OPEN ACCESS Freely available online

Journal of Geography & Natural Disasters

Research Article

Modeling and Assessing Temporal Distribution of Anthropogenic Factors in a Protected Area for Fire Danger Assessment

Dipuo Olga Mofokeng[1] and Adewale Samuel Adelabu[2]

[1]*Department of Geography; Afromontane Research Units (ARU); University of the Free State, Phuthaditjhaba; Free State, RSA*

[2]*Department of Geography and ARU, University of the Free State, Bloemfontein, Free State, RSA*

ABSTRACT

Human activities threaten the effectiveness of Protected Areas in preserving key natural resources. Ignoring the temporal dimension of human on fire occurrence can lead to ineffectiveness fire management and preserved outcomes. This study analyzes the intra-annual dimensions of fire occurrence and human-caused fire ignition factors for the Golden Gate Highlands National Parks of South Africa. We constructed four occurrence data scenarios from fire ignition data extracted from MODIS active fire product (2007 -2017 by splitting occurrence data into two seasons and further split the seasons into weekdays and weekends. Application of MaxEnt method was used to assess the performance of the models and to explain the importance of each explanatory variable. Results revealed ROADS as the highest contributor across all the models except in Spring weekend model where INFRA outperformed ROADS. In addition, we observed strong temporal variation with ROADS strongly influencing weekdays of both seasonal scenarios while INFRA shows strong influence in the weekends. Model overall performance is satisfactory, above 0.8 AUC values for all the models (Winter Weekend = 0.977; Winter Weekday = 0.929; Spring Weekend = 0.896) except Spring Weekday (0.641). In addition, Winter models are more robust in explaining the temporal distribution of human-caused fire ignition factors of the study. Our results are reliable and significant for advising practical wildfire management and resource allocation as well as to predict the human-caused fire ignition.

Keywords: Wildfires; human/anthropogenic factors; MaxEnt; temporal dimension. Protected area

INTRODUCTION

Fire is a natural disturbance in many ecosystems and is applied as one of the management tools for maintaining a healthy ecosystem particularly in Protected Areas (PAs). International Union for Conservation of Nature (IUCN) defined PA as a clearly defined geographical space, recognized, dedicated and managed through legal or other effective means to achieve the long-term conservation of nature with associated services and cultural values. Africa has a long history of fire longer than any other continent but current fire management issues on the continent are complicated. For instance, the global pressure to initiate climate mitigation programme in Africa often involve changes in how fire is applied. Application of fire in the PAs is conundrum driven by the safety policies and regulations that have led to the reduction of fire ecological benefits.

Fire management strategy which includes fire prevention may be the most cost-effective and effective mitigation programme. The strategy includes but not limited to awareness campaigns and or risk mitigation. In wildfire, risk is a chance of fire starting and spreading (danger) as well as its potential damage over environmental and human resources (vulnerability). Therefore, wildfire risk is a combination of wildfire “danger” and vulnerability. The concept of wildfire danger describes the factors affecting the inception, spread and resistance to control. Wildfire danger is related to both fire ignition and propagation. The former depends on the fuel amount and moisture and the presence of external cause (anthropogenic or natural) leading to fire start.

Correspondence to: Dipuo Olga Mofokeng, 1Department of Geography; Afromontane Research Units (ARU); University of the Free State, Phuthaditjhaba; Free State, RSA, Tel +27 839907122, E-mail: olgamofokeng55@gmail.com

Received: May 25, 2020; **Accepted:** August 27, 2021; **Published:** September 7, 2021

Citation: Mofokeng D O (2021) Modelling and assessing temporal distribution of anthropogenic factors in a protected area for fire danger assessment. J Geogr Nat Disas. 11:p358

While fire ignition is an integral component of wildfire factors, it is critical in wildfire danger because the chances of wildfire to start is minimal no matter how dry weather conditions and how the vegetation flammability is. As confirmed by data all over the world, human presence in landscape increases the number of ignition even above the background from lightning. Human affects fire regime directly by altering the number and timing of ignition of fire and indirectly by altering fuel. Henceforth, an improved understanding of wildfire risk should address the patterns of human activity and its relation to fire ignition. A key resource for wildfire risk is risk zoning and mapping, a subject on which Geospatial technology (Geographic Information Systems and Remote Sensing) and spatial statistic have been traditional applied.

