

Article

Spatial Predictions of Human and Natural-Caused Wildfire Likelihood across Montana (USA)

Adrián Jiménez-Ruano ^{1,*}, William M. Jolly ^{1,†}, Patrick H. Freeborn ^{1,†}, Daniel José Vega-Nieva ², Norma Angélica Monjarás-Vega ², Carlos Iván Briones-Herrera ² and Marcos Rodrigues ³

¹ Missoula Fire Sciences Laboratory, Rocky Mountain Research Station, USDA Forest Service, 5775 Hwy 10 W, Missoula, MT 59808, USA; william.jolly@usda.gov (W.M.J.); patrick.h.freeborn@usda.gov (P.H.F.)

² Facultad de Ciencias Forestales, Universidad Juárez del Estado de Durango, Durango 34000, Mexico; danieljvn@gmail.com (D.J.V.-N.); normonjaras@gmail.com (N.A.M.-V.); carlos.briones.ipi@gmail.com (C.I.B.-H.)

³ Department of Agriculture and Forest Engineering, University of Lleida, Alcalde Rovira Roure 191, 25198 Lleida, Spain; marcos.rodrigues@udl.cat

* Correspondence: jimenez@unizar.es

† These authors contributed equally to this work.

Abstract: Spatial wildfire ignition predictions are needed to ensure efficient and effective wildfire response, and robust methods for modeling new wildfire occurrences are ever-emerging. Here, ignition locations of natural and human-caused wildfires across the state of Montana (USA) from 1992 to 2017 were intersected with static, 30 m resolution spatial data that captured topography, fuel availability, and human transport infrastructure. Once combined, the data were used to train several simple and multiple logistic generalized linear models (GLMs) and generalized additive models (GAMs) to predict the spatial likelihood of natural and human-caused ignitions. Increasingly more complex models that included spatial smoothing terms were better at distinguishing locations with and without natural and human-caused ignitions, achieving area under the receiver operating characteristic curves (AUCs) of 0.84 and 0.89, respectively. Whilst both ignition types were more likely to occur at intermediate fuel loads, as characterized by the local maximum Normalized Difference Vegetation Index (NDVI), naturally-ignited wildfires were more locally influenced by slope, while human-caused wildfires were more locally influenced by distance to roads. Static maps of ignition likelihood were verified by demonstrating that mean annual ignition densities ($\# \text{ yr}^{-1} \text{ km}^{-1}$) were higher within areas of higher predicted probabilities. Although the spatial models developed herein only address the static component of wildfire hazard, they provide a foundation upon which dynamic data can be superimposed to forecast and map wildfire ignition probabilities statewide on a timely basis.

Keywords: wildfire occurrence; ignition location; GLM; GAM; slope; NDVI; road network



Citation: Jiménez-Ruano, A.; Jolly, W.M.; Freeborn, P.H.; Vega-Nieva, D.J.; Monjarás-Vega, N.A.; Briones-Herrera, C.I.; Rodrigues, M. Spatial Predictions of Human and Natural-Caused Wildfire Likelihood across Montana (USA). *Forests* **2022**, *13*, 1200. <https://doi.org/10.3390/f13081200>

Academic Editor: Xiangwen Deng

Received: 3 June 2022

Accepted: 15 July 2022

Published: 29 July 2022

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1. Introduction

Wildfires are present in practically all vegetated environments worldwide [1–3] and they can have profound affects on global ecosystems. Wildfire events can heavily impact the global carbon cycle [4] and can also impact global water supply and quality [5,6]. They are a natural process in many ecosystems [7] but they can pose a threat to life and property in populated areas [8,9]. In many cases, wildfires that would otherwise be beneficial in the long term are immediately suppressed to prevent or limit losses to highly valued resources [10]. However, if a newly ignited wildfire escapes suppression and burns uncontrollably during severe weather conditions, it has the potential to become an extreme wildfire event, causing a disproportionate amount of losses [11]. Although effective wildfire planning requires early information about where new ignitions are likely to start, for example, to increase

prevention activities or allocate sparse resources prior to and during the fire season [12], this information is generally not available across large areas at high spatial resolution.

New wildfires start when there is an ignition source, sufficient fuel, and suitable weather conditions. Ignitions can be from either natural or human sources [13], and from 1992–2012, natural ignitions accounted for 16% of all wildfires across the United States [14]. Natural ignitions in the United States are mainly caused by cloud-to-ground lightning strikes and thus depend on the timing and characteristics of the flashes in relation to fuel condition [15,16]. Intentional human ignitions in the United States occur less frequently than those from negligence, such as escaped campfires, discarded cigarettes, or other careless uses of fire [17], and are heavily favored by road networks used for transportation and access to recreational opportunities [18,19]. Therefore, differentiating the spatial distributions of natural and human-caused ignitions is crucial to designing and implementing source-specific prevention and mitigation strategies [20,21].

Natural and human-caused wildfire ignition likelihood may be suitably modeled if proxies are included to represent the fuels, weather, topography, and human presence that control their spatial distribution [22]. While weather is spatially and temporally variant, fuel loadings, topography, and human pressure change slowly over time and could be captured by a static model. Terrain metrics, such as slope, can impact wildfire ignition and propagation potential [23]. Road networks affect fire occurrence and fire spread in two ways: first, they make wildlands accessible to humans, thus promoting new anthropogenic wildfire ignitions [24,25]; and second, roads enable ground-based firefighting resources to respond quickly to new events and can be used as potential containment locations [26]. Finally, although fuel conditions such as moisture content and chemical composition are seasonally dynamic, static fuel factors such as loading and continuity may limit the location of fires where insufficient fuels prevent propagation [27]. Regarding this last variable, in contrast to a more documented effect of human and topographic factors (e.g., [28]), spatially detailed proxies of fuel availability have been less explored in the literature (e.g., [27,29,30]) and deserve further research. Furthermore, the majority of previous predictions of fire occurrence have used coarse spatial resolutions, ranging from 50–100 km (e.g., [2,29]) to 1 km (e.g., [27,30]). Therefore, there is a need to analyze the human, topographic, and fuel drivers of fire activity at finer spatial resolutions, such as those provided by sensors such as Landsat at 30 m. In summary, if ignition sources are differentiated and adequate spatial biophysical and demographic drivers are identified at detailed scales, wildland fire ignition likelihoods could be better modeled, mapped, and predicted across large areas, potentially improving fire management strategic planning.

In this study, we develop and evaluate spatial logistic models of new wildfire occurrences that can be used to map ignition likelihood across the state of Montana, USA. To achieve this, we decouple the static and dynamic components of wildfire occurrence (Figure 1) and focus solely on constructing static ignition models. Simple and multiple logistic generalized linear models (GLMs) and generalized additive models (GAMs) are built by relating records of new wildfire occurrences with several temporally invariant explanatory variables (i.e., the biophysical environment and proximity to roads). We evaluate the efficacy of increasingly more complex models and select the best-performing models to produce statewide static maps of natural and human-caused ignition probabilities.

