577.667±24.214
Slope (Degree)	11.867±2.455	20.854±6.079	23.036±5.364	28.934±9.136	21.041±3.36	13.733±1.137

** Indicating significance at the P 0.01 level according to Kruskal–Wallis test forest, and agricultural lands. Fire line intensity, flame length, and rate of spread of the observed fire were recorded by local fire managers and forest service based on fire effects on vegetation in the study area. Based on official fire reports and also the local foresters, the fire ignited from agricultural lands and lasted for 18 hours; in the first hour, the rate of spread was high (about 1.5 km h^{-1}) and then decreased in the pine plantation (about 0.15 km h^{-1}). In this vegetation type, the fire converted to a high crown fire. However, in the broadleaved vegetation types, there was a surface fire with low to moderate fire intensity.

Fire line intensity is one of the main factors of fire behavior. Generally, this factor is measured accurately in the prescribed fires or by educated fire fighters at the fire duration. Since, the occurred fire in this study not only was not a prescribed fire also, the local fire fighters did not record it due to undetermined duties and education. So, to overcome the lack of this data, fire severity can be seen as a function of fire line intensity (Chatto & Tolhurst, 2004; Cram *et al.*, 2006; Rossi *et al.*, 2019). Therefore, a fire severity map by remote sensing images was used as a measure of fire line intensity. It was estimated at 140 random plots taken in the case study (burned areas, unburned areas) after the fire occurred, and bi-spectral indices (NBR + NDWI2 + BAI + NDW1 + NBR2) of Landsat 8-OLI images were used for fire severity mapping using the Random Forest algorithm (Fig. 2). Also, the fire severity in each plot was estimated as described in Table S3 [suppl.].

The output of the FlamMap simulations, which are the surface rate of fire spread (m min^{-1}), fire line intensity (Kw m^{-1}), flame length (m), and crown fire activity, were exported and analyzed in a GIS environment. Also, the rates of spread and flame length were reclassified into 4 classes (low to very high), and fire line intensity was reclassified into fire severity based on 3 classes (low to high) (Scott

Figure 2. Flow chart of the methodology implemented in the study.

& Burgan, 2005; Rossi *et al.*, 2019). The fire line intensity and flame length of the observed fire were estimated depending on the fire severity obtained in the study area. The simulation maps were then validated using a ground truth of the burned area in the study area and measured by Cohen's kappa coefficient (KC, Congalton, 1991), the Sorensen coefficient (SC, Sørensen, 1948), and overall accuracy (Congalton & Green, 2002).

Results

Fuel models characteristics

In this study, six custom fuel models were developed for vegetation types found in the study area. Results of K means cluster analysis with Ward's method for values of forest fuel characteristic parameters of these custom fuel models are shown in Table 1 and Fig S1 [suppl.]; the significance of results at the P ≤0.01 level according to Kruskal–Wallis tests are also shown. The result of cluster analysis showed that each fuel model represents a vegetation type found in the study area (Fig. 3; Fig. S2 [suppl.]). Not all custom fuel models included the down woody debris from the 1000-hr class in the study area, although 1000-hr fuel moisture is not usually needed for fire behavior calculations (National Wildfire Coordinating Group (NWCG, 2019). The live herb fuel load was generally low because the data were collected in late summer, and the majority of live herbs dried entirely and converted to the 1-hr class (Rebain *et al.*, 2010).

