

Simulating seasonal weather influences on wildfire behavior in Glacier National Park, Montana

A comparative analysis and geospatial visualization toolkit

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Abstract

Wildfires play a critical role in ecosystem functionality throughout Glacier National Park (GNP), but require accurate modeling to mitigate risks to human lives and property. The process of modeling fire behavior is a computationally intensive, multi-scalar effort involving approximation of interactions between wind, climate, fuel sources, and the fire itself; the degree of sophistication in how models approach these phenomena largely determine the projected impacts of a burn. Despite its importance to understanding fire behavior, the most commonly used fire model (FARSITE) does not integrate fire-weather feedback. My analysis provides a deeper understanding of the seasonal behavior of fire in GNP by comparing the spread of numerous simulated fires during the height of summer against the end of the fire season in October. To explore the variance caused by each model's treatment of local weather feedbacks, I compare the commonly used FARSITE model—which is easy to use, but relies on steady state temperature and wind inputs—to the performance of the experimental WRF-FIRE model—which requires supercomputing capabilities, but provides the ability to model advanced weather dynamics and feedback loops at multiple spatial and time scales. As an intermediate approach, I added diurnal and orographic wind influences to FARSITE with the WindNinja extension. I ran all models for a 24-hour period for two time periods, on 1 July and 20 October 2013, to determine the relative difference in burned area over the fire season. Across all time intervals, the July runs demonstrate a greater area burned than in October, but the magnitude of this variability immensely decreased with models that added complex wind-fire interactions. In addition to reducing seasonal variability, the addition of feedback mechanisms cause WRF-FIRE to predict overall more area burned and a faster rate of spread than with FARSITE. This pattern continues with the addition of diurnal and orographic wind dynamics with WindNinja, generating nearly twice of the total area burned compared to the standard FARSITE model. These results demonstrate that the fire-wind relationship (both via orographic and local-weather feedbacks) is critical for accurately modeling the impact of wildfires, and that fire-weather feedbacks largely override the impacts of seasonal climatic factors in terms of driving the amount of area burned. The results of these simulations provide powerful information to fire managers and ecologists in Glacier National Park, suggesting that models using wind dynamics are essential for understanding the impact of fire in the Northern Rocky Mountains.

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Introduction

Background

Almost every year, large-scale fires sweep across much of the Western United States, creating significant challenges for land managers seeking to protect ecosystem functionality and human welfare. Wildfires play a hugely important role in natural systems, driving plant regeneration, forest succession, and carbon cycling among numerous ecological processes. While the disturbance regime of much of the western United States can be characterized by relatively frequent brush-fires, several factors have coalesced to cause dramatic changes in both the frequency and intensity of burns. Suppression of the vast majority of fires over the past century has substantially increased the fuel loading of forested landscapes—both by allowing buildup of dead wood as well as promoting the growth of dense, closed-canopy forest structure (Keane et al 2002). This growth in the amount of potentially burnable fuel is coupled with the effects of anthropogenic climate change, which under most projections is expected to increase the risk and frequency of large-scale burns by raising temperature and dryness throughout the West. These projected changes in fire behavior mandate improved approaches to understanding and modeling wildfires across sensitive regions, allowing land managers to promote ecologically beneficial burns while mitigating potentially catastrophic uncontrolled burns.

Glacier National Park (GNP), in western Montana, is a vast protected region in the Northern Rockies encompassing over a million acres of land, ranging from subalpine and boreal forests to glaciated fell-fields and open alpine meadows. The park has immense ecological and recreational value, hosting extremely high numbers of rare and endangered species across a largely undeveloped landscape (Debinski & Brussard 1994). Forested land accounts for a vast majority of the non-glaciated or alpine sections of the park (Allen & Walsh 1996), with surrounding region composed primarily of coniferous forests managed by the United States' and Canadian Forest Services— providing a spatially continuous forested landscape.

Ecosystem functionality in GNP effectively depends on wildfire for ecological health: both of the dominant tree species in the region, Western Larch (*Larix occidentalis*) and Lodgepole Pine (*Pinus contorta*), require high levels of heat to open their serotinous cones (Hellum, 1983). The fire regime across the park historically is characterized by a return interval of 25-75 years for small brushfires and 100-150 years for stand-replacing crown fires (Barret et al 1991). Unlike in many Sierran ecosystems

traditionally characterized primarily by small ground fires (Turner & Romme 1994), large crown fires play a significant role in maintaining forest structure in the Northern Rockies: McKenzie et al (2012) demonstrate stand-replacing fires as a mechanism for regeneration of the dominant tree species, *P. contorta*, while subsequently decreasing the density of competitor shade-intolerant species. Keane et al (2002) notes losses in landscape heterogeneity and a rise in insect and disease epidemics following fire exclusion in the region. Crown fires play a significant role in ensuring a mosaic structure of forest patches at different successional ages, increasing landscape complexity and biodiversity (Turner & Romme 1994).

Fuel suppression and climate change threaten to increase the relative frequency of these events to an ecologically untenable level (Litschert et al 2012). These climate-change induced fires have profound impacts on sensitive species throughout the park: Loehman et al (2011) discover significant reductions in the density of the 'keystone' species *Pinus albicaulis* with wildfires under climate change. Managing crown-fire adapted ecosystems provides an immense challenge to managers seeking to preserve the 'pristine' aesthetics of the park and mitigate projected massive catastrophic wildfires while recognizing the role stand-replacing fires have upon the landscape.

Seasonal variations in weather and fuel dynamics play a fundamentally important role on the behavior of wildfires. Generally the 'fire season' experienced in GNP follows snow thaw in June through the onset of heavy rain and declining temperatures in late October (Barret et al 1991). During that period, the region experiences significant changes in average precipitation and temperature, which both directly affect the relative moisture content of ground fuels—and thus the behavior of potential wildfires during those periods. Further, average wind speed and direction also change variably depending on season, influencing the rate of spread and intensity of a fire (Johnson & Miyanishi 2001). While these variables are dependent on local topography and land-use type, broad seasonal changes result in typically larger, more intense fires during the summer months (Johnson & Miyanishi 2001; Litschert et al 2012). Effective understanding of wildfires across Glacier National Park must understand the disturbances in the context of seasonal variability, and integrate these dynamics into future management actions.

Fire Modeling

The complexity and multi-dimensional natures of fire make accurate numerical approximation extremely difficult. In a broad sense, fire modeling concerns itself with one of two specific tasks: predicting the likelihood of a wildfire occurrence on a landscape (“fire risk modeling”), or anticipating the spread of a fire given an ignition (“fire behavior modeling”) (Baker & Ehle 2001). Wildfire behavior is primarily driven by three factors: wind speed and direction, ambient temperature, and fuel structure and composition (Albini 1976), but those are complicated by numerous feedback loops and complex fire phenomena (such as fire whirlwinds or flying embers) (Johnson & Miyanishi 2001). Wildfire modeling is further complicated by the operational needs of fire managers, who often must adaptively alter models based on real-time changes in environmental or atmospheric conditions. There are numerous theoretical models used to measure the behavior of fire, varying in ease of use, precision, and underlying algorithms, and are reviewed extensively by Papadopoulos et al (2011), and Alexander et al (2013). The currently accepted “workhorse” fire modeling software in operational fire-fighting and land management is FARSITE (Finney, 1998; Stratton 2006), which operates by interpolating a two-dimensional fire grid onto a geographic surface using Roethermal’s (1972) semi-empirical fire spread model. FARSITE provides data in faster-than-real time once the model run is parameterized, and is relatively easy to use in concert with other geospatial tools, such as ESRI ArcMap, ENVI, or other GIS programs, as output files are created as commonly used raster or vector formats (Andrews 2007).

FARSITE has been used extensively in both experimental and operational environments. Finney et al (1995) demonstrate its widespread use to predict wildfire spread in National Parks during operational fire-suppression activities, and Stephens (1998) explored its efficacy for experimental analysis, using it to understand the influence of silvicultural treatments on fire behavior. Results from Sanders (2001) demonstrate very minor differences between various modeled simulations and actual fire events in the short-term. Despite validation and overall common use, FARSITE is inherently limited by its lack of complex weather dynamics: the model treats wind flow as single directional variable across an entire study region, and does not dynamically model its effect on fire conditions (Finney 1998). Moreover, FARSITE does not account for topographical effects on wind direction and velocity—a given area is assumed to be homogeneously flat for the purposes of the wind variable. These limitations impose significant challenges due to the model’s inability to simulate feedback between fire, weather systems, and topographic features, particularly as wind speed and direction are some of the most

important variables for fire behavior (Johnson & Miyanishi 2001). Wildfires often generate distortions in local atmospheric conditions by heating air and increasing the velocity of low-level winds, which in turn have profound impacts on fire behavior (Clark et al 1996). Accurate modeling of these feedback loops (particularly as they change across the year) is critically important for researchers seeking to model ecological impacts of fire, as well as land managers seeking to control the extent of burning or ensure effective and safe placement of firefighting resources—insufficient understanding of weather impacts on fire has the potential for tragic consequences, such as the recent firefighting deaths from the Yarnell Hill fire in Arizona.

To address these wind-fire feedback limitations, Forthofer et al. (2009) developed the WindNinja extension to FARSITE, providing a significantly more powerful understanding of local wind patterns across the landscape based on local topography. WindNinja, though it does not provide the critical dynamic feedback integration necessary to model the interchange between multi-scalar weather systems and fire, differs from the basic FARSITE model in that it provides wind data for every cell of the landscape grid, rather than assuming a single homogenous wind direction for the entire study area. The model can be easily initialized to add diurnal influences, wind stability input, and even provides an option to integrate data from several weather models from the National Centers for Environmental Prediction (NCEP). While WindNinja is limited insofar that it still does not harness fire-weather feedback mechanisms, its use of diurnal and orographic wind dynamics allows for increased nuance in modeling fire behavior. While Butler et al (2006) validated WindNinja's treatment and interpolation of wind across study areas in the Sierra Nevada mountains in California, they did not extend that wind treatment to direct fire interactions due to the complexity of measuring fire-weather feedbacks in a live fire-fighting context.