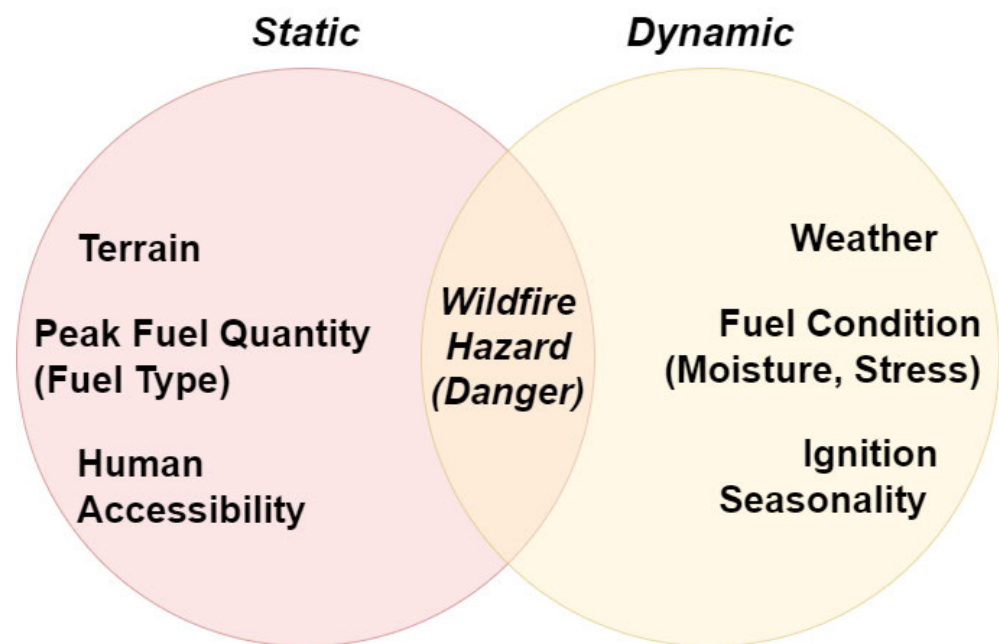


Figure 1. Conceptual scheme of the dual component of wildfire hazard or danger: the static factors and the dynamic factors.

2. Material and Methods

2.1. Study Area

With a land area of 376,962 square kilometers, the study area covers the state of Montana, USA. Montana was chosen because of its west-to-east gradients in climate, topography, vegetation types, and wildfire causality (Figure 2). Western Montana has a terrain-driven climate whereby maritime air arrives from the Pacific with continental modifications, and topography controls the local precipitation and temperature. Winter precipitation falling as a mix of rain and snow increases with elevation [31], and summer rainfall is dominated by localized, high-intensity thunderstorms [32]. The continental divide is a predominantly north-to-south geographical feature that acts as a barrier, resulting in a precipitation–temperature gradient with warmer and drier conditions and greater cloud-to-ground lightning flash densities in the east [33,34]. Based on data from the LAND-FIRE project [35], the main existing vegetation types (EVT) in MT are shrublands, conifers, grasslands, and agricultural lands, covering 30.8%, 24.7%, 19.9%, and 13.9% statewide, respectively; however, these proportions vary across the state, with conifers and shrublands prevailing in the west and shrublands, grasslands, and agricultural lands prevailing in the east. Variations in the biophysical environment coupled with differences in land use result in a gradient of wildfire causes such that human-caused ignitions exceed natural ignitions in the eastern half of the state.

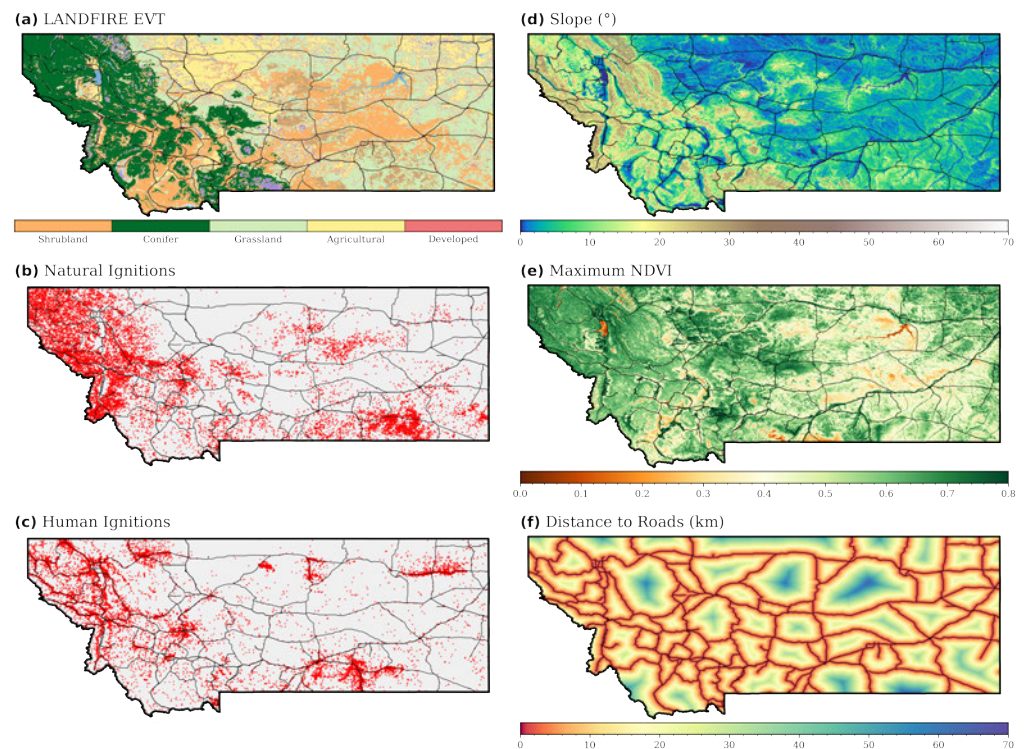


Figure 2. Maps of Montana, USA, shown with primary and secondary roads. (a) LANDFIRE Existing Vegetation Type (EVT) (b) and (c) natural and human-caused ignition locations recorded in the Fire Program Analysis Fire-Occurrence Database (FPA FOD) from 1992–2017. (d) Slope from LANDFIRE. (e) Maximum Normalized Difference Vegetation Index (NDVI) from 1992–2011. (f) Distance to roads.

2.2. Data Preparation

Federal, state, and local wildfire records within Montana from 1992–2017 were obtained from the Fire Program Analysis Fire-Occurrence Database (FPA FOD) [36]. Point records in the FPA FOD contain geographic coordinates of the ignition location as well as an ignition cause. After excluding records with an unknown cause, wildfires were partitioned into either natural or human-caused. Of the 12 fire cause codes recorded in the FPA FOD, all natural ignitions consisted of lightning strikes while human ignitions consisted of, among others, campfires, debris burning, equipment use, fireworks, arson, children, smoking, and powerlines. Ignition points (Figure 2b,c) were projected onto the 30 m gridded LANDFIRE domain [35] covering Montana to produce two binary masks (one for natural and one for human-caused ignitions), indicating the locations where at least one new wildfire was reported or not (i.e., presence = 1 and absence = 0).