The FM15 (AG1), which represents the wheat crop residue after harvesting, only includes fuel load from the 1-hr class (2.207 Mg ha^{-1}). It also has the highest value of SAV (65.62 cm^{-1}) (Table 1; Fig. 3). FM16 (BR1) represented broadleaves species, mainly dominated by *P. orientalis* and *Acer Sp*. trees and *P. granatum*, *P. avium, Z. carpinifolia*, and *Crataegus azarolus* L. shrubs. It has a high load from the 10-hr class (3.59 Mg ha^{-1}), moderate dead fuel moisture, and low fuelbed depth. FM17 (CO1) represents coniferous stands with high litter load characterized by *C. sempervirens*, and a high tree density. FM18 (RC1) is representative of shrublands with moderate density and low live herb loads (0.59 Mg ha^{-1}) by a mixture of *P. spina-christi* and *P. granatum*, where the herbs were completely dried (Table 1; Fig. 3; Fig. S2 [suppl.]). FM19 (CO2) represented mixed forest, mainly dominated by *P. brutia* trees, *P. spina-christi*, *C. azarolus*, and *Cerasus*

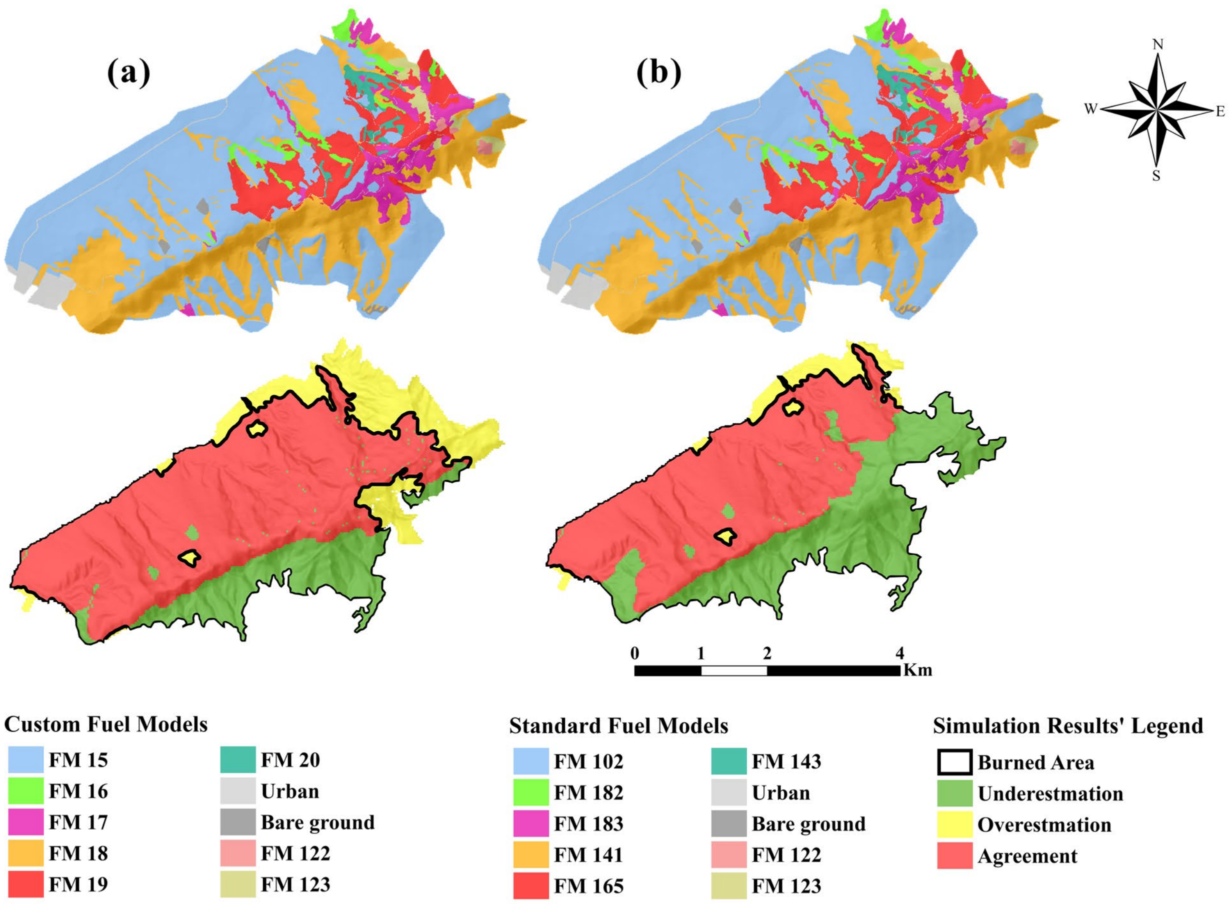

Figure 3. Comparison of simulated burned area using custom fuel models (a), and standard fuel models (b).