Rapid advances in supercomputing technology and advanced weather forecasting in the last decade have allowed for the development of several powerful models that couple fire spread and behavior with realistic weather dynamics. These models, such as FIRETEC (Linn et al 2002) developed from Los Alamos National Lab, and the Wildland-Urban Fire Dynamics Simulator (WFDS) from the U.S. Forest Service (Mell et al 2007), as well as the Coupled Atmospheric Wildland Fire Environment (CAWFE) from NCAR (Clark et al 1996), use the parallel processing capabilities of supercomputing clusters to overcome the immense computational challenges of dynamically modeling weather patterns and fire behavior at multiple intersecting scales. WRF-FIRE, another advanced fire model, combines the

advanced mesoscale Weather Research and Forecasting model (WRF) with Roethermal's (1972) spread equations, and is capable of anticipating highly local fire-weather feedback (Coen et al 2013). The model was eventually chosen due to its non-proprietary nature, and presence of an online support community¹. While WRF-FIRE has been extensively validated by Coen et al (2005) in Colorado, Dobrinkova et al (2010) in Bulgaria, Peace et al (2011) in Australia, Kochanski et al (2013) in San Diego, and Coen et al (2013) in New Mexico, the model has not been tested in Glacier National Park. While highly dependent on the local context, Kochanski et al (2013) demonstrate a very close spatial pattern as San Diego's 2007 Witch Fire, though a rough 6.5% overprediction of fire area burned. Given the WRF-FIRE's capabilities to dynamically model weather across multiple nested geographic scales, this analysis represents a powerful tool for understanding the role of seasonal variability in fire behavior throughout the park.

Broad surveys of the literature demonstrate no comparison of these three fire models (FARSITE, WindNinja, and WRF-FIRE) against each other, and no treatment of seasonal variability across the entire fire season. Further, no model comparisons have been conducted in the GNP region. Due to this lack of study, this study attempts to bridge that gap: modeling seasonal changes in fire area burned as well as the model performances, to understand how both the model's treatment of wind and seasonal climate affect fire behavior in the Northern Rockies. I expect that WRF-FIRE will outperform the other fire models in terms of overall fire area, and that WindNinja will produce more fire area burned than the original FARSITE model—further that the July models will generate more area burned in July than October.

Methods

Study Area

The region of focus in this analysis encompasses Glacier National Park and the surrounding mountains in the Northern Rockies (Figure 1), at approximately 49°N latitude by 113° longitude. Ecosystem variability in the region is largely structured along an elevation mosaic, with lowland intermountain rangelands transitioning to mixed-conifer, and then *P. contorta* dominated forest, eventually to high-alpine fell fields, snow, and retreating glaciers (Allen & Walsh 1996).

¹ Openwfm.org



Figure 1: The region of focus is bounded by the darker blue rectangle of the map, ending at the northern boundary of the United States. This region is also highlighted on the subset map. Map imagery from USGS Landsat 7 EMT+ (pre-SLI) and USGS 7.5 Minute Topo available from the USGS National Map database ("nationalmap.gov/viewer").

Glacier National Park possesses extremely steep topography as a legacy of Pleistocene glaciation, and the disturbance pattern throughout many of the higher valleys is driven by frequent avalanche occurrence (Butler 1979). The steep slopes of the mountainous terrain, ranging from elevations of 1400 to 3000 meters, exhibit significant orographic wind effects, with strong down-valley winds at night following a cooling of surface temperatures. Dominant species include Lodgepole Pine (*Pinus contorta*), Whitebark Pine (*Pinus albicaulis*), Western White Pine (*Pinus monticola*), and Western Larch (*Larix occidentalis*). Temperature varies roughly from -4 to 20° C annually, with monthly precipitation ranging from 250 to 10 mm (Figure 2), demonstrating significant seasonal changes across the year. The fire season spreads generally from July—the warmest and least wet month of the year—to October, when temperatures begin to drop precipitously following the beginning of snow accumulation (Keane et al 1998).

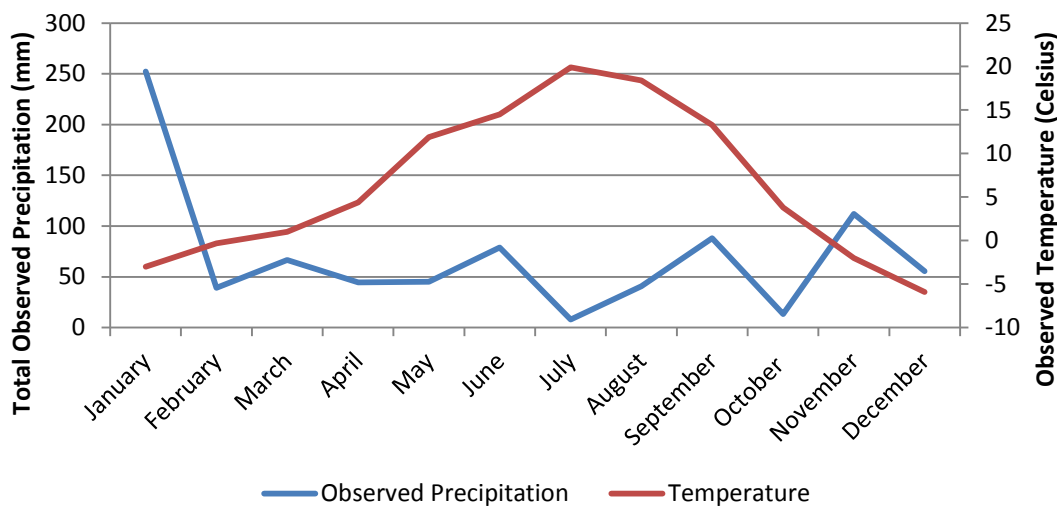


Figure 2: Observed temperature and precipitation for 2013. Data points adapted from daily summaries from the West Glacier Montana RAWS 2013 output.

Model Inputs and Data Processing

Regional temperature and precipitation data were obtained from the NOAA's West Glacier Montana RAWS (Regional Atmospheric-Weather Station) station and used to simulate climate for the two time periods (Table 1). The WRF model relies on a static land cover dataset for the entire globe, consisting of MODIS imagery upscaled to 1 arc-second. This data were obtained as a single download from NCAR (NCAR 2013). This coarse-resolution dataset, while suitable for regional weather analysis, is insufficient to measure the relatively fine differences in topography and fuel across the geospatial mosaic upon which fire model operates. WRF-FIRE overcomes this difficulty by integrating high-resolution landscape level data for elevation and fuel. Data from the National Elevation Dataset (Gesch et al 2002) was obtained from the USGS "National Map" database (Dollison 2010) as a series of 30m. resolution raster files for the study region, using NED data rather than MODIS for elevation. High-resolution fuel data was obtained from the LANDFIRE database corresponding to Anderson's (1982) 13 models of wildland fuels (LANDFIRE 2010). Both data sets were chosen due to their collection in 2010, which represented the closest possible temporal resolution to the study date in the year 2013. Both high-resolution datasets were clipped to the extent of the study area in ArcMap 10.2 (ESRI 2013) (Figure 3). All non-fuel categories in the LANDFIRE data (such as snow, urban, barren, etc) were reclassified to 'no fuel' to avoid data errors in the WRF-FIRE model. Weather data for the time periods were obtained

from the North American Regional Reanalysis (NARR) dataset (NARR 2013), which provides global-scale 32 km² resolution files at three-hour time intervals.

Data for the FARSITE runs were obtained from the LANDFIRE (LANDFIRE 2010) database as 'Landscape Package Files' (LCP) of bundled geospatial layers. Weather and wind data for the time periods were obtained from the West Glacier RAWS observatory (Table 1), as well as using WindNinja (Forthofer & Butler, WindNinja, 2013) to create a topographically-oriented grid of wind direction. Fuel moisture data was interpolated using readings from the National Fuel Moisture Database at the Six Mile North Station (Forest Service 2014). Default settings were used for the other variables given a lack of reasonable data sources or field observations. The WindNinja model extension was run using the LCP file from LANDFIRE, using the same wind observations from RAWS used in the FARSITE runs. The WindNinja outputs were integrated to FARSITE as gridded weather files using the same parameters as the non-WindNinja runs for all other variables.

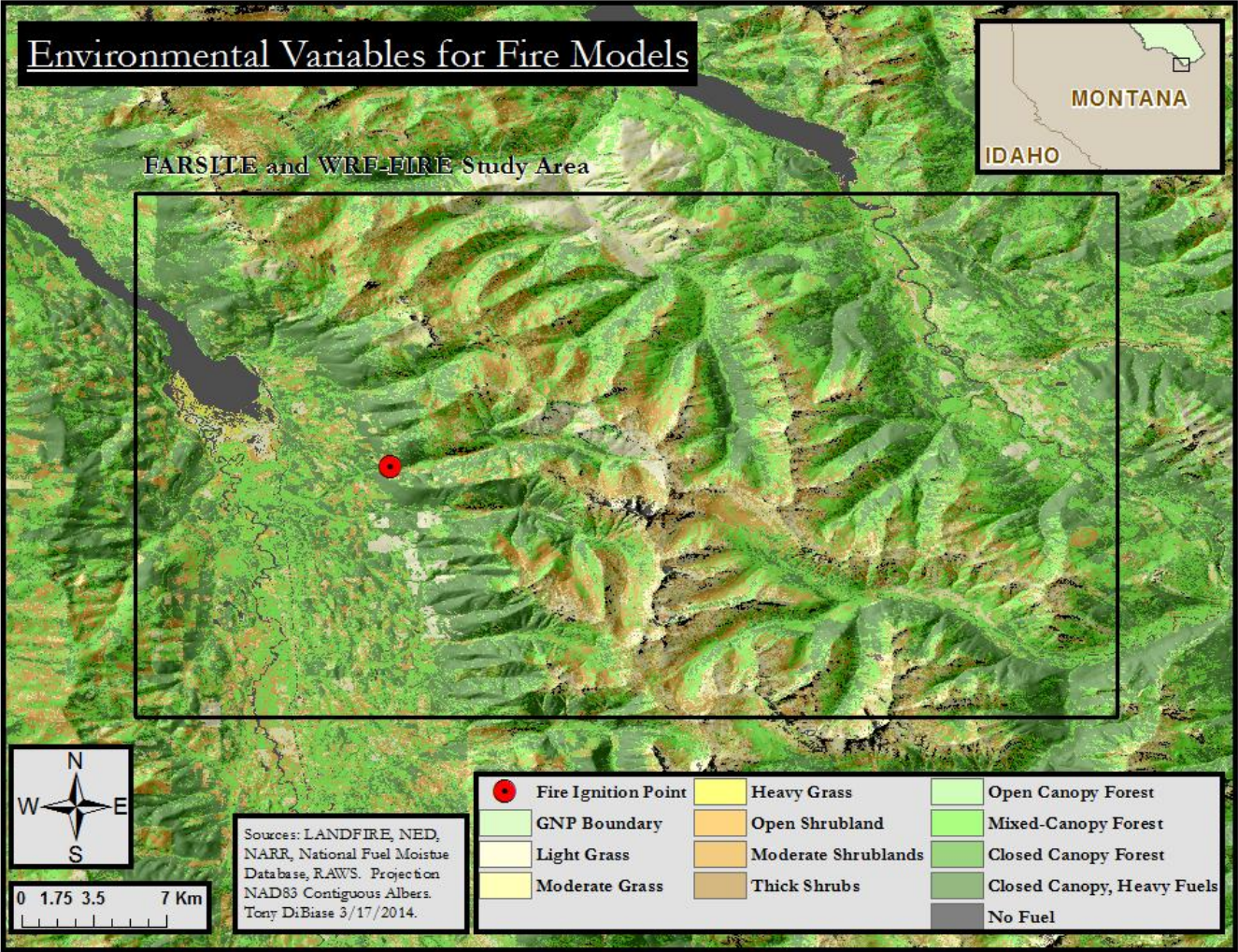


Figure 3: Environmental variables composing the study area. Anderson fuel category is overlaid on a NED elevation layer to demonstrate the spatial distribution of fuels across the elevation gradient