Several static explanatory variables were explored to predict and map wildfire ignition likelihood. To represent fuel availability, a single 30 m raster of maximum Normalized Difference Vegetation Index (NDVI) was generated in Google Earth Engine [37] using 20 years (1992–2011) of Landsat 5 Thematic Mapper (TM) Collection 1 Tier 1 Annual NDVI Composites available in the Earth Engine public data catalog. Given the relationships between NDVI, primary productivity, and vegetation type [38], maximum NDVI was chosen to capture the peak amount of aboveground live biomass, which is found to be related to fire occurrence in other parts of North America [27]. To coincide with the binary masks of ignition locations, the raster of maximum NDVI was resampled to the 30 m LANDFIRE domain covering Montana using the nearest neighbor method. Topography was represented by slope (degrees), obtained from the LANDFIRE 30 m resolution digital elevation model [35]. Distance from roads (i.e., the straight-line distance in kilometers from the center of each grid cell to the nearest road) was used to represent accessibility, which has been shown to influence the ignition locations of human-caused wildfires across large

areas [39]. Primary and secondary roads across Montana were downloaded as a shapefile from the United States Census Bureau [40], and a raster of distance to roads was created at LANDFIRE 30 m resolution. Maps of all potential static explanatory variables are shown in Figure 2d–f.

The datasets used for model building and evaluation were derived from the 30 m presence/absence masks of wildfire ignitions and the co-registered rasters of potential explanatory variables (Figure 3). First, presence datasets were created by using the grid cells containing a new wildfire report to extract the explanatory variables. This produced two presence datasets, one for natural ignitions and one for human-caused ignitions, such that every location with a new wildfire report had an associated value for slope, maximum NDVI, distance to roads, and longitude and latitude. The presence datasets were then split into training (70%) and testing (30%) datasets. Absence datasets were created by randomly selecting grid cells from the binary masks at locations without any recorded wildfire ignitions. To provide balanced datasets, the number of randomly selected absence grid cells was set equal to the number of presence grid cells. After using the absence grid cells to extract the explanatory variables and geographic coordinates, the absence datasets were themselves split into training (70%) and testing (30%) datasets. Combining the presence and absence datasets for each ignition source yielded four datasets: the natural-caused training and test datasets, and the human-caused training and test datasets.

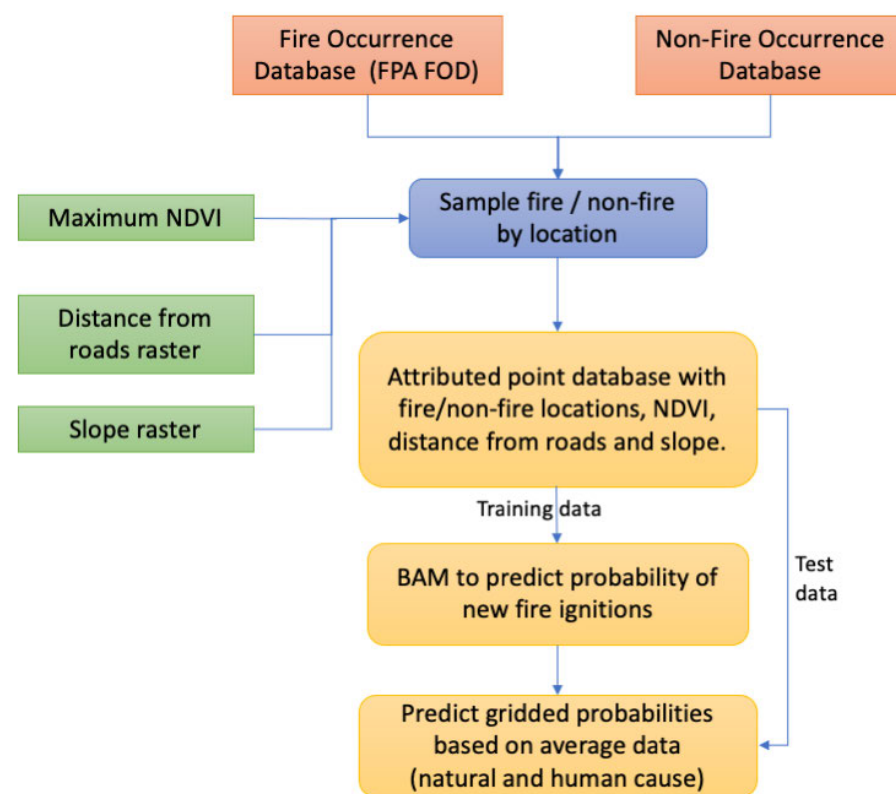


Figure 3. General workflow for model building and evaluation including inputs, sampling of wildfire presence and absence locations, extraction of explanatory variables, creation of an attributed point wildfire database, model fitting of new wildfire occurrences, and the final spatial predictions of wildfire ignition probabilities.

2.3. Model Construction and Evaluation

A common approach to modeling the probability (pr) of a new wildfire ignition is to use a generalized linear model (GLM) to relate the natural logarithm of the odds, otherwise known as *logit*(pr), to a linear combination of the explanatory variables [41,42]. However, it is likely that some or all relationships between dependent and independent variables may

be nonlinear. Generalized additive models (GAMs) overcome the a priori assumption of linearity by replacing the linear terms with smoothed, nonlinear functions to model ignition probabilities [43]. In this work, a suite of logistic GLMs and GAMs were built to model the probability of a new wildfire ignition. In practice, all models were built in R [44] using the ‘mgcv’ package [45]. Specifically, the ‘bam’ function was called, which is an implementation of GAM fitting designed for use with large datasets [46] and has the advantage of using less memory and can also leverage parallel processing, thus gaining computational speed for both model training and prediction. Both logistic-GLMs and logistic-GAMs were built by specifying a binomial family (the logit link). Whereas the GLMs were fit without specifying any smoothed terms, the GAMs were fit by specifying all smoothed terms. In the case of the GAMs, the fast restricted maximum likelihood (fREML) method was used to optimize the smoothness parameter due to its numerical stability and ability to avoid overfitting [47]. Additionally in the case of the GAMs, the default basis type (thin splines) was used and the basis dimension, k , which controls the maximum number of basis functions and thus the maximum allowable “wigglyness” for the specified basis type, was set to its default value.

To examine the isolated effects, simple logistic-GLMs and simple logistic-GAMs were built using slope, maximum NDVI, and distance to roads as the sole explanatory variables. Then, explanatory variables were procedurally added [48] to create increasingly more complex multiple logistic models with the goal of achieving the best fitting model with the fewest explanatory variables. Additional explanatory variables were retained if they were statistically significant ($p \leq 0.01$) and if the percent deviance explained increased by more than 0.1% compared to the more basic model. A final multiple logistic-GAM, referred to hereafter as the spatial-GAM, was built by adding the longitude and latitude of the ignition location—and their interaction—as a smoothed explanatory variable. Once added, all basis dimensions, k , in the spatial-GAMs were iteratively increased from their default values to ensure that all smoothed terms had sufficient degrees of freedom without being overfitted or computationally intractable.