Noteworthy, studies have been undertaken to explore the relationship between wildfire and its causative factors with the main aim of building predictive and explanatory models. A review study on human cause fire occurrence modelling by **Costafreda-Aumedes, Comas, and Vega-Garcia (2018)** revealed that on annual average 14 papers were published between 2012 and 2016. Most of these researchers construct these models with the different motivations ranging from fire prevention, fire suppression, for supporting fire management strategies and to develop early warning system as well as for conservation goal. However, suggested that modeling on human activity and its pattern is more appropriate for supporting decision making in wildfire preventions rather than firefighting and management after ignition. Although modeling and evaluating of human activity as an agent of ignition is a complex task since it requires the identification and quantification of human behaviour, a number of authors have showed that fire ignitions exhibit strong preference for distance to roads, settlement and infrastructure. However the effects of different human-related drivers on fire ignition change over time and space, and among ecosystems.

Several methods have been employed to model and evaluate the human-related drivers to fire ignition. Logistic regression has been intensively applied as they can handle unbalanced sample for rare wildfire presence versus common wildfire occurrence and geographically weighted regression. However, most of the used techniques suffer from multicollinearity problems. Machine learning algorithms such as random forest, classification and regression trees and weight of evidence properly predict and explain fire occurrence. One of the advantages of these algorithms is that they are non-parametric models and their input explanatory variables interrelationship are not defined a prior but rather derived from iterative training and testing using random data subset. Recently, one of the existing machine learning tools, presence only Maximum Entropy (MaxEnt) saturated the wildfire literature since it demonstrated high prediction and explanation accuracy than other plant and animal species distribution methods. As fire ignition distribution may be compared to species distribution, some researchers applied MaxEnt to model human-related drivers to wildfire occurrence.

Wildfire occurrence contain a temporal dimension which often requires temporal perspective. However, these temporal perspectives of anthropogenic drivers are frequently overlooked and these drivers enter the modelling as structural “static”. For instance the models developed by. This implies that they have no temporal variation in its influence as fire-trigger factors as explained by. By considering the temporal dimension of fire occurrence and fire-trigger factors in their study, they found out that modelling utilizing temporal scenarios enhances understanding of anthropogenic drivers. Although previous studies have created the models for predicting and explaining the human-related drivers in wildfire occurrence, fewer studies have focused on Afromontane grassland protected landscape or taking into account the temporal dimension of these drivers. This study using fire occurrence data spanning for 11-year period (2007 to 2017) aim to create seasonal and day-type models that consider temporal behaviour of anthropogenic drivers over wildfire occurrence applying MaxEnt method to explore the influence of anthropogenic drivers as a causal agent of the fire ignition either by accident or negligence to each model and how sensitive are these models are to the anthropogenic drivers. Finally, determine the best temporal model that can be used to facilitate the decision making on the preparation of the fire prevention plan.

MATERIALS AND METHODS

Study Area

Golden Gate Highlands National Park (GGHNP), our study area is a famous mountainous tourist destination in eastern Free State Province of South Africa (Fig.1.) with the total area coverage of 340km2. The park was established in 1963 to protect a pristine area with much emphasis on conserving the montane and Afro-Alpine grassland biome. GGHNP has a rugged topography with the highest peak at 2797 meters (m) above sea level. Climate is sub-tropical highland with dry winter according to Köppen classification; mean annual temperature ranging from 130C to 260C in summer. Mean annual rainfall ranges from 1,800 mm to 2,000 mm with a period of water deficit extending from June to August, and winter precipitation in the form of snow. GGHNP is vulnerable to wildfires that mainly occur between May and November which coincides with the onset of dry season and ends at the beginning of rainy season. The park has experienced area burnt in the past. For instance, in the year 2000, 30704,22ha of burnt area with low to high severity, 31352.13 in the year 2005, 4697 ha in 2013 and 30009.33 ha in 2017. The areas vulnerable to the greatest danger include valleys and low lying plains towards the eastern portion of the park.