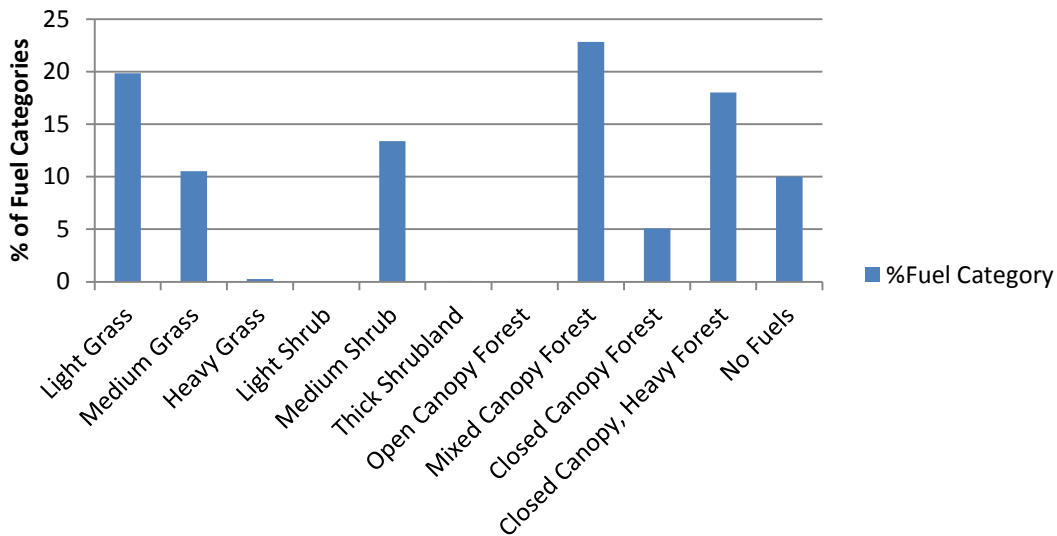


Figure 4: Fuel Category Percentage in study area.

The spatial fuel component of the data demonstrates a high loading of fuels, with almost exclusively mixed and heavy-closed canopy types representing the forested regions. There is a fairly large amount of grassy areas across the study region, particularly on the steep valley slopes. The valley where the ignition point was placed represents a nearly spatially continuous forested cover, with transition zones between extremely heavy fuel loading and mixed forest patches.

Table 1: Ambient Weather for the West-Glacier RAWS for both time periods

Time Period	July 1-2 2013	October 20-21 2013
Average Temperature (Celsius)	24.8	4.8
Maximum Temperature (Celsius)	35	16.1
Average Wind Velocity (m/s)	0.9	0.7
Total Precipitation (mm)	0	0
Mean Humidity (%)	61	80

Fire Models and Parameterization

Seasonal changes in wildfire behavior in Glacier National Park were simulated using WRF-FIRE for two one-day periods, from July 1-2 and October 20-21 2013.

WRF-FIRE

The technical equations and computational architecture underpinning WRF-FIRE are described in great detail by Michalakes et al (2004), Mandel et al (2011), and Coen et al (2013) among many others. Briefly, WRF is a highly advanced mesoscale climate model capable of simulating weather patterns in a three-dimensional environment using a series of nested vertical and horizontal grids. Weather processes are sequentially interpolated and downscaled to increasingly smaller, higher resolution domains situated within the original coarse layer. The smallest horizontal layer—the only one to directly interact with surface wind flow over local topography—forms the basis for an even finer-resolution subgrid that is the surface operated on by the fire model. The two-dimensional fire spread model adapts equations developed by Roethermal (1972) to a three-dimensional topographic environment influenced by surface-level winds calculated from the WRF model. As the fire spreads across the mesh subgrid, the model calculates the relative fraction of the fuel burned in each cell. Fuel properties per subgrid cell are input as fuel categories following Anderson (1982). At every time-step, the model interpolates wind at a height of 6.1 m, influencing fire spread via the level-set function. The resulting heat flux from the fire is averaged across the cells that compose a single higher-order atmospheric cell, providing an iterative feedback between the fire and atmospheric models.

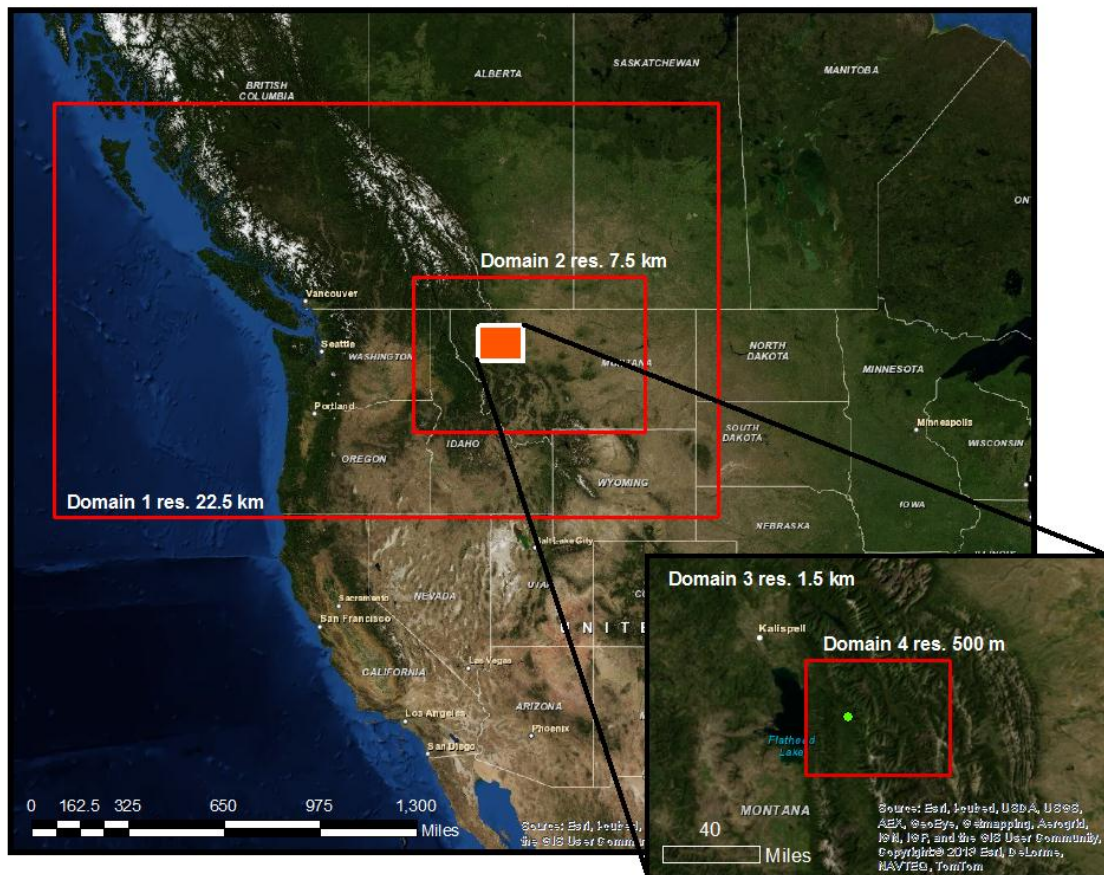


Figure 5: WRF-FIRE domains and resolutions. The fire itself is modeled only on the smallest domain at a subgrid resolution of 20 meters. The fire ignition point is indicated as a green point in the smallest domain.

The two WRF-FIRE runs were both initiated using the same geographic domain structure and physical parameters, with the time of year (and corresponding weather) as the only variable changed across runs. Parameterizing WRF is an elaborate process involving interpolation of geographic data to a multiple nested three-dimensional grids at increasingly smaller resolutions (Table 2, Figure 6), which allows weather processes across regional scales (such as circulation currents) to interact with local-scale atmospheric phenomena (such as eddy turbulence). The actual fire model was initialized in a separate subgrid of the smallest domain of 20 m². The 24-hour model runs were run on NASA's *Pleiades* supercomputer using 8 Ivy Bridge Xeon nodes, each with 20 available CPUs for a total of 160 CPUs running the model. The entire model run was given 8 hours of walltime—running time on a supercomputer— but both completed in slightly over 6 hours of computation. The model ran on a 1-

minute time step for the largest domain (and followed an equivalent nesting ratio for time), but output files were only saved every 15 minutes to limit overloading hard drive capacity.

Table 2: Dimensions and Resolution of WRF-FIRE Setup

Domain	Dimensions (X, Y, Z)	Resolution (m)
1	100, 61, 41	22500
2	76, 46, 41	7500
3	121, 91, 41	1500
4	166, 121, 41	500
Fire Grid	4150, 3025, 41	20

FARSITE

While FARSITE operates similarly to WRF-FIRE using Roethermal's (1972) semi-empirical fire-spread equations, the fire-propagation algorithm instead uses an ellipsoidal wave method adapted from Huygen's principle (Finney 1998). Fire is visualized as a series of wavelets that consume fuel across a three-dimensional landscape, influenced by a uni-directional wind parameter (Finney 1998). Unlike WRF-FIRE, FARSITE takes detailed measurements of crown-fire instance by integrating crown-bulk density and forest canopy composition (Finney, 2004). Additionally, users are able to specify numerous experimental scenarios modeling suppression activities in very rapid progression, making the model suitable for operational use, unlike WRF-FIRE which requires the use of a parallel supercomputer and significant technical expertise and training for sophisticated weather-fire feedback processing.

FARSITE was run twice for one-day periods, from July 1-2 and October 20-21 2013. The study area, defined by the LCP file from LANDFIRE, corresponds to the region outlined by WRF-FIRE Domain 4 (Figure 6). The model was run using a 15 minute time-step. Default options were selected for fire behavior, acceleration, and dead-fuel parameters, aside from average wind and weather for the study data, which was obtained from the West Glacier RAWS station, and fuel moisture, which was obtained using the National Fuel Moisture Dataset.