After fitting the models with the training datasets, each model was applied to the held-back testing datasets to predict the probabilities of natural and human-caused ignitions. Receiver operating characteristic (ROC) curves [49] were then built by plotting the false positive rate (FPR) versus the true positive rate (TPR) calculated at every predicted probability threshold. The probability along the ROC curve closest to the top-left corner was selected as the optimum threshold, and the area under the ROC curve (AUC) was used to assess the overall ability of each model to differentiate locations with and without natural and human-caused ignitions. Lastly, we assessed the ability of the best-performing models to capture new wildfire occurrences by calculating the annual ignition density (AID , # yr^{−1} km^{−1}). The models were applied to the 30 m raster stacks of slope, maximum NDVI, and distance to roads to generate static probability maps of ignition likelihood. The natural (n) and human-caused (h) probability maps were classified into five equal probability intervals (i), and the areas covered by each probability interval ($A_{n,i}$ and $A_{h,i}$) were calculated based on the number of 30 m grid cells in each interval. Locations of all natural and human-caused ignitions reported from 1992–2017 were intersected with their respective static probability maps and sorted into years (y) to yield the annual count of natural ignitions ($c_{n,y}$) and human-caused ignitions ($c_{h,y}$) that occurred in each probability interval ($c_{n,y,i}$ and $c_{h,y,i}$). For each year and probability interval, the AID was calculated for both ignition sources as follows:

$$AID_{n,y,i} = \frac{c_{n,y,i}}{A_{n,i}} \quad (1)$$

$$AID_{h,y,i} = \frac{c_{h,y,i}}{A_{h,i}} \quad (2)$$

The 26 values for AID in each probability interval were then summarized by their mean, median, and interquartile range.

3. Results

From 1992 to 2017, there were 45,488 wildfires reported in Montana, resulting in 3.1 Mha burned area. Of those, 18,986 were natural ignitions (Figure 2b) and 23,255 were human-caused ignitions (Figure 2c). After excluding records with an unknown cause, and after gridding the point records onto the LANDFIRE domain, the number of 30 m grid cells containing at least one newly reported wildfire was nearly evenly split between natural and human-caused ignitions (47% vs. 53%).

Simple logistic-GLMs and simple logistic-GAMs built with a single explanatory variable each illustrate the isolated effects of slope, maximum NDVI, and distance to roads on the probability of a new wildfire ignition across MT (Figure 4). In contrast to the GLMs, which either increase or decrease monotonically across the full range of the explanatory variables, the GAMs, with their greater flexibility, capture nonlinearities in the response, particularly at the lower and upper limits of slope and maximum NDVI. Since all natural and human-caused model fits exhibit monotonic behavior over most of the range (i.e., from the 5th to the 95th percentiles) of slope (Figure 4a,b) and distance to roads (Figure 4e,f), the AUCs are quite similar between the GLMs and GAMs, never differing by more than 0.01. However there is sufficient nonlinearity in the responses between the 5th and 95th percentiles of maximum NDVI such that the GAMs outperform the GLMs, with differences in AUCs ≥ 0.03 (Figure 4c,d).

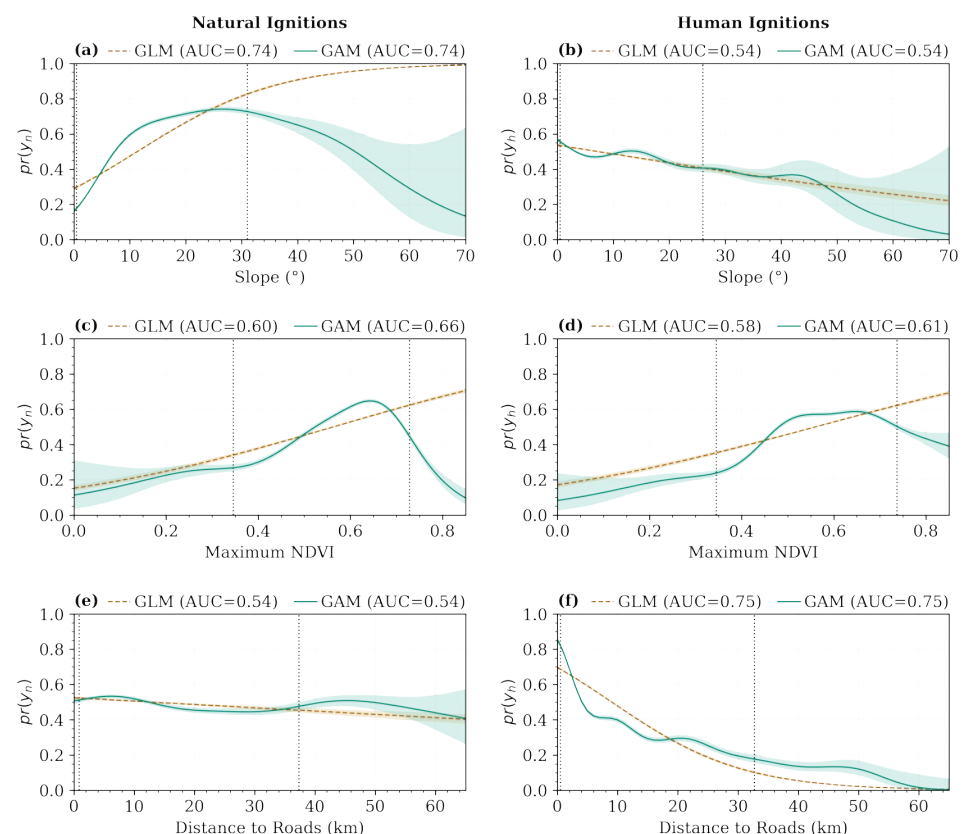


Figure 4. Univariate simple logistic general linear models (GLMs) and simple logistic general additive models (GAMs) to predict the probability of natural ignitions, $pr(y_n)$ (left column), and human-caused ignitions, $pr(y_h)$ (right column). Models were built using a single explanatory variable each, shown for slope (a,b), maximum NDVI (c,d) and distance to roads (e,f). The dotted vertical lines indicate the 5th and 95th percentiles of the explanatory variables and therefore capture 90% of the training data. The area under the receiver operating characteristic curve (AUC) is based on the testing data.

Table 1 shows the evolution of model construction, starting with the multiple logistic-GLMs, and then including the smoothed terms in the multiple logistic-GAMs, and finishing with the multiple logistic spatial-GAMs. All explanatory variables were statistically significant ($p \leq 0.01$) and increased the percent deviance explained by more than 0.1% when included in the models of human-caused ignitions. However, for the models of natural-caused ignitions, distance to roads was not significant in the multiple logistic-GLM and did not improve the percent deviance explained by more than 0.1% when included in the spatial-GAM.

Table 1. Summary of the multiple logistic general linear model (GLM), the general additive model (GAM), and spatial-GAM. Formulas are presented for modeling the probability of a natural ignition, $pr(y_n)$, and human-caused ignition, $pr(y_h)$, where α is the intercept, $v1$ = slope, $v2$ = maximum NDVI, $v3$ = distance to roads, x = longitude, and y = latitude. The $s()$ functions indicate the smoothed terms in the GAMs. The area under the receiver operating characteristic (ROC) curve (AUC) is based on the testing data, and the ROCs themselves are shown in Figures 5 and 6, respectively.