avium shrubs, and *Umbilicus intemedius* herbs and annual grasses from the Gramineae family (Table 1; Fig. 3; Fig. S2 [suppl.]). This fuel model has a high fuelbed depth (56.1 cm), moderate dead fuel extinction moisture (23%), and a high load of 1-hr class (4.97 Mg ha^{-1}). FM20 (RA1) represented dense and branched shrubland, dominated by *R. caesius* with (4.15 Mg ha^{-1}) of live wood loads.

The canopy cover characteristics varied according to the dominant species and tree density, where the FM17 and FM19 had the highest bulk density (0.22 and 0.24 kg m^{-3}, respectively) and cover percentage (54.35% and 52.50%, respectively). The high value of CBD for conifer species due to the high load of dead branches attached to live trees because there are no silviculture treatments in the study area, also in the FlamMap software we linked the CBD to canopy cover where the highest value for each species inserted then the CBD values automated be calculated for each pixel. These values are corresponded with CBD values reported by Riano *et al.* (2003) , Kucuk *et al.* (2007), and Ruiz-González *et al.* (2010) for *Pinus sylvestris*, *Pinus nigra* and *Pinus radiata* species.

Standard fuel models selection

Custom fuel models and standard fuel models in the study area were mapped (Fig. 3).

The custom fuel models and standard fuel models were thus related as follows: FM102 (GR2) from Scott & Burgan's (2005) list was selected as a standard fuel model similar to the custom FM15 due to the similarity of the description provided by Scott & Burgan (2005) for similar regions (Table 2). Also, Jahdi *et al.* (2015) used the same standard model for a similar geographic region. However, the standard FM15 has a 1-h class fuel load lower than the custom fuel model. Also, the standard fuel model has live herb loads. For custom FM16, we selected the standard FM182 (TL2), which contained similar fine fuel loads (3.46 Mg ha^{-1}), but the custom fuel model includes live fuel load, unlike the standard fuel model. FM183 (TL3) was selected as a standard model corresponding to the custom FM17 due to the high litter load, fuelbed depth, and live fuel load. However, the custom fuel model has a higher1-h class fuel load than the standard fuel model (Table 2). The description and photos provided by Scott & Burgan (2005) for FM141 were similar to the characteristics of the custom FM18 developed herein. For the custom FM19, the standard FM165 (TU5) was selected, although it has a higher fuel load than the custom fuel model (Table 2). Finally, based on a high live wood fuel load, fine fuel load, and fuelbed depth, the standard FM143 (SH3) was selected as most closely related to the custom FM20. Two standard fuel models GS2, GS3 (FM122, 123) were selected for two vegetation types (the mixed shrubs with a height of 0.5-1.5 m and annual grasses, respectively) in the study area based on the similarity of photos taken from similar areas and descriptions by the local fire managers and forest service's because the area covered by these models was completely burned.

Fire Behavior Simulation results

The simulated burned area using FlamMap MTT with custom and standard fuel models shown in Fig. 3 and the other parametres including, rate of fire spread, fire line intensity, flam length, and fire type are shown in Fig. S3 [suppl.]. Fire parameters values for each fuel model under fire observed conditions are shown in table S4 [suppl.]. In addition, Fig. S4 [suppl.] shows the arrivial time countors and the fire severity estimated by spectral indices and Random Forest classification with a Kappa coefficient of 0.96.