FARSITE with WindNinja

The WindNinja extension to FARSITE provides individual wind data for each cell of the study landscape, using local topography and diurnal influences to model wind velocity and direction. The local

wind data is calculated using Scire and Robe's (1997) 'CALMET' micrometeorological model. The program calculates the expected heat flux from incoming solar radiation on surface temperature, and then computes the atmospheric boundary layer height using and resulting wind speed. The influence of terrain on wind is modeled using Mahrt's (1982) slope-flow algorithm, which uses heat flux, percent-sop, and expected drag to simulate the directionality of wind given topography. Wind direction was calculated in terms of flow towards each of the surrounding 16-cells on the surface grid. WindNinja was parameterized using RAWS wind data for every four-hours of the study period for both of the time periods (1 July and 20 October 2013), as well as the underlying elevation data for the study area; the diurnal flow and . The resulting outputs were added as gridded atmospheric files to FARSITE, and the fire model was run using the same parameters as the previous non-WindNinja scenarios.

Spatial Analysis

The netCDF outputs from the WRF-FIRE model runs both exceeded 100 gigabytes, and required conversion to a usable (and much more highly compressed) format to export from NASA's remote server. I used the wrf2kml Python script developed by Jonathan Beezley (<http://github.com/jbeezley/wrf2kml>) to extract perimeters of wildfire spread as .KML files suitable, which were imported into Google Earth Pro (Google 2013) as animations. The files were also converted to ESRI shapefiles and imported to ArcMap 10.2. In ArcMap, I visualized the data at intervals of 6 hours to demonstrate the spatial extent, rate of spread, and direction of the wildfires for both time periods, and obtained fire spread data at 3-hour intervals. The outputs from the equivalent FARSITE runs for both time periods were exported as ESRI shapefiles, and imported to ArcMap. These were also visualized at 6-hour intervals, with fire area extracted every three hours.

Differences among the WRF-FIRE and FARSITE data, both in terms of model performance and seasonal changes in fire behavior, were assessed by mapping fire spread in 6-hour intervals, as well as measuring fire area over 3-hour periods. The WRF-FIRE runs were also compared visually in Google Earth as animations to demonstrate changes in seasonally-driven behavior (as a function of both spread rates as well as relative spread over the fuel mosaic).

Results

FARSITE and WRF-FIRE – July

Every effort was made to parameterize both models similarly, yet the output results for the FARSITE and WRF-FIRE runs demonstrate very large differences. At a time period of six-hours post-ignition, FARSITE’s burned area totaled 9.65 hectares, compared to WRF-FIRE’s 26.78 ha (Table 3). This difference becomes starker as time progresses, with the WRF-FIRE run burning a total area of nearly 1500 ha, just under three times that of the FARSITE run. The fireline rate of spread differs between the models as well: while the FARSITE model predicts a roughly linear progression of 19.5 ha/hour, the WRF-FIRE model anticipates 68.72 ha burned/hour, though also resembling a linear function (Figure 6).

In addition to the amount of area burned over time, the spatial extent of the July model runs are very different—the initial FARSITE area remains very closely confined to the ignition point, whereas the WRF-FIRE model rapidly consumes the closed-canopy forest regions nearby, continuing to burn uphill until 18-hours, when the fire begins to “fill in” the valley floor (Figure 7). The equivalent FARSITE run appears to be limited by the initial presence of less-burnable grassy fields near the ignition at the foot of the valley, and initially expands along all directions rather than following purely the topography of the valley. Both models demonstrate more rapid rises upslope, and a significantly faster rate-of-spread across grasslands than closed-canopy regions.

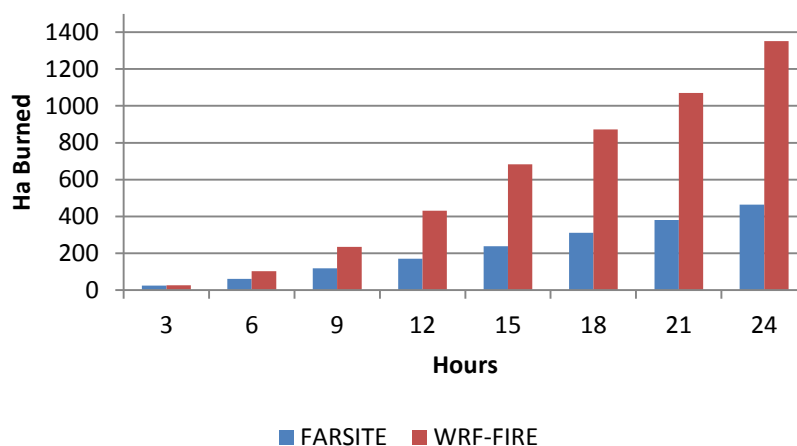


Figure 6: Comparison of Area Burned by Model, July Runs

WRF vs. FARSITE - July 1 2013

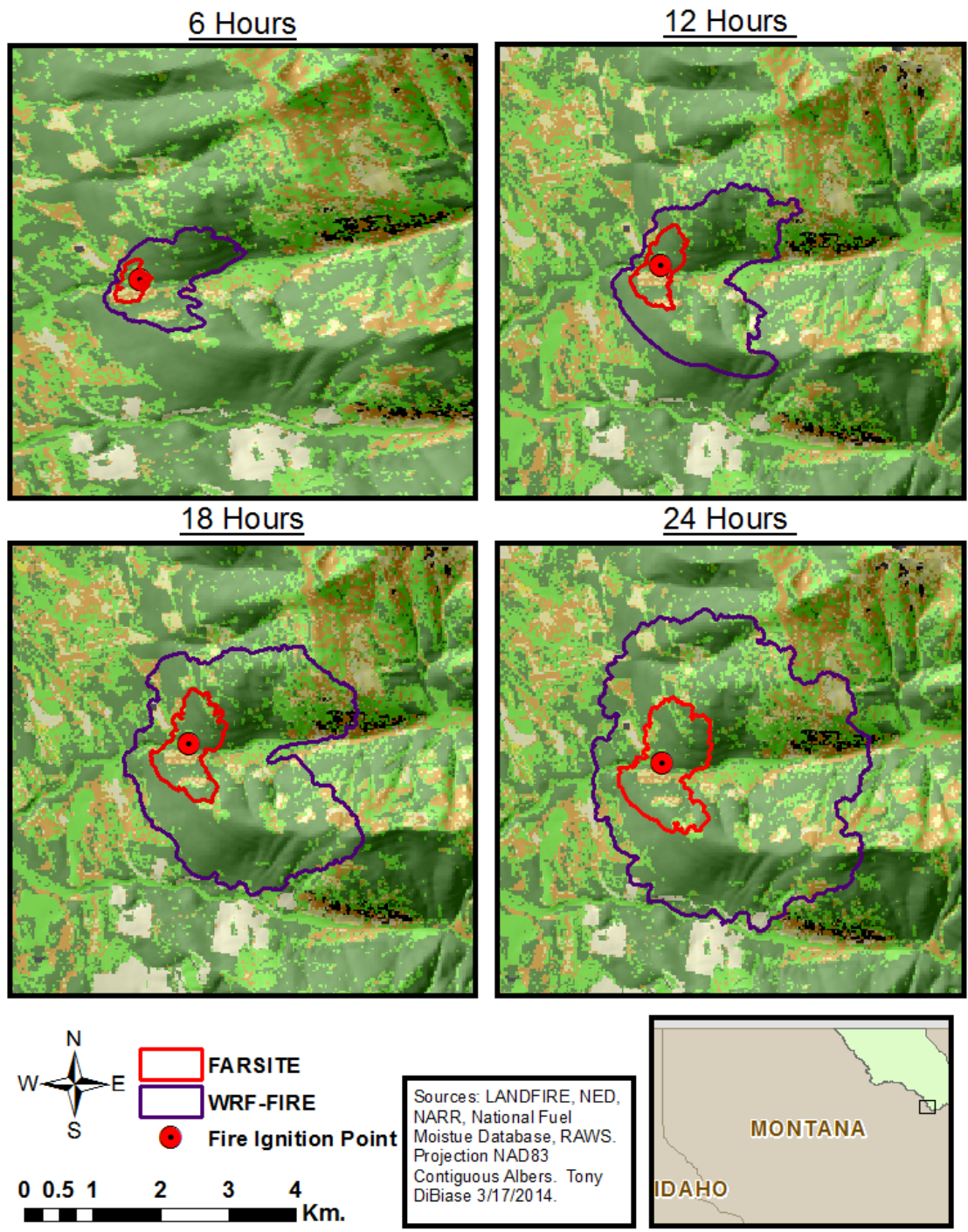


Figure 7: Comparison of WRF-FIRE and FARSITE runs in July over six-hour time intervals.

FARSITE and WRF-FIRE – October

A comparison of the extent of the two models in October demonstrates significant overall differences in terms of hectares burned (Table 4). The FARSITE run initially develops at an area an order-of-magnitude lower than WRF-FIRE, 2.54 vs. 26.88 hectares at an elapsed time of three hours. This difference becomes progressively greater over time, yielding a maximum area burned of 1070.82 hectares for the WRF-FIRE model, and merely 83.46 for FARSITE under theoretically similar conditions. The rate of spread for the models demonstrates this difference: while both yield a roughly linear relationship between time and area burned, the WRF-FIRE model vastly exceeds that of FARSITE in terms of the relative slope, 52.84 vs. 3.65 hectares burned/hour.

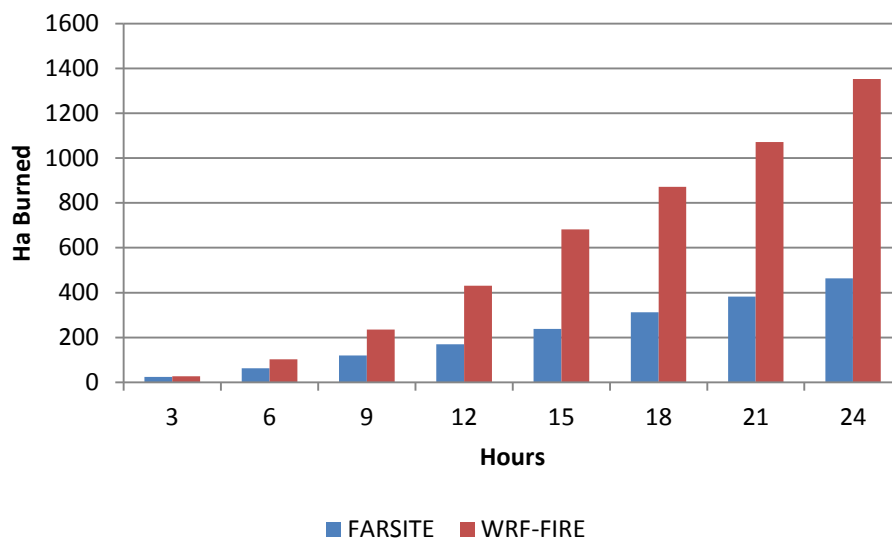


Figure 8: Comparison of Area Burned over Time by FARSITE and WRF-FIRE, October

Similar to the previous run, the WRF-FIRE model initially climbed upslope of the valley following ignition, and progressively continued as a head fire uphill, and climbing down the south-facing slope of the southern valley wall—essentially stopping as the fireline reaches a period of less dense fuel (Figure 9). FARSITE in October demonstrated significant changes compared to the July run—the extent of the burned area, while also lower in absolute terms, is completely contained on the northern slope of the southern valley from the ignition point. The FARSITE run appears to rapidly consume nearby shrub and grass regions, but increase at a much slower rate in the closed-canopy forest—eventually hitting a boundary at the model termination at a forest clearing.