Version	Cause	Formula	AUC
GLM	Natural	$pr(y_n) = \alpha + v1 + v2$	0.74
	Human	$pr(y_h) = \alpha + v1 + v2 + v3$	0.73
GAM	Natural	$pr(y_n) = \alpha + s(v1) + s(v2) + s(v3)$	0.77
	Human	$pr(y_h) = \alpha + s(v1) + s(v2) + s(v3)$	0.77
Spatial GAM	Natural	$pr(y_n) = \alpha + s(v1) + s(v2) + s(x, y)$	0.84
	Human	$pr(y_h) = \alpha + s(v1) + s(v2) + s(v3) + s(x, y)$	0.89

After building the initial spatial-GAMs, the default basis dimensions were iteratively increased for all smoothed terms. Increasing the values of k for slope, maximum NDVI, and distance to roads had very little effect on the on the spatial-GAMs and did not increase the percent deviance explained by more than 0.1% at any given value of k selected for the smoothed geographic coordinates. Therefore, the basis dimensions for slope, maximum NDVI, and distance to roads were left unchanged from their default values of $k = 10$. In contrast, increasing k for the smoothed geographic coordinates continually increased the percent deviance explained, albeit at a slower rate at higher values of k , indicating less improvement in model performance for incremental changes in k as the models became more complex. Ultimately, for the sake of model generality and computational speed, the basis dimension for the smoothed geographic coordinates was increased until the rate of change in percent deviance explained dropped below 0.1%, at which point $k = 42$ and $k = 50$ for the natural and human-caused ignition models, respectively.

Evaluating all models using the held-back testing datasets revealed increases in model efficacy with increasing model complexity (Figures 5 and 6). The multiple logistic-GLMs exhibited the most uniform frequency distributions (and thus the greatest overlap in predicted probabilities) for locations with and without wildfire ignitions. Including the smoothed terms in the multiple logistic-GAMs shifted the frequency distributions towards higher probabilities for the presence locations and towards lower probabilities for the absence locations, indicating better differentiation between locations with and without wildfire ignitions. Ultimately, the spatial-GAMs that included geographic coordinates as smoothed terms (and with optimized k values) yielded the greatest separation between the frequency distributions, with AUC = 0.84 and AUC = 0.89 for the natural and human-caused ignition models, respectively. For the spatial-GAMs, the optimum probability threshold for distinguishing locations with and without natural wildfire ignitions was found at $pr(y_n) = 0.53$, with 78% of presence grid cells (i.e., TPR = 0.78) and 24% of absence grid cells (i.e., FPR = 0.24) in the testing datasets lying above this threshold. Similarly, the optimum probability threshold for distinguishing locations with and without human-caused ignitions was found at $pr(y_h) = 0.55$, with 81% of presence grid cells (i.e., TPR = 0.81) and 18% of absence grid cells (i.e., FPR = 0.18) in the testing datasets lying above this threshold.

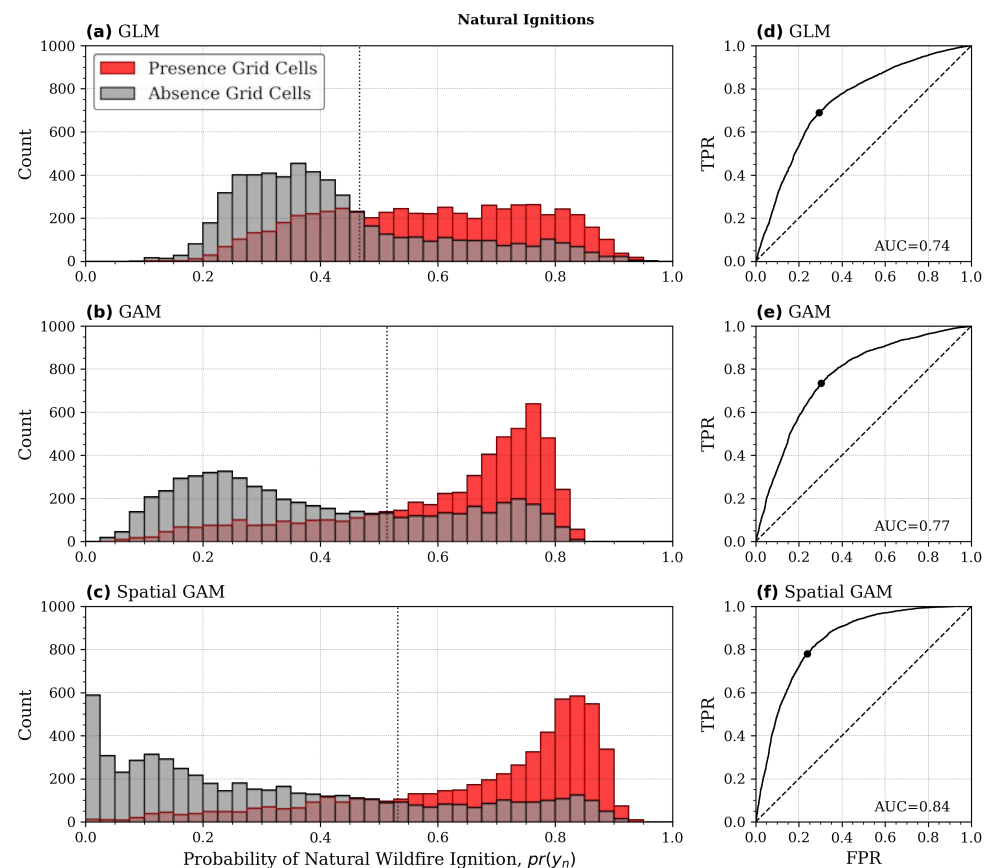


Figure 5. Evaluation of the multiple logistic general linear model (GLM), general additive model (GAM), and spatial-GAM used to model natural wildfire ignition probability. Model definitions are shown in Table 1. Each model was applied to the held-back testing datasets and the frequency distributions shown in (a–c) indicate the count of presence (red) and absence (black) grid cells according to their predicted probability. The receiver operating characteristic (ROC) curves and area under the ROC curves (AUC) shown in (d–f) were also generated from the testing datasets. The optimum probability thresholds (i.e., closest to TPR = 1.0 and FPR = 0.0) are shown as dotted vertical lines in (a–c) and solid circles in (d–f).

Partial effects plots for the spatial-GAMs show how the most complex models respond to each smoothed explanatory variable with all other covariates held constant (Figures 7 and 8). For both natural and human-caused ignitions, the response of the spatial-GAMs to slope, maximum NDVI, and distance to roads was similar to that of the simple logistic-GAMs. The probability of a new naturally ignited wildfire increased up to a slope of $\sim 30^\circ$ and then decreased thereafter with greater uncertainty in the prediction due to fewer training data. Natural and human-caused wildfires were least likely to start at locations having the lowest and highest maximum NDVI values, and were most likely to start at locations having intermediate NDVI values between 0.55 and 0.65. Notably, distance to roads played a prominent role in the spatial-GAM of human-caused ignitions, where half of the 30 m grid cells containing the origin of a human-caused wildfire were located within 2.5 km of a road. Including the geographic coordinates of the origin in the multiple logistic-GAMs essentially imparted spatial smoothers on the models. Whereas locations in the Northern Rocky Mountains shared the highest probability of new natural and human-caused wildfires, differences in the pattern of ignition likelihoods between causes were more evident in the eastern half of Montana.