Table 2. Comparison between custom fuel models and the corresponding fuel models developed by Scott & Burgan (2005)

Parameter		Custom fuel model											
		FM15	102	FM16	182	FM17	183	FM18	141	FM19	165	FM20	143
Loading (Mg ha^{-1})	1-h	2.2	0.25	3.59	3.46	7.9	1.24	1.07	0.62	4.97	9.88	1.26	1.11
	10-h	0	0	3.67	5.68	0.89	5.44	0.21	0.62	1.21	9.88	0	7.41
	100-h	0	0	0.13	5.44	1.24	6.9	0	0	0.99	7.41	0	0
	Live herb	0	2.47	1.97	0	0	0	0.59	0.37	2.22	0	0	0
	Live wood	0	0	1.05	0	0.06	0	4.6	3.21	1.45	7.41	4.15	15.32
SAVR (cm^{-1})	1-h	65.62	65.5	11	65.62	36.75	65.6	8.56	65.6	52.49	49.21	8.2	52.49
	Live herb	NA*	59	80.33	NA	NA	NA	50.2	59	77.3	NA	NA	NA
	Live wood	NA	NA	61.81	NA	62.34	NA	62.7	51.2	62.34	24.60	49.21	45.9
Fuel Bed Depth (cm)		30.5	30.48	10	6.1	12.2	9.14	51.6	30.48	91.4	30.48	56.1	73
DM (%)		17	15	24	25	30	20	16	15	17	25	23	40

*There is no fuel load from this class, FM: fuel model, DM: Dead fuel extinction moisture (percent), Heat Content (KJ kg^{-1}) equal to 18608 for all fuel models

The results of applying the custom fuel models showed that more spatial variability has been seen in most of the modeled parameters. Accuracy assessment with ground truth showed an overall accuracy with Kappa coefficient of 0.68 for surface fire higher than simulation with standard models where the simulated burn area was 1378 ha, and about 1070 ha matched with observed fire (Fig 3; Table 3).

Given to differences between standard and developed fuel models; the agricultural lands (FM15), the simulation results showed different values between the standard and custom fuel models. The standard fuel model had lower values than the custom fuel model which had a high to moderate flame length, moderate fire line intensity, and a high to moderate rate of spread.

The FM16 and the corresponding standard FM182 had low values of rate of spread, flame length, and fire line intensity (Table S4 [suppl.]). These results were consistent with the observed fire data where the fire was a surface fire and had low to moderate severity Fig. S4 [suppl.]. Custom model FM17 had values for flame length (1.12±0.18 m) and fire line intensity (527.11±722 Kw m^{-1}) higher than values of the corresponding standard fuel model (0.21±0.08 m, 65.84±71.14 Kw m^{-1}, respectively) (Table S4 [suppl.]; Fig. S3 [suppl.]). Fire simulation on custom FM18 and standard FM141 showed low values of fire behavior parameters, perhaps due to the low load of fine fuels (1.07 Mg ha^{-1} of 1-hr class). However, the rate of fire spread in the custom fuel model was higher than the standard fuel model. This result was completely consistent with the observed fire severity and better described the rate of spread values according to observations of local fire managers and forest services. This fuel model's fire behavior characteristics in areas characterized by *P. spina christi* had higher values of rate of spread,

The FM19 representing conifer forest mainly covered by *P. brutia* was the largest part of the plantation. The simulation results on this stand type showed a significant difference between the custom and standard fuel models, especially in fire line intensity and rate of spread. Also, the flame length map had moderate to very high values, and the fire line intensity and rate of spread map had moderate to high values (1874.67±2173.99 Kw m^{-1}, 4.59±3.22 m min^{-1}, respectively) (Table S4 [suppl.]; Fig. S3 [suppl.]),