WRF vs. FARSITE - October 20 2013

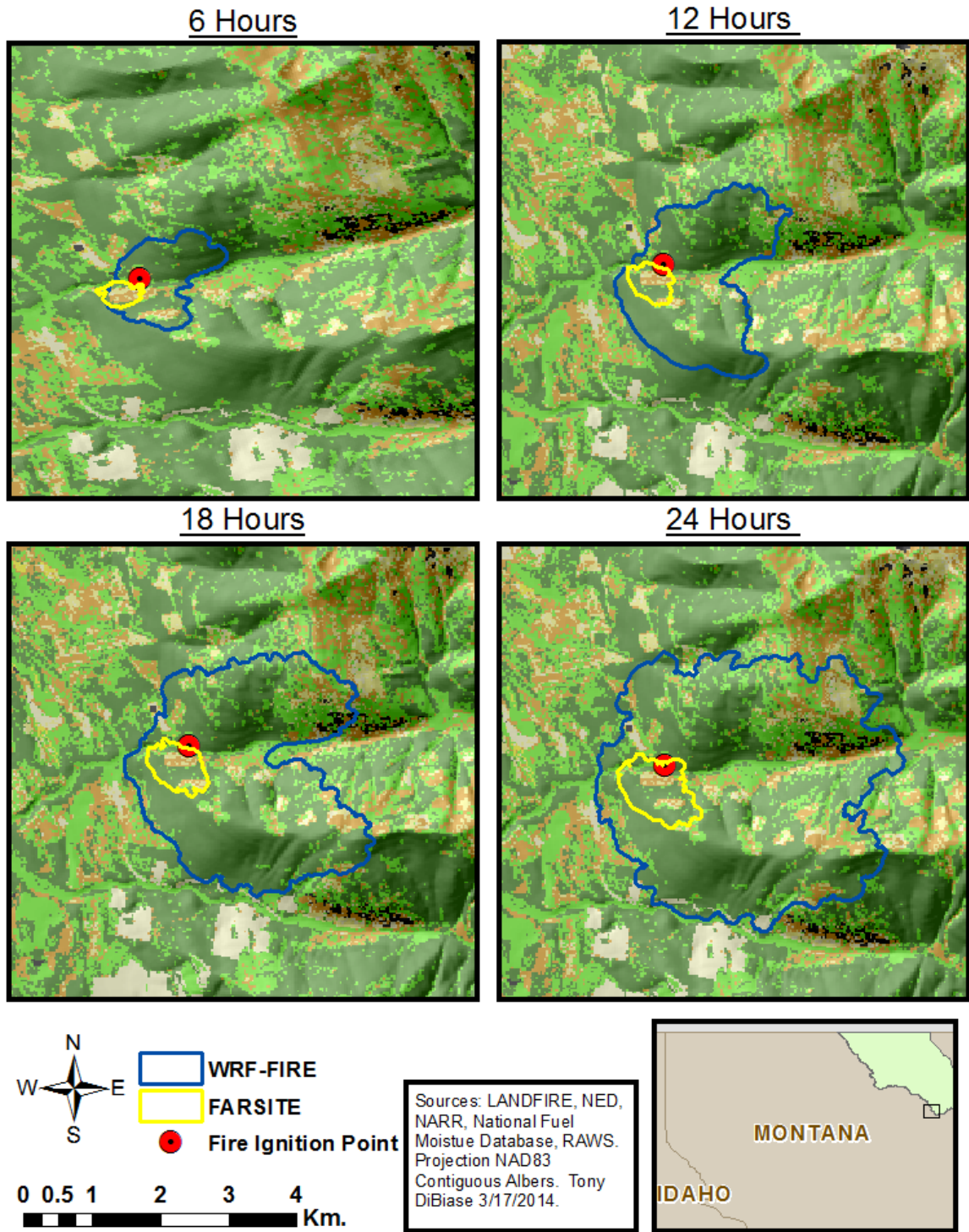


Figure 9: Comparison of FARSITE and WRF-FIRE runs in October over six-hour time intervals.

FARSITE with WindNinja vs. WRF-FIRE – July

WindNinja’s addition of diurnal and orographic wind influences to the FARSITE model substantially increases the relative area burned compared to the non-WindNinja runs (Tables 3, 5). For the first six hours, both FARSITE and WRF-FIRE predict a similar area burned, and the difference between the two does not substantially change 12-hours into the simulation. At the first measured interval of 3:00PM, the FARSITE/WindNinja area burned actually exceeds that of WRF-FIRE, 40.25 vs. 26.78 ha. This difference reverses and then widens significantly by the termination of the simulation at 24-hours, eventually with WRF-FIRE 800 ha more (Table 5). The rate of spread for both models is relatively linear, but the slope of the spread for WRF-FIRE is substantially greater than that of the FARSITE/WindNinja model at 29.09 ha/hr vs. 68.72 ha/hr. The increase in rate of spread from the original FARSITE model (19.5 to 29.085 ha/acre) demonstrates a 50% increase in relative rate of spread under the local simulated wind conditions.

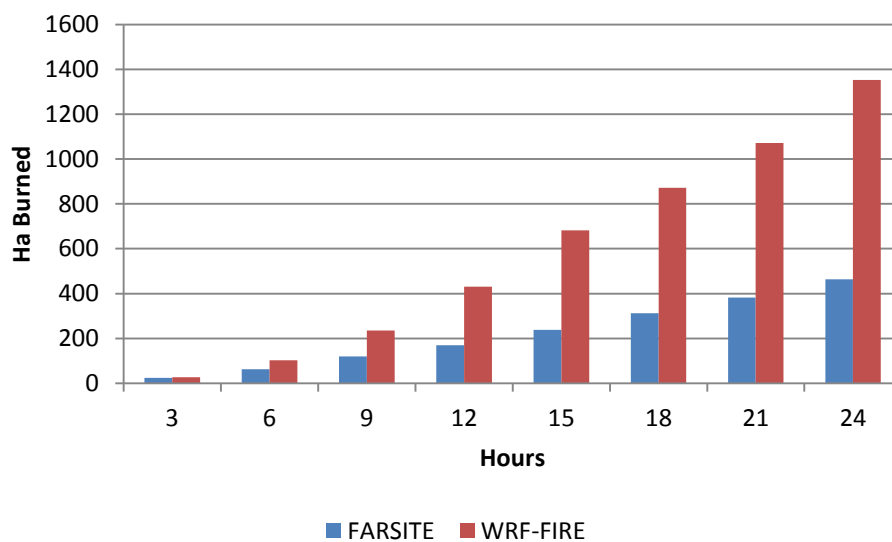


Figure 10: Comparison of Area Burned for WindNinja/FARSITE and WRF-FIRE, July

While still burning overall less area than the WRF-FIRE runs, a map of the progression of both simulated fires over time (Figure 11) shows that the WindNinja addition to FARSITE yields a very similar spatial pattern as the WRF-FIRE; the two runs appear to follow the same region burned over the time period. The “head fire” uphill spread for both models is much faster than the progression laterally in the valley floor. The fuel type appears to play a significant role in the FARSITE/WindNinja run compared to the WRF-FIRE run—the fire progression on the south aspects of the northern valley appears to halt at a

region of shrubs and open forest from 18-24 hours. Compared to the non-WindNinja FARSITE run (Figure 12), the WindNinja region is much less constrained to the region around the initial ignition point.