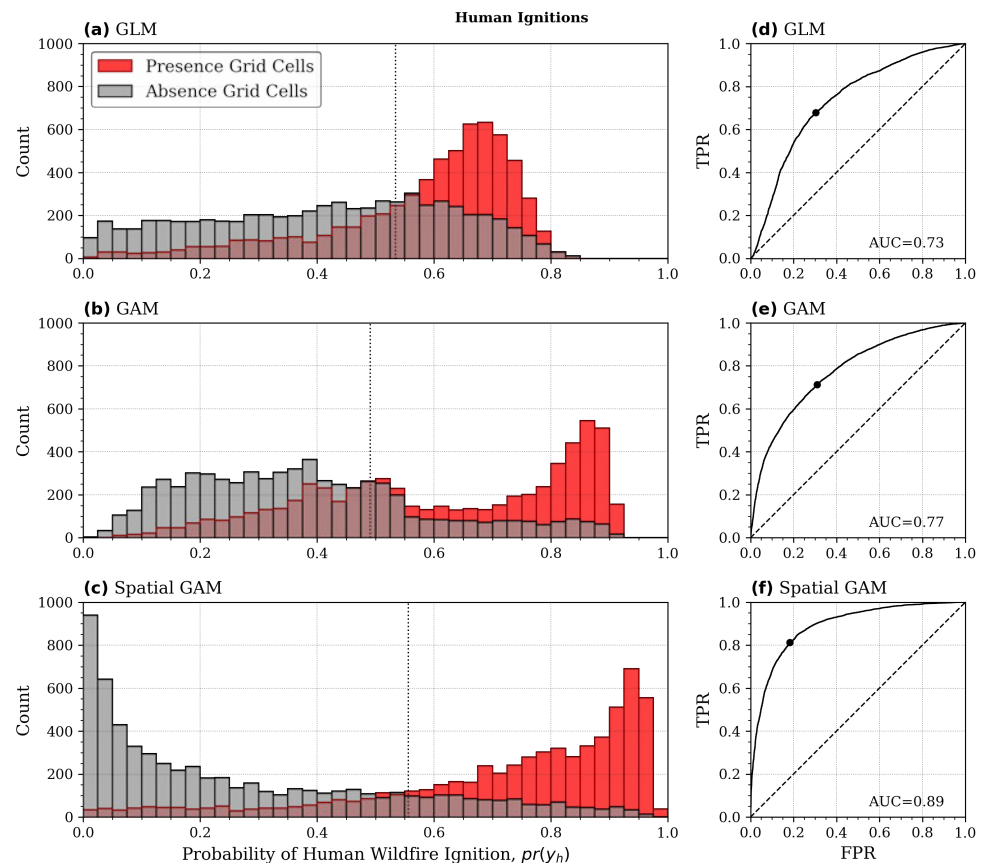


Figure 6. Evaluation of the multiple logistic general linear model (GLM), general additive model (GAM), and spatial-GAM used to model human-caused wildfire ignition probability. Model definitions are shown in Table 1. Each model was applied to the held-back testing datasets and the frequency distributions shown in (a–c) indicate the count of presence (red) and absence (black) grid cells according to their predicted probability. The receiver operating characteristic (ROC) curves and area under the ROC curves (AUC) shown in (d–f) were also generated from the testing datasets. The optimum probability thresholds (i.e., closest to TPR = 1.0 and FPR = 0.0) are shown as dotted vertical lines in (a–c) and solid circles in (d–f).

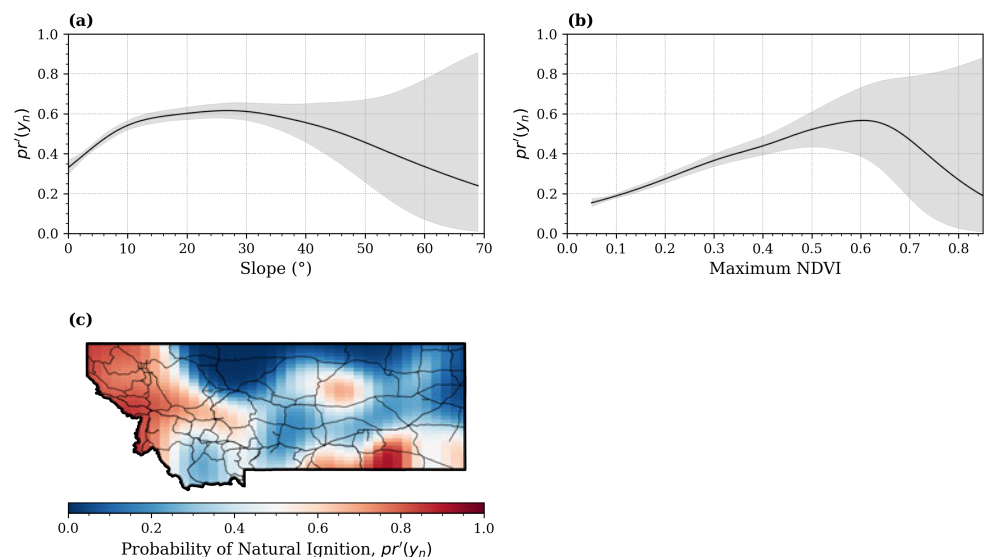


Figure 7. Partial effects plots for slope (a), maximum NDVI (b) and longitude and latitude (c) included in the spatial-GAM built to predict the probability of a naturally ignited wildfire, $pr(y_n)$.

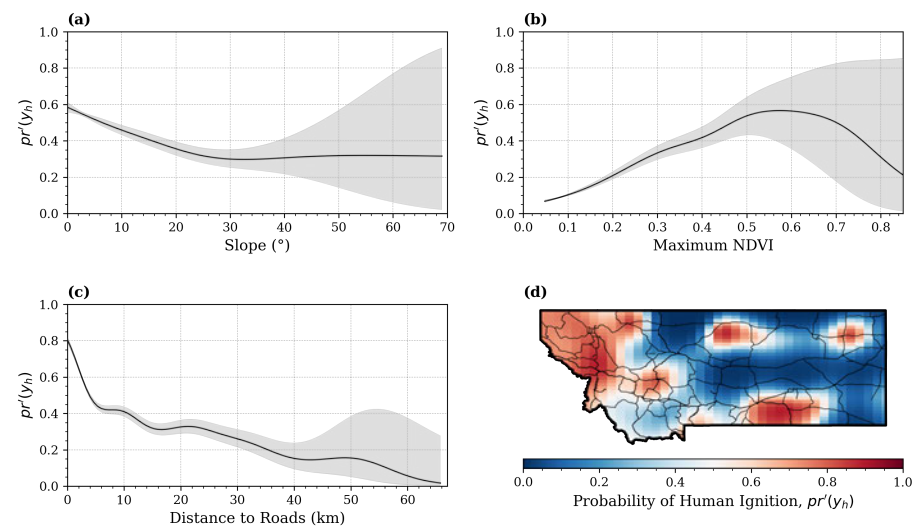


Figure 8. Partial effects plots for slope (a), maximum NDVI (b), distance to roads (c) and longitude and latitude (d) included in the spatial-GAM built to predict the probability of a human-caused wildfire ignition, $pr(y_h)$.