Fire occurrence data

The dependent variable – wildfire occurrence was extracted from Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6 of NASA Fire Information for Resource Management (FIRM). The dataset has limitations as it does not distinguish between fire causes (either natural or human) and as a result makes it difficult to analyze each explanatory variable in its causality context. However, the MODIS active fire points represent fire activities being recorded at given times and locations that implies they contain information on both ignition and spread. The provisions of how the dataset is acquired and algorithms used are available on **Davies, Ilavajhala, Wong, and Justice (2008)** . The fire events of the 11 years spanning from 2007-2017 was selected for this study.

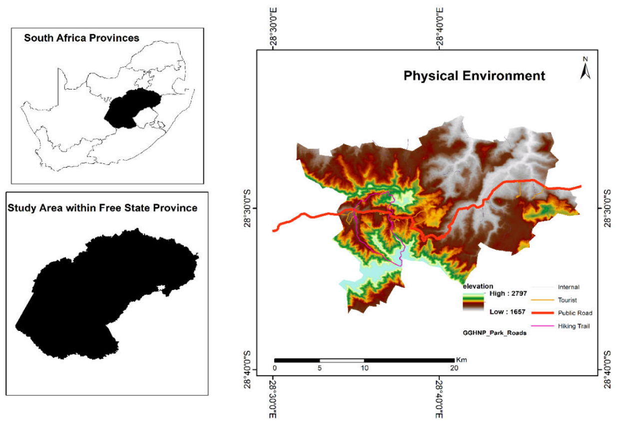

Figure 1. Location of the study area

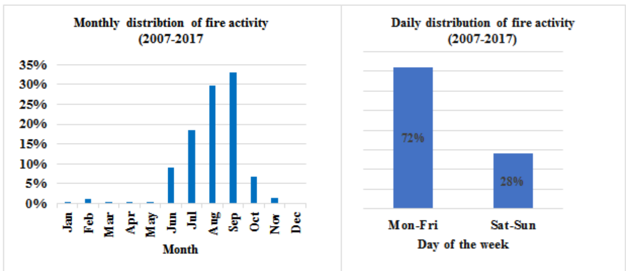

Figure 2. Monthly and daily distribution of fire frequency (2007 -2017)

Independent variables

According to the basis of variable performances and their relationship with wildfire ignitions, the distances to roads and railways, and tourist sites are mostly considered as anthropogenic drivers that possible cause of wildfire ignition by accident or negligence. A vector road and infrastructure map were obtained from South African National Parks (SANParks), Scientific Service Department. Multi-ring Buffer maps were generated for these two layers (100m, 200m, 300m, 400m, 500m). Variables were spatialized in ASCII raster format with spatial resolution of 30m x 30m using ArcMap Software.

Modelling approach

Firstly, we created temporal scenarios. Figure 2 illustrates the uneven temporal distribution of wildfire at both monthly and daily scale for the period of 11-year (2007 -2017). The monthly distribution shows bimodal pattern with peaks in August and September, which is conditioned by seasonality of human behaviour and weather conditions as described by **Martín, et al. (2019)**. Similarly, the daily distribution is biased towards weekends showing a variation in the temporal pattern of wildfire activity. Based on the preliminary evidence of this temporal variation of fire activity, four (4) scenarios were created as described in Table 1. Seasonal models were defined, Winter (June, July, August) and Spring (September, October, and November). In addition, days of the week were separated from weekdays (Monday to Friday) and weekend (Saturday to Friday).

Maximum Entropy (MaxEnt), a machine learning method was applied for modeling the anthropogenic factors for fire ignition in this study. MaxEnt is described as estimating a distribution across geographic space and was originally developed to be used for species distribution and environmental niche. The method has been extensively used for fire modeling studies. MaxEnt iteratively contrasts environmental layers (anthropogenic predictor values) at occurrence location (fire ignition points) with those large backgrounds sample of random locations taken across the study area. Data for running MaxEnt software, sample data (fire occurrence data) and environmental predictors (road and tourist's facilities _ infra) were prepared guided by the approach applied by **Brown (2014)** using ArcMap. A standalone MaxEnt Species Distribution Modeling Version 3.4.1. software version was chosen and the following were checked before the model runs: create a responsive curve, make pictures of predictions and do jackknife to measure variables importance.