WRF-FIRE vs FARSITE/WindNinja - 1 July 2013

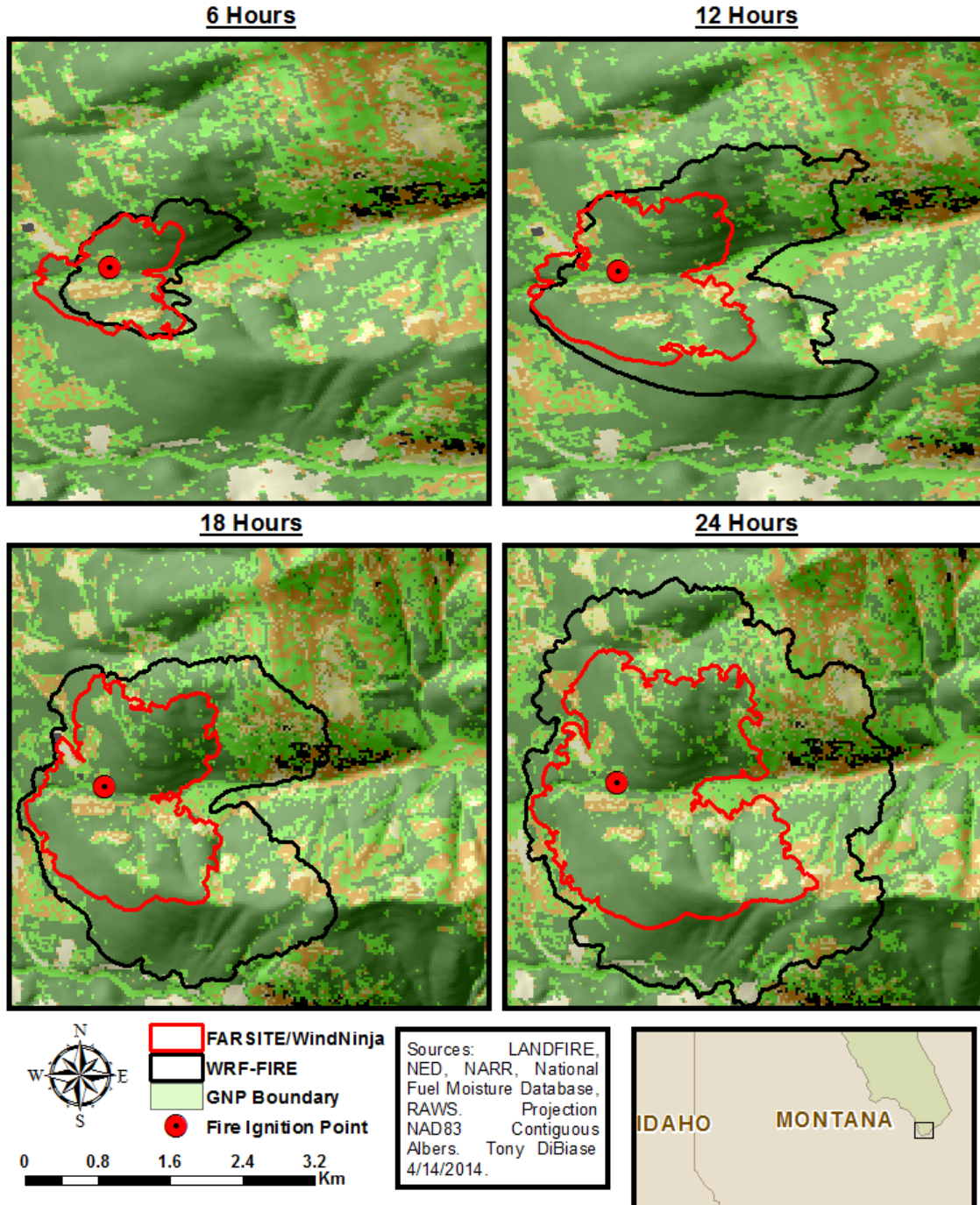


Figure 11: Comparison of FARSITE (with WindNinja) and WRF-FIRE in 6-hour intervals

FARSITE with WindNinja vs. WRF-FIRE – October

Similar to the previous WindNinja vs. WRF-FIRE comparison in July, the October runs closely followed each other in terms of area burned, until 12 elapsed hours into the simulation (Table 6), after which the area burned between the two models diverges significantly. The maximum area burned over the simulation time for the FARSITE with WindNinja run is 463.85 hectares, compared to the 1352.04 hectares burned by WRF-FIRE under similar environmental conditions. Similar to the July results, the addition of the WindNinja extension results in a greatly increased amount of area burned over all time periods compared to the original FARSITE runs without the extension. The rate of spread and resulting slope of the FARSITE/WindNinja run is significantly larger than the non-modified FARSITE simulation, an increase of 3.65 hectares burned/hour to 21.118 ha/hr—but both of those remained less than the rate of spread for the WRF-FIRE model in October: 52.84. The rate of spread, and total area burned over the time period, is overall less in October compared to equivalent runs in July.

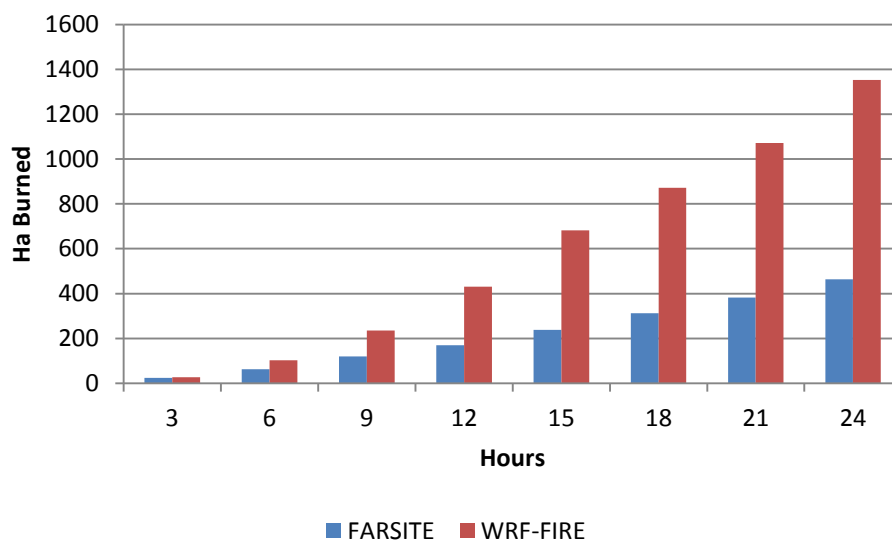


Figure 12 : Comparison of area burned (ha) between FARSITE with WindNinja and WRF-FIRE, October

WindNinja's addition of diurnal and orographic wind for every cell of the study area lessens the dramatic difference in extent burned between the FARSITE July and October runs (Table 7). The modified FARSITE runs, while clearly burning less total area, follows a similar spatial pattern as the WRF-FIRE simulation: spreading from the ignition point up the valley rapidly via head fires, and gradually increasing laterally across the valley floor. Similar to the previous July runs, the FARSITE/WindNinja simulation in October appears to be spatially constrained by the fuel type being burnt, and essentially

halts in spread on the southern valley from 18-24 hours when the flaming front encounters a change from closed-canopy forest to open woodlands.

WRF-FIRE vs FARSITE/WindNinja - 20 October 2013

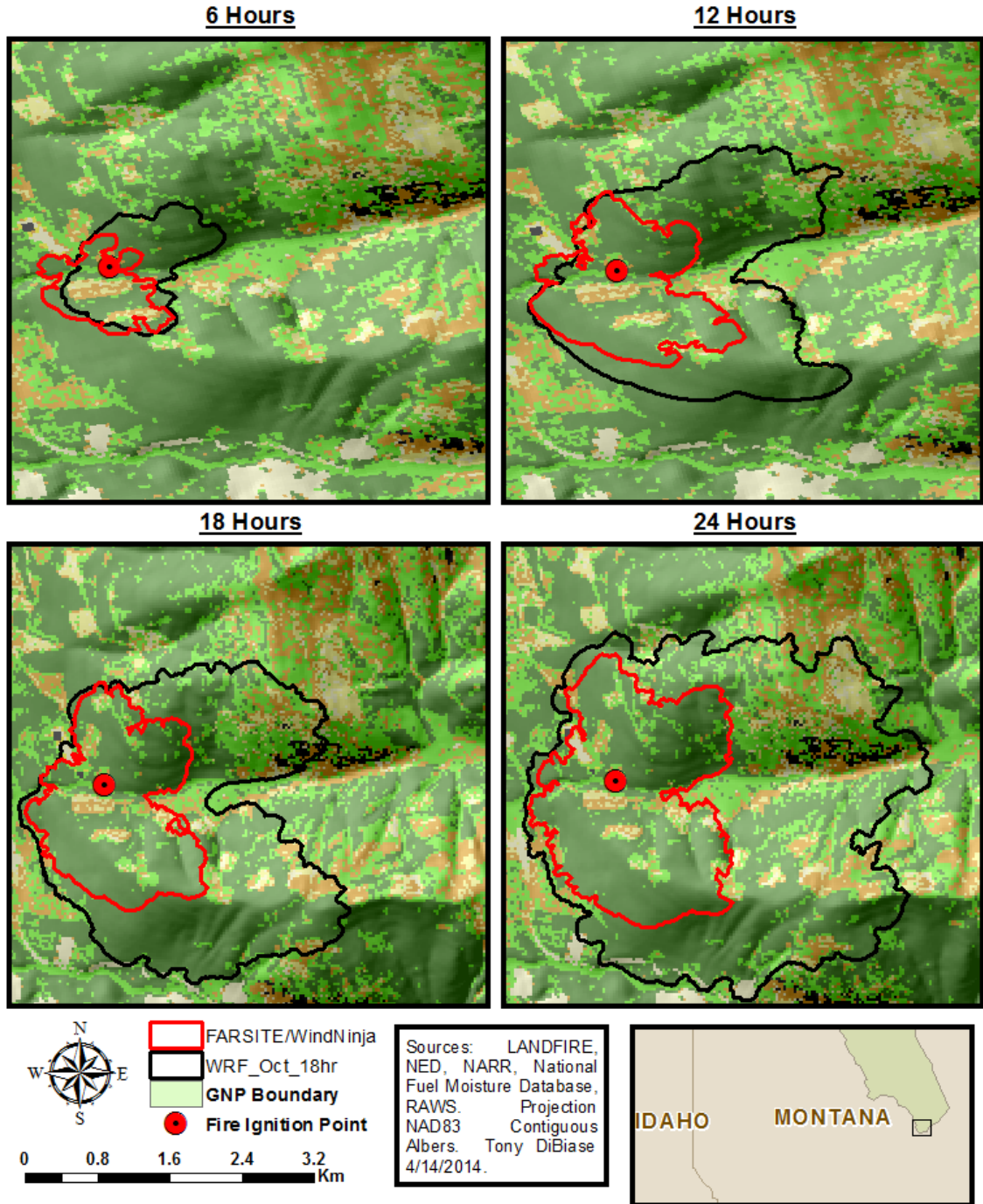


Figure 13: Comparison of FARSITE (with WindNinja) and WRF-FIRE in 6-hour intervals

Seasonal Comparisons – July vs. October

Seasonal variables appear to play a larger role in the extent of the FARSITE model compared to the WRF-FIRE runs, though the 1 July 2013 period for both models demonstrate a larger overall area burned across all time intervals (14). FARSITE demonstrates a clear difference both in the relative magnitude of the burn as well as its spatial extent—only burning to the south in October versus across both slopes in a nearly circular pattern in the warmer July time period. The amount burned (visualized via the ‘contours’ of the burned-area polygons, Figure 15) shows a greater distance for each time period in July compared to October, demonstrating a faster rate-of-spread, also quantitatively shown in Figure 14. Holding all other factors constant other than seasonal weather, the FARSITE model in July appears to predict nearly twice as much burned area compared to the equivalent period in late October, as well as drastically different fire behavior favoring an immediate progression away from the south-facing slope of the northernmost valley.