Applying the spatial-GAMs to the stacked rasters of explanatory variables produced 30 m static probability maps indicating the likelihood of natural and human-caused ignitions (Figure 9). The static probability maps were broadly influenced by the spatial smoothers (Figures 7c and 8d) and were locally modulated by slope, maximum NDVI, and distance to roads. This is most evident in the spatial-GAM of natural ignitions, where probabilities are lower in the valley bottoms and drainages with shallower slopes, and most evident in the spatial-GAM of human-caused ignitions, where probabilities are highest along the road network. Given the sparsity of ignition locations compared to the overall size of MT, both spatial-GAMs reassuringly predicted large areas with low probabilities of a wildfire ignition. Half of all land area is predicted to have less than a 23% and 15% chance of a natural or human-caused ignition, respectively. Conversely, locations with the highest predicted probabilities are rare. By area, less than 1% and 2% of the state had >90% chance of a natural or human-caused ignition, respectively. When using the optimum thresholds of $pr(y_n) = 0.53$ and $pr(y_h) = 0.55$ to classify the probability maps into binary masks of presence and absence, only 23% and 17% of the area across MT can be considered to have conditions most suitable for natural and human-caused ignitions, respectively.

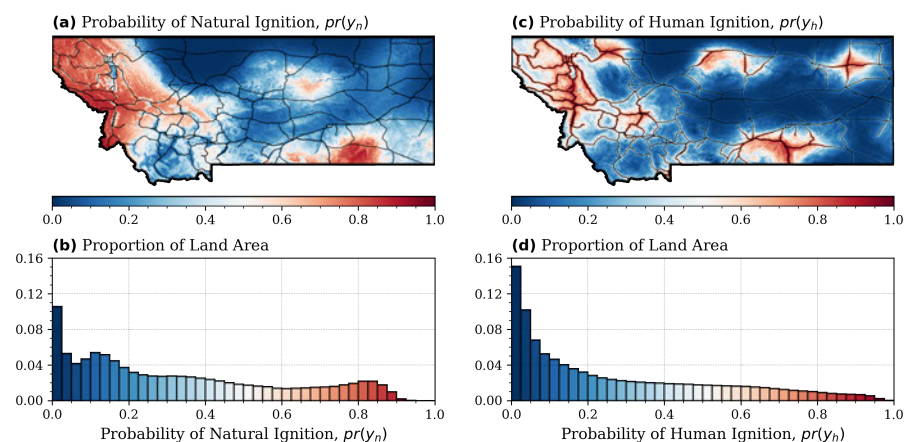


Figure 9. Maps of (a) the probability of a naturally ignited wildfire, $pr(y_n)$, and (c) the probability of a human-caused wildfire, $pr(y_h)$, in Montana obtained from the spatial-GAMs. Distributions of the proportion of land area as functions of $pr(y_n)$ and $pr(y_h)$ are shown in (b) and (d), respectively.

Intersecting 26 years of all ignition locations with the static maps shown in Figure 9a,c revealed that new wildfires were more often reported inside areas with higher modeled probabilities. Similar to the testing datasets, 78% and 83% of all natural and human-caused wildfires were ignited at locations with modeled probabilities above the optimum thresholds of $pr(y_n) = 0.53$ and $pr(y_h) = 0.55$, respectively. Given the smaller areas with higher modeled probabilities (Figure 9b,d), mean annual ignition densities for natural and human-caused wildfires were $10\times$ and $21\times$ greater in locations with modeled probabilities above the optimum thresholds compared to below. Although the occurrence of more ignitions inside smaller areas resulted in greater mean annual ignition densities within areas of higher predicted probabilities (Figure 10a,b), there was nevertheless variability in AID around the mean. Since the area covered by each probability interval in the static maps is constant, the variability in AID is due to fluctuations in the annual number of statewide ignitions (Figure 10c,d).

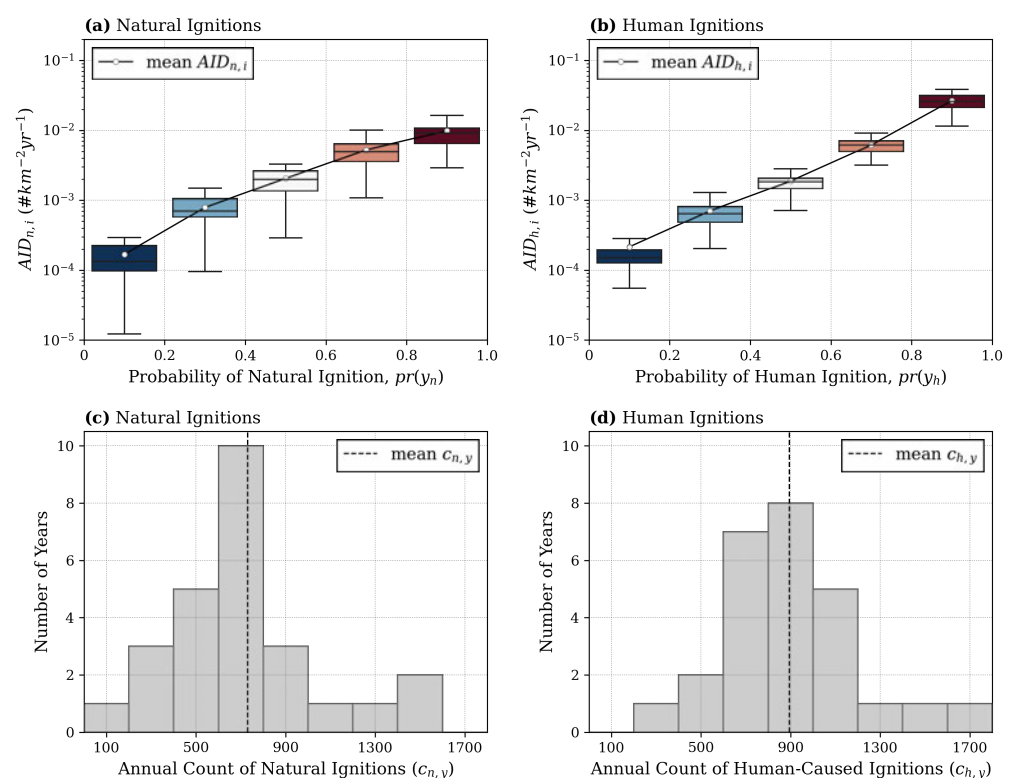


Figure 10. Shown in (a,b) are the distributions of annual ignition densities (AID , $\#yr^{-1} km^{-1}$) for natural (subscript n) and human-caused (subscript h) wildfires calculated within each probability interval (subscript i). Shown in (c,d) are the frequency distributions of the yearly (subscript y) count of natural and human-caused ignitions along with their mean values.