A jackknife test was used to investigate the importance of an individual anthropogenic variable for MaxEnt predictions. The area under the curve (AUC) of the receiver operating characteristics (ROC) was used to measure each model 's performance and validation. The ROC curve is a graphical representation of the false-positive error (1-specificity, where specificity is the proportion of incorrect prediction) versus the true positive rate (also known as sensitivity or proportion of correct prediction) for binary classifier system and different values of the discrimination threshold. AUC is a threshold-independent metric because it evaluates the performance of a model at all possible threshold values by adding up the area between the ROC and random performance line. AUC is valid to estimate AUC values range from 0.5 to 1. Excellent model performance is suggested by AUC values higher than 0.9, a moderate good performance by values between 0.7 and 0,9, and poor model performance by values from 0.5 to 0.7.

	Name	Description
1	Winter_W_Day	Weekdays of Winter
2	Winter_W_End	Weekend of Winter
3	Spring_W_Day	Weekdays of Spring
4	Spring_W_End	Weekend of Spring

Table 1: Temporal Scenario

RESULTS

Variable contributions to the models

The analysis of variable contributions as depicted in Fig.3 revealed that ROADS as the strongest variable in two (2) models. The highest contribution variable in Spring_W_End with 97.9 %, Winter_W_Day with 83.4% and decrease to almost equal contribution with INFRA in Spring_W_Day with 51% for ROADS and 49% for INFRA. However, in Winter_W_End the importance of ROADS was weaker in favour of INFRA with 27.7% and 72.3% contribution to the model for ROADS and INFRA respectively. According to the jackknife test of variable importance, the anthropogenic variable that gains most was ROAD during weekdays when it was omitted, which therefore appeared to have more information that was not present in INFRA (Fig 4). In contrast, INFRA performance a key role during weekends in both Summer and Winter seasons.

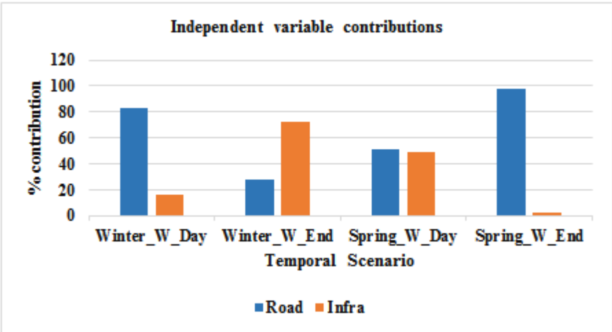

Figure 3. Independent variable contributions to each model

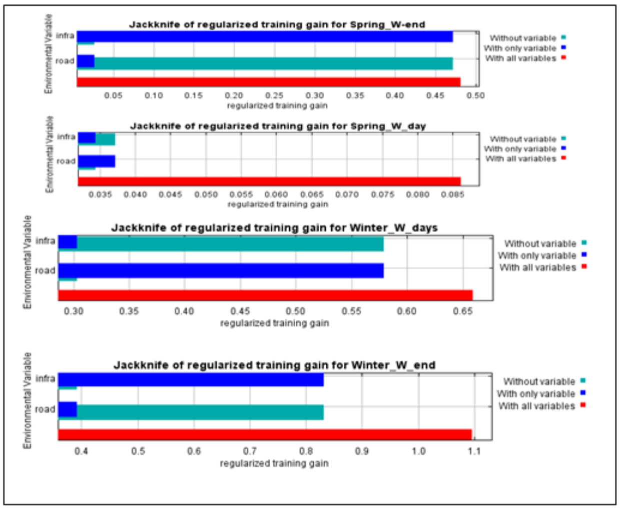

Figure 4: Jackknife estimation of variables importance of four models

The response curve of fire occurrence to the anthropogenic variables classifies the quantitative relationship between logistic probability and anthropogenic variables. Moreover, we can deepen the niche of fire ignition by explaining the response of each model to the distance of these variables. According to the response curve as shown in Fig 5, which reveals that the likelihood of fire ignition is higher at 100m from the distance to the infrastructure during weekdays, 200m during weekends in Winter. While in Spring models are at 200m and 400m during weekdays and weekends respectively. Looking at the response curve of winter models to ROAD, a higher likelihood of fire ignition in relation to distance to the road is observed at 500m and 200m during weekdays and weekends respectively. Both Spring weekday and weekend models show the maximum probability of likelihood of fire ignition is 300m from the distance to the road.