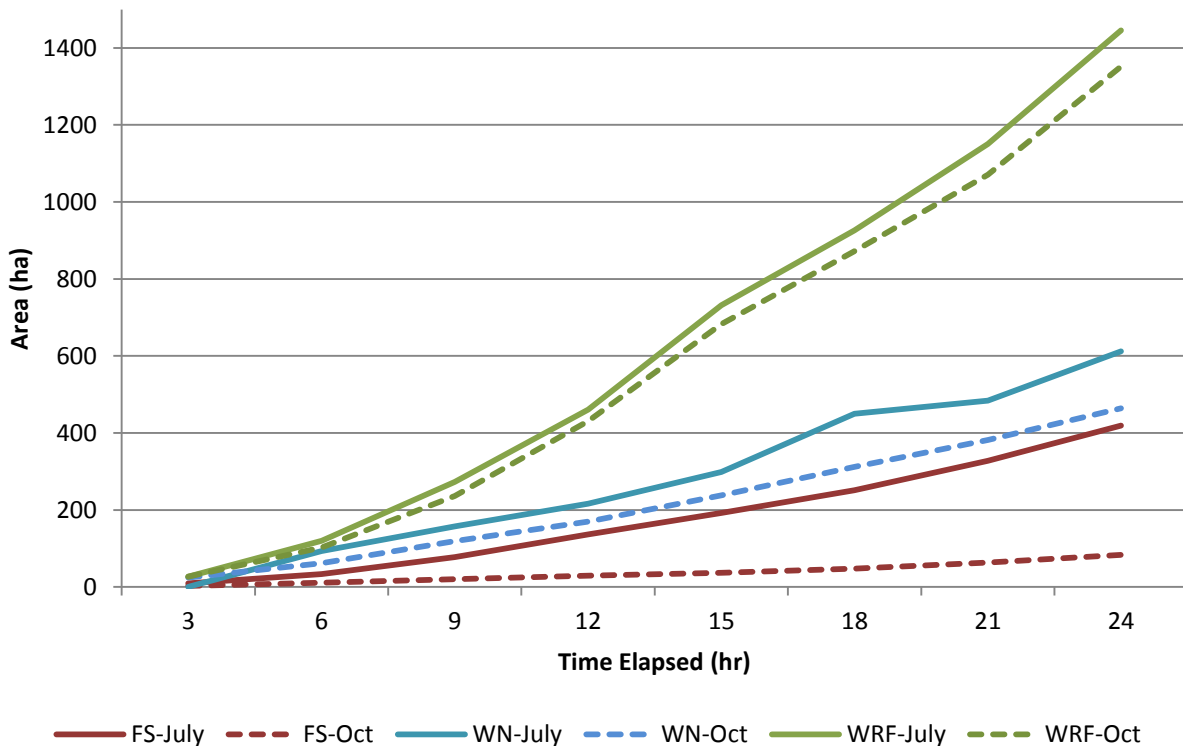


Figure 14: Graphical comparison of total area burned by each model over time. Each model is represented by the same color and seasons are indicated by solid (July) or dashed (October) lines. FARSITE (FS), FARSITE with WindNinja (WN), and WRF-FIRE (WRF).

While the non-modified FARSITE runs demonstrate significant seasonal variation (Figure 15), when the local diurnal and orographic wind influences from WindNinja are added this seasonal difference decreases by an order of magnitude—changing from a difference of 349% between July and October to 37% difference with WindNinja. This is visually apparent in maps of the WindNinja runs for both time periods (Figures 15), which show both WindNinja simulations spreading over similar extents. The seasonal difference in area burned by the WindNinja runs demonstrates increasing relative difference as time progresses, but this difference is significantly less than the divergence of the non-modified FARSITE runs (Table 7).

The difference between the two seasonal periods is less evident in the two WRF-FIRE model runs, which follow a very similar progression initially. As visually demonstrated in Figure 14, and spatially in Figure 15, the July run demonstrates a larger area burned over each time period than the October one, though the difference in absolute terms is very small. This seasonal variation, however, appears to significantly increase following an elapsed time of 18 hours, with the October run increasing much more slowly after that time period than the July period, such that at the termination of the WRF-FIRE sequences at 24 hours, there is nearly a 400-hectare difference between simulations in 1 July and 20 October 2013. Unlike in the previous FARSITE comparison, there does not appear to be a substantial difference in terms of the spatial pattern of the fire across the time periods: both, though increasing at different rates, particularly following the 18-hour mark, show much the same progression over space—though following an acceleration of the July rate of spread in the late time intervals, the fire area increases towards the northern extent of the map compared to October (Figure 15).

Comparing the average percent-difference in fire extent between each model between October and July reveals the influence to which the wind influences and feedback play on fire spread. While the FARSITE models demonstrate a 349.36% difference between seasons. The WindNinja produces to 37.89% extent difference, and the WRF-FIRE model only exhibits a small 8.30% difference between July and October.

Table 3: Average Percentile Differences between July and October in terms of hectares burned

Model	Average Difference (%)
FARSITE	349.36
FARSITE w/ WN	37.89
WRF-FIRE	8.30

Seasonal Comparison of Three Models

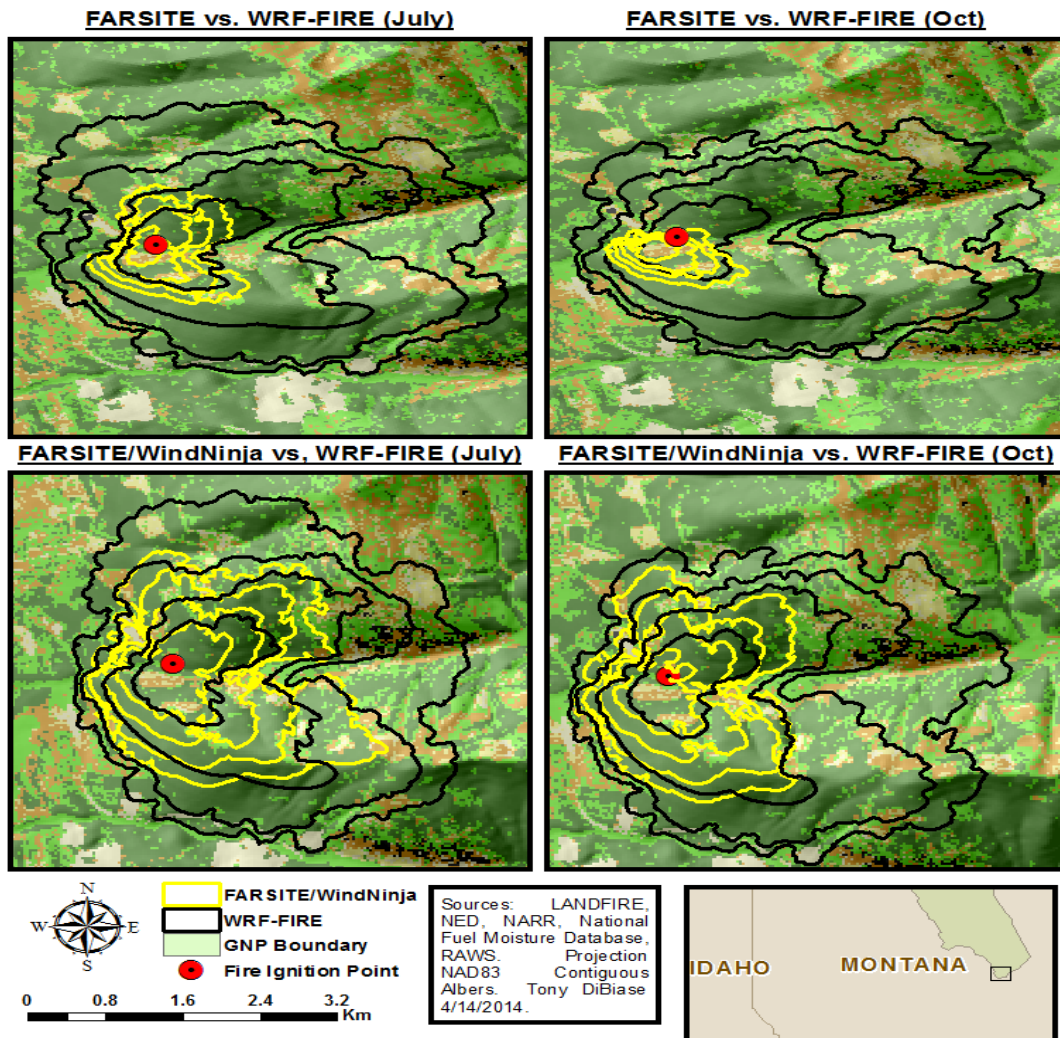


Figure 15: Seasonal variation between July and October for all model runs

Discussion

Model Comparisons

While FARSITE (Finney and Ryan 1995; Stephens 1998; Arca 2006), WindNinja (Forthofer 2009; Forthofer 2010; Jin et al 2012) and WRF-FIRE (Dobrinkova et al 2010; Peace et al 2011; Kochanski et al 2013) have been independently validated and tested against real fire events and shown to show close spatial extents as actual measured fires, all three models demonstrate an unexpected level of divergence from each other (Table 7). The difference in total area burned after the 24-hour time period ranges from roughly 402 ha with FARSITE, 611 with the WindNinja extension, and 1445 ha using WRF-FIRE—all using environmental conditions as similar as possible initial parameterization.

The results of the fire simulation experiments demonstrate the importance to which fire-wind dynamics function in determining wildfire behavior. Adding diurnal and orographic wind effects in the WindNinja model roughly doubled the average area burned (both July-October) compared to the basic unmodified FARSITE run (Figure 16). WindNinja's addition of orographic effects expands a fundamental

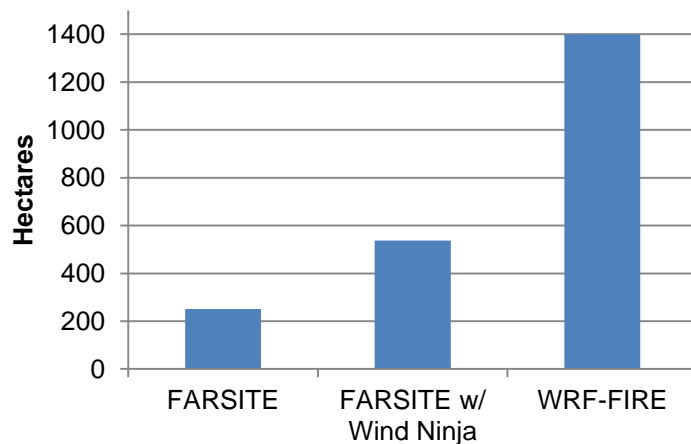


Figure 16: Average area burned at 24-hrs between both time periods

limitation of the unmodified FARSITE model by providing interaction with wind and local topography—effectively enabling fire behavior to account for head/back-fire effects, a critical aspect of fire behavior (Johnson & Miyanishi, 2001). These influences are clearly shown in both seasons of the WindNinja runs (Figure 15), where the fire progresses uphill extremely fast compared to lateral progression across

the valley floor or downhill to the West. In essence, WindNinja provides a nuanced, more accurate understanding of wind across the landscape, in a manner consistent with observed phenomena—and these influences are able to heavily alter fire behavior by pushing a faster rate of spread in uphill sloped cells. These orographic and diurnal effects also integrate a gradient response to temporal and elevation change for every cell of the study area, as opposed to FARSITE which assumes homogenous wind

distribution throughout the entire region. While the October WindNinja produces a greater area burnt than the July FARSITE run, across all time intervals the orographic influences produce a net greater area burned compared to the basic model (Figure 14).