4. Discussion

In this study we evaluated the efficacy of logistic-GLMs and logistic-GAMs to predict the spatial distribution of natural and human-caused wildfire ignitions across Montana, USA. Our final models adequately described the areas where each ignition source was likely to occur without being overly complex or dependent on dozens of data sources. Compared to other studies, the list of potential explanatory variables investigated here was not exhaustive. Future work is planned to expand this framework to cover the continental US at 30 m spatial resolution, and including additional explanatory variables may make predictions computationally intractable. Likewise, the basis dimensions, k , for the spatial smoothers were kept at a minimum to minimize computation time. In this regard, the spatial smoothers were used to capture the general patterns of ignition likelihood whilst slope, maximum NDVI, and distance to roads were used to refine and focus in on

the localized patterns of ignition likelihood. Nevertheless, with only three variables and information about the historical, spatial distribution of wildfires, we were able to model the static ignition probabilities accurately. Given the simplicity of the final models and the few variables used, achieving AUC values of 0.84 and 0.89 for natural and human-caused ignitions is quite remarkable and it suggests that temporally-invariant components of the fire environment that are proxies for fuel availability, terrain, and accessibility are important factors to include in any fire danger rating system.

Generalized additive models have several useful characteristics for this type of application. First, they do not assume linear relationships. Recent work exploring relationships between biomass and fire activity has shown that there is an optimum biomass where fires occur [27]. In areas with low biomass, fire occurrence can be fuel-limited (e.g., [50,51]). Contrarily, areas with high biomass may indicate closed canopies where understory fuels, generally composed of lighter grass and shrub loads [30], remain sheltered from the sun-light and wind and are wet and unable to burn. We noted the same relationship where the optimum, nonlinear, influence of maximum NDVI on wildfire ignitions occurred at intermediate values, supporting the intermediate productivity hypothesis of fire occurrence (e.g., [52]). Nevertheless, in contrast to previous analyses performed at coarse scales (1–100 km) (e.g., [27,29]), we documented this relationship at finer (30 m) spatial resolutions, which can better serve operational fire management planning. Moreover, we noted a strong, nonlinear increase in the probability of a human-caused ignition with proximity to the transportation network, especially within 5 km from a primary or secondary road (Figure 8c), which is consistent with other findings [22,39,53,54]. Ultimately, having a robust modeling framework that does not assume linear relationships between the response and explanatory variables allows us to develop better wildfire ignition predictive models. Further, the ability to include spatial terms and spatial interactions means that these methods can better characterize regional differences in fire activity that is not captured by the biophysical variables alone. This combination of characteristics was a key factor in the choice to use spatial logistic GAMs for this work.

Our work demonstrates that we can effectively model the spatial variations of wildfire ignition across a large area. However, we know that temporally-variant fire environment drivers are also critical components of assessing dynamic fire hazards (Figure 1). While these static models adequately predict the mean annual ignition densities, interannual variability in both natural and human-caused wildfire ignitions (Figure 10) and these variations are likely a direct result of interannual weather variations that either favor or impede new ignitions. Future work should focus on coupling our static wildfire probability maps with dynamic ignition triggers to effectively model the seasonal variations in both natural and human-caused wildfire probabilities across large areas (e.g., [55,56]). Previous work has shown that outputs of the US National Fire Danger Rating System, such as the Energy Release Component and Burning Index, are closely correlated with the timing of new ignitions as reported in the FPA FOD across the Continental United States [57]. Fortunately, preliminary work on utilizing GAMs to predict both the spatial location and timing of new ignitions throughout the fire season shows promise and will be the subject of future work.

Decoupling the static and dynamic controls of wildfire ignition has some distinct computational benefits. The static variables used in these predictive models can be mapped ahead of time, thus reducing computation time if predictive models are used to forecast new ignition potential. If suitable dynamic ignition probability models can be developed for natural and human-caused ignitions, then a final predictive map over some time interval could be computed as follows:

$$pr(NewWildfireIgnition) = pr(Static) * pr(Dynamic) \quad (3)$$

The final choice to use a generalized additive model mainly involved the evaluation of the final predictive model and its efficacy to predict the spatial locations of wildfires across Montana. However, there are many choices for machine learning models, and several

methods have been effectively applied to produce models of wildfire likelihood across large areas. For example, Parisien et al. [58] used the MaxEnt method across the Western US, while others have used random forest [22] and support vector machine (SVM) methods [59] and artificial neural networks [60] for regional studies. Ultimately, more work is needed to evaluate the strengths and weaknesses of various machine learning approaches but AUC values of about 0.75 across various methods suggest that the choice of the exact method may not be as important as selecting good spatial covariates for model training and prediction.

While this simple, static wildfire ignition likelihood model can serve as the foundation of a more robust wildfire ignition potential forecast system, it can also be used independently. For example, wildfire management programs can leverage these probability maps to focus their prevention activities in areas with the highest ignition likelihood. Areas with the highest ignition probability (>0.8) in our final prediction maps were restricted to just 7.3% of the statewide land area for natural ignitions and 3.6% of the area for human-caused ignitions, and this could help focus pre-fire prevention and during-season resource pre-positioning efforts to focus on the places where new fires are mostly likely to start.

5. Conclusions

This study investigated several logistic regression models of increasing complexity for predicting the probability of natural and human-caused ignitions across the state of Montana, USA, by relating 26 years of wildfire locations with biophysical and human infrastructure drivers that can be mapped at high spatial resolution. In general, natural ignitions were more locally influenced by slope while human-caused ignitions were more locally influenced by distance to roads. This study provides the framework whereby the ignition probabilities produced herein can be efficiently modeled with high spatial resolution data to provide 30 m resolution maps. These static wildfire ignition probability maps can build the foundation of a robust fire potential prediction system. These models can easily be updated as new data become available. Overall, this predictive framework facilitates more concrete fire management decisions, including the allocation of firefighting resources and the location of future fuels reduction treatments, to reduce risk of new wildfire ignitions.

Author Contributions: Conceptualization, W.M.J., A.J.-R., P.H.F., D.J.V.-N., N.A.M.-V., C.I.B.-H., and M.R.; methodology, P.H.F., W.M.J., and A.J.-R.; software, A.J.-R., and P.H.F.; validation, A.J.-R., W.M.J., and P.H.F.; formal analysis, A.J.-R., and P.H.F.; investigation, A.J.-R., and W.M.J.; resources, W.M.J., and P.H.F.; data curation, W.M.J., and P.H.F.; writing—original draft preparation, A.J.-R., P.H.F., W.M.J., and M.R.; writing—review and editing, W.M.J., P.H.F., D.J.V.-N., and M.R.; visualization, P.H.F., and A.J.-R.; supervision, W.M.J.; project administration, W.M.J.; funding acquisition, W.M.J., and M.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research funded in part by Project FIREPATHS (PID2020-116556RA-I00), Spanish Ministry of Science and Innovation.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable

Conflicts of Interest: The authors declare no conflicts of interest.

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