Table 3. Comparison of simulation accuracies in the fire types

Fuel Models	Custom models		Standard models	
Fire Type	**Surface**	**Crown**	**Surface**	**Crown**
Underestimation(ha)	296.6	78.47	547.4	159.43
Overestimation(ha)	307.76	66.64	96.23	0.99
Agreement(ha)	1070.023	84.92	819.79	3.96
OA	0.84	0.89	0.83	0.1
Kappa	0.68	0.52	0.61	0.04
Sorensen	0.78	0.54	0.72	0.05

applying the custom fuel model was more realistic than the standard fuel model, which did not simulate crown fire. The simulation result showed that FM20 had fire behavior parameter values higher than the corresponding standard FM143 (SH3). This custom fuel model had high values for flame length (5.21±0.83 m), very high values for fire intensity (5432.64±2368.93 Kw m^{-1}), and moderate values for the rate of spread (7.25±3.04 m min^{-1}). The corresponding standard fuel model had low values for flame length , the rate of spread and fire line intensity parameters (0.68±0.11 m, 1.05±0.58 m min^{-1}, 95.92±81.17 Kw m^{-1}, respectively). For mixed shrub-grass vegetation, only standard fuel models (FM122, 123) were used. The simulation result for these models showed that (FM122) had moderate values for all parameters in custom fuel models, and (FM123) had moderate values for flame length and fire line intensity, and moderate to high values for the rate of spread. The fire did not arrive at vegetation types corresponding to standard fuel models FM122 and 123 when only standard fuel models were used in the simulation (Table S4 [suppl.]; Fig. S3 [suppl.]).

However, the simulation using the standard fuel models showed almost no crown fire. Concerning the fire intensity and fire severity, the simulation results showed that the fire parameter had a low value in most vegetation types to moderate values in *Pinus brutia* vegetation type. While custom fuel models showed low to high values, where the FM15 had a moderate value, the FM18 had low values, and the FM19 had moderate to high value, and this result is similar to the estimated fire severity based on spectral indices (Fig S3 [suppl.] and Fig. S4 [suppl.]).

The Kappa coefficient of simulation maps obtained for crown fire with custom fuel models was about 0.45. The congruence of values for all fire behavior parameters between custom and standard fuel models was evaluated through the Kappa coefficient, where the Kappa coefficients were about 0.60 to 0.68 for flame length, fire line intensity, rate of spread, and burned area (Table S5 [suppl.]). Since the standard simulation predicted almost no crown fire, there was congruence for this type of fire between simulated maps of standard and custom models

Discussion

The present study illustrates the results obtained using the FlamMap simulator in a historic fire in a replanted area in Hyrcanian forests, were compared the fire behavior of standard fuel models described by Scott & Burgan (2005) with the custom fuel models developed by field sampling.

As far to fuel models obtained, each fuel model represents a vegetation type found in the study area; This result agrees with the description provided by Wu *et al.* (2011), Elia *et al.* (2015), and Salis *et al.* (2016) for their fuel models, where those fuel models have differed from one another in average cover and height of understory shrub and herbaceous layers. Not all custom fuel models included the down woody debris from the 1000-hr class, because no silviculture treatments were done on this forest (Table 1). The live herb fuel load was generally low because the data were collected in late summer, and the majority of live herbs dried entirely and converted to the 1-hr class (Rebain *et al.*, 2010). Several studies have accentuated the weakness and limitations of the use of standard fuel models in areas different from those in which they were customized and developed and confirmed the need to develop custom fuel models in different areas to produce more reliable predictions with fire simulators (Arca *et al.*, 2007; Salis *et al.*, 2016). This study confirmed that the accuracy of FlamMap predictions can be improved by using developed fuel models where the custom fuel models appeared more realistic of the characteristics of the vegetation stands generating an increase in the accuracy of simulation results concerning standard fuel models. This result is in agreement with the results of Cruz *et al.*, (2008), that expressed it is difficult to predict wildfire behavior in pine plantations.