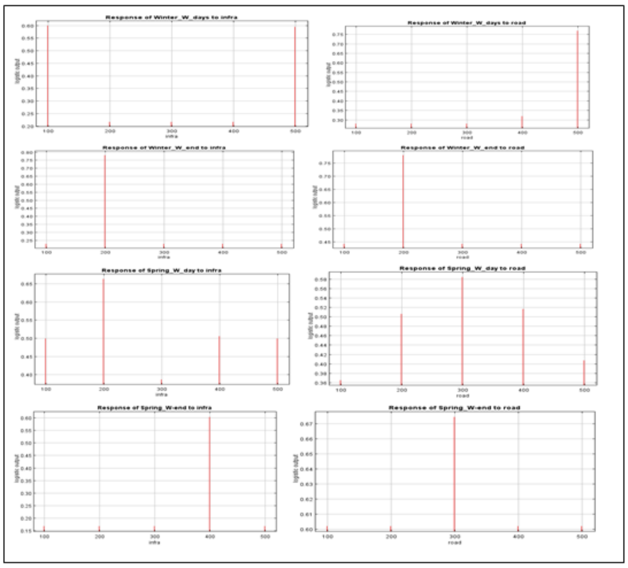

Figure 5: Response curves showing the relationship between all the models and anthropic drivers (ROADS & INFRA)

Model Performance

Figure 6 represents the ROC results with AUC values of the models. According to AUC values, the highest prediction capacity is reached in winter especially during the weekend (0.977), followed by weekdays (0.929) and spring weekend with 0.896. While the lowest is found during spring weekday (0.641). However, the overall performance of the models based on the average performance is moderate good performance (0,861) as the prescribe accuracy threshold proposed by Fawcett (2006).

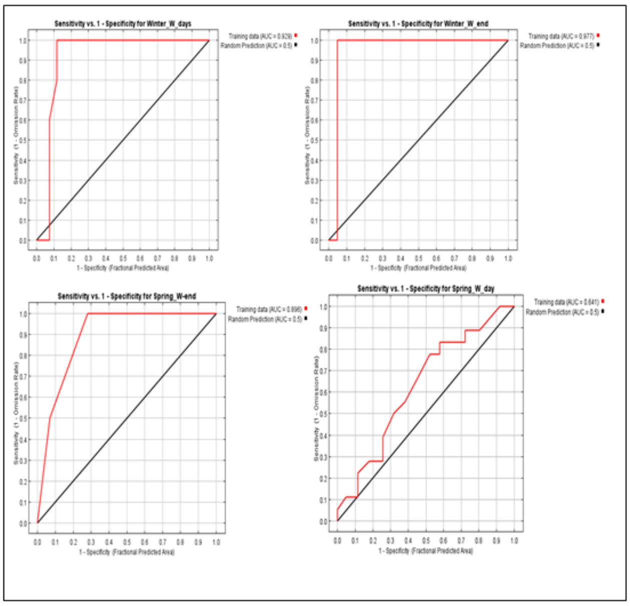

Figure 6: The ROC curve and AUC values of all the models

DISCUSSION

Our models can explore the influence of anthropogenic drivers as the causal agent of wildfire ignition. The results of this study confirm the dominance of ROADS as the key contributor to wildfire ignition, which is in consistent with the findings of earlier studies. Fire ignitions are more likely to occur close to roads due to accident, negligence or arson since roads act as conveyors for arsonists, careless drivers, and campers. ROADS is consistently the highest contributor in all the models. However, the contribution to temporal distribution is not similar in all models, it was dominant in all models except Spring Weekend. Similarly, as observed in Figure 5 the influence of ROADS is highest during weekdays of both seasonal scenarios. This finding disagrees with the common conclusion that ROADS contribute more during weekends which can be attributed to the traffic increase experience during weekends and holidays as people tend to travel more frequently during these days especially in natural or forest environment. The maximum importance of ROADS during weekdays in the study area may be related to the regional or public road (R712) passing through the park that connects major towns within the district (Fig 1). Activities by passers-by in such a road increase the probability of ignition. INFRA (tourist's facilities) finds its maximum contribution to the models during Spring Weekends and has low overall contribution along all models. Moreover, the influence of INFRA was found to be strong in weekends day-