The influence that orographic and diurnal wind dynamics play in determining wind behavior is further compounded when feedback mechanisms and broader meteorological effects are added. The WRF-FIRE results easily outpaced both of the FARSITE-based models, doubling average final fire area compared to the WindNinja results. Through all simulations, the WRF-FIRE results demonstrate similar results as WindNinja until roughly six hours in the simulation, after which growth increases measurably higher than all of the other simulations (Figure 14). These results are consistent with the original predictions: wind feedback mechanisms drive fire behavior by altering the direction and velocity of the flaming front, and this in turn speeds and changes the direction of surface winds—in effect, driving fire behavior in an iterative positive feedback cycle, and greatly expanding the area burned than if wind effects were not present. From the results of the simulations, it is evident that fire winds play a critical role in controlling the behavior of wildfires, with dramatically larger area burned for model runs that integrate feedback controls than those that do not.

Seasonal Variation

While the intensity and duration of a fire is expected to be higher in the summer months compared to late-October due to less precipitation and higher temperatures (Albini, 1976; Johnson & Miyanishi 2001), the degree to which fire area burned changes seasonally immensely differs based on the fire model used. While all three models demonstrated a higher net amount of area burned in July versus October across all time steps (Figure 14), the magnitude to which seasonality played a role in fire behavior is the largest in the FARSITE run, with a tenfold difference averaged across all measured intervals (Table 7).

While all three July fire models demonstrated larger areas burned (and thus a progressively faster rate of spread) than the subsequent October runs, the very large range of seasonal variance from 8-350% was unexpected, as was the fact that the more advanced models integrating weather and wind dynamics exhibited significantly less difference between seasons as the model that did not use weather influences. The results of the fire modeling scenarios suggest that seasonal variables (precipitation and ambient surface temperature primarily) could be overemphasized in the FARSITE model—even the

addition of orographic and diurnal wind influences override the effect of temperature differences when WindNinja was used. The orographic wind influences drive a major change in fire behavior compared to FARSITE, strongly increasing the influence that local topography plays on the rate of spread of the wildfire—for instance, visual inspection of maps of the simulation isolines shows the rate of spread uphill with WindNinja as much greater than the dual FARSITE runs. This result is logically consistent with the purpose of the WindNinja model, and known fire behavior principles (Johnson and Miyanishi 2001): instead of assuming wind and temperature as unidirectional across the study area, the gradient of surface roughness and slope weigh local topography as a major factor in determining fire progression (and thus mitigating seasonal climatic variance, which is not as influenced by microgradients in topography as much as by daily solar radiation).

The results of the WRF-FIRE model simulations generated an even lesser degree of variation than WindNinja between seasons: 8.3%, compared to the 37.89%. These results suggest that the addition of advanced fire-weather feedback loops and inclusion of multi-scalar weather phenomena decrease seasonal variability, in effect lessening the influence of annual climatic factors over fire behavior. While the WRF-FIRE July run still produced marginally more area burned compared to the October simulation, this difference was significantly less than expected given that the WRF-FIRE model was the only one that integrated broader regional and continental-scale meteorological processes as well as micro-scale topographic effects. While broader climatic variables do appear to produce a greater overall area burned and a faster rate of spread in July than October, the relatively small difference implies that WRF-FIRE's use of fire-weather feedback may be overriding weather variables (beyond the local orographic influences from WindNinja), and actually prove a more powerful control of fire behavior than seasonal climate. That the only model that actually integrates fire-weather dynamics has the least seasonal differences suggests that the feedback cycle produced by a wildfire plays a significant role in fire spread: rather than purely being driven by orographic influences and climate, the inclusion of dynamic iterative cycles strongly influence wildfire behavior. In addition to simply creating a positive feedback loop generating additional area burned compared to the previous two models (Figure 5), the WRF-FIRE results demonstrate the common adage that “fire creates its own weather”—that internal thermal input from flaming front has an overriding effect on fire behavior than underlying climatic variables.

Limitations and Assumptions

While all three models have been independently verified against real-world fire instances, the limits and inherent assumptions of each model make comparisons between the output difficult. While the treatment of wind in each model is used as an experimental variable in the model simulations, it innately limits comparison of the weather influences on fire spread for each run—WRF-FIRE, which uses iterative weather feedback for every time step including broad meteorological patterns, can hardly be compared to FARSITE’s weather influences, which assume homogeneity of wind across the entire study area. Both FARSITE and the WindNinja extension are strongly limited by their treatment of wildfire spread while not integrating feedback dynamics—the simulations, in effect, have two treatment effects: of the treatment of wind, as well as seasonal variability, but there may very well exist autocorrelation between wind dynamics and season that are not explored further in the testing (Mandel et al 2011).

The WRF-FIRE model is inherently limited in its treatment of weather across the entire study area: while the model possesses sophisticated downscaling algorithms for modeling sequentially higher-resolution weather phenomena using multi-scalar nesting, the North American Regional Reanalysis (NARR) dataset from which the global weather data for WRF-FIRE was extracted operates using a 32 km resolution. While this coarse level of resolution is appropriate for global and continental scale analysis (Michalekes, et al., 2004)—and no similar proxy dataset exists at a lower resolution (Coen 2005)—it makes approximation of very high resolution weather difficult, particularly in wildfire scenarios, where very local-scale influences may override broader regional patterns (Mandel et al 2011). While there remains no other effective options for datasets at a lower resolution, this limitation must be considered for understanding the results of the analysis, particularly because the WindNinja and pure FARSITE results were modeled specifically using weather data from the West Glacier RAWS station rather than NARR. The Fuel Moisture data for the FARSITE runs was obtained from the National Fuel Moisture Dataset (USDA Forest Service, 2014), which only measures fuel moisture values using point calculations at a small number of locations for Glacier National Park, and thus likely does not represent the gradient of fuel moistures across the park. While the simulations used as similar initialization parameters as possible, the difference in datasets as well as the resolution of data used for each model mandated small-scale changes that may account for a certain amount of variation in the modeling outputs.

Further, due to the adaption of the mesoscale Weather Research and Forecasting Model (which is primarily intended for low-resolution continental and regional scale meteorological analysis) to very high resolution (sub-50m) wildfire modeling, a certain degree of data simplification was necessary. While this is addressed in most WRF-FIRE literature (Mandel 2011; Coen 2013) and found to be an unavoidable issue that was balanced with the sophistication with which the model handled fire-weather feedback, the issue remains: such high-resolution analysis requires, for instance, a smoothing of elevation data to avoid Courants-Friedrichs-Lowry condition errors (where wind passes through a spatial cell faster than the actual time step of the model). For both the FARSITE runs as well as the WRF-FIRE simulations, the LANDFIRE database provided fuel model data according to Anderson (1982), but this metric of fuel classification simplifies the innate properties of burnable wildfire fuels and ignoring potential micro-scale spatial heterogeneity that is incredibly important to the spread of wildfires (Coen & Schroder 2013) – a problem that is noted specifically in the LANDFIRE guiding documentation, noting that the database is suited more towards broad regional scale analysis than modeling of individual wildfire events (LANDFIRE 2010). Despite these limitations, given the absence of comparable datasets, and the absence of widely collected field data, it is somewhat impossible to envision another alternative to the LANDFIRE data.

While the FARSITE model runs were completed in a matter of seconds, the WRF-FIRE model requires hours of computational time and a high degree of technical training to run—as well as access to a massively parallel supercomputer to run with any degree of efficiency (for instance, the 24-hour runs were completed in faster-than-real-time, but still over six hours each, and at over 100 gigabytes of output produced). Both these high-level computational requirements and the sheer amount of output produced create inherent limitations on the applicability of the WRF-FIRE model to wildfire modeling endeavors. The WRF-FIRE model requires a small amount of time to actually ‘spin up’ and generate ambient conditions resembling the ‘real world’ (Michalekes 2004), unlike the FARSITE model, so the choice of a 24-hour time period may be slightly inappropriate; while a longer time-frame would likely produce an extremely large amount of data in terms of disk space, a time period initializing the wildfire after three days of run-time may be more ideal for simulating actual wildfire conditions (Dr. Hiro Hashimoto, *personal comm.* 2014). Further, running the wildfire simulation for longer than 24 hours would likely allow for more complicated weather-feedback dynamics and demonstrate a better degree of variability between the two time periods, given that Figure 5 suggests that seasonal influence becomes increasingly potent towards the end of the simulation time for WRF-FIRE.

Conclusion

The results of the wildfire simulations using three different behavior models during both the height and end of the fire season in Glacier National Park provide a more nuanced understanding of forest fires in the park, and fire behavior generally. The results demonstrate the extent to which understanding the variability and interconnectedness of wind patterns with fire is absolutely critical for accurate modeling—by simply adding orographic and diurnal winds from local topography, the final fire area was roughly doubled from FARSITE to the WindNinja runs. When fire-weather feedback loops and broad-scale meteorological factors were added with the WRF-FIRE model, the total area burned experienced another near doubling by the end of the 24-hour period.

Beyond simply increasing the relative area burned, the manner in which each model treated wind patterns had a profound influence on the level of seasonal variability experienced between 1 July and 20 October 2013. Adding diurnal and orographic winds reduced the influence of ambient climate (and subsequently raising the importance of local-gradients in topography and vegetation type)—reducing seasonal variability by 300%. The addition of fire-weather feedbacks using WRF-FIRE compounded this reduction of seasonal variability down to barely above 8% between the July and October runs. These results strengthen anecdotal accounts that fire “creates its own weather”, and imply that fire-weather feedback dampens seasonal variability between fires in Glacier National Park, as the thermal input from the fireline exceeds relatively minor annual changes in climatic conditions.

The influence on wind and weather patterns on fire behavior in Glacier National Park—both in terms of overall area burned and the importance of season—have profound implications for wildfire modeling and management across the park. Given that wind so strongly influences fire behavior in GNP, research in fire’s impact on ecosystems across the park would be best informed by integrating WRF-FIRE runs to future analyses—however difficult to run and computationally intensive, the results of these fire modeling simulations demonstrate significant differences between current fire models and WRF-FIRE. In an operational context, using a massively parallel supercomputer to conduct analyses may be inappropriate, but fire managers would be well-served to use the WindNinja extension, which represents a “middle ground” between approximating real-world phenomena and ease of use. One of the most powerful analytical capabilities of WRF-FIRE is the modeling of dynamic fire-weather feedback,

and managers in a firefighting operations context are encouraged to frequently re-instantiate FARSITE runs (using WindNinja) according to changes in observed weather conditions. By using the most appropriate model for analysis, scientists and wildfire managers may better understand and mitigate wildfire's impact on ecosystems and human welfare throughout Glacier National Park.

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