When using custom fuel models in simulation, the highest rate of spread values was observed in areas covered by agricultural fuel which were, however, characterized by low to moderate flame length values, also the fire intensity values were consent with fire severity obtained from random forest classification. The flame length of fire obtained using the custom fuel models (1.81±0.45 m) was similar to the flame length of the harvested crop model reported by Cruz *et al.*, (2020) in Mediterranean ecosystems (1.8 ±0.3 m). However, the fire line intensity of Cruz's harvested crop model (10879 ±2476 $Kw.m^{-1}$) was higher than our custom fuel model (489.38±277.96 $Kw.m^{-1}$). The areas covered by broad leaves trees had a low-value fire line intensity and flam length; this is due to the fuels located in valleys with low elevations and high fuel moisture content, which leads to low values of fire behavior parameters (Elia *et al.*, 2015). The Pinus stand type presented high values. In contrast, the lowest fire line intensity and flame length were observed in areas covered by *Cupressus sempervirens* stand. The output simulations (flame length and rate of spread) of the *Pinus brutia* custom fuel model were similar to outputs of mature Anatolian black pine with an understory, developed by Yavuz *et al.* (2018). With regard to shrubs fuels which were divided into custom fuel models (18 and 20), it had shown different values depending on wind and slope effects. it may be due to the effect of wind speed on the open stand types (Fernandes, 2001). Simulation results of these fuel models similar to results reported by Fernandez (2001), Saglam *et al.* (2008), and Salis *et al.* (2016).

Using custom fuel models generated an appear the crown fire with moderate accuracy, in contrast, in simulation using standard fuel models, the simulated crown fire was active and mainly observed in cover land by *Pinus brutia* stand. This due to the high crown fuel load as well as the high value of CBD (i.e greater than of 0.2) in this type (Xanthopoulos & Athanasiou, 2020), in addition, the fuel load from live wood classes increases the fuel bed depth and, as a result, increases the flame length and facilitates the transfer of fire from the surface to the crown (Stratton, 2004). While the *Cupressus* stand has a very low fuel load from shrubs and therefore no crown fire inside it, the simulated map showed that there is a passive crown fire in part of this stand. It is worth mentioning that in some areas, crown fire has been transferred from the Pinus stand, but it has not spread inside due to wind direction and slope (Scott & Reinhadt, 2001; Cruz & Fernandes, 2008).

Fireline intensity is directly related to the quantity of fuel available for combustion, but knowledge of the relationship between fire intensity and potential damage to vegetation is a big challenge at the field scale (Rossi *et al.*, 2019). Fire severity is usually wont to provide a correlation between fire intensity and degree of environmental change and is often seen as a measure of the impact of fire on the biota (Chatto & Tolhurst, 2004). Overall, the fire line intensity values observed in custom fuel models were higher than standard fuel models. These results were corresponding to fire severity values estimated by spectral indices, in spite of using fire severity values as a proxmity of fire line intensity and its limitations. Acctually, it should be recorded in field and fire occuring and spreading times, however as it was expressed in the last paragraph of fire behavior simulation section.

Conclusions

The high variability in composition and structure of vegetation across space and time leads to difficulty in determining precise fuel models in wildlands. In this study, six custom fuel models were developed, and their results of wildfire behavior simulation from these fuel models were compared with Scott & Burgan's standard fuel models (2005) using FlamMap MTT. Although overall results were broadly similar, simulations using custom fuel models were more accurate and better represented spatial variability in the FlamMap outputs. This was especially the case with crown fire and, to a lesser extent, flame length. Site-specific fuel models enhance the accuracy of fuel management planning and help forest managers in fuel management decision-making. In addition, effective implementation of this research method in the study area creates a firm foundation for advancing wildland fire behavior knowledge and improving our predictive capabilities. Viable methods to calibrate custom fuel models are also needed in fire modeling systems based on the Rothermel model. To reduce the uncertainty, more calibration and validation must be carried out with additional wildfires in and around the study region.

Although this is the first study to build custom fuel models in a forested area in Iran, the results of the study highlight the need for further studies of fuels and fire in northern Iranian ecosystems and the need for the development of custom fuels for different vegetation types in other regions in Iran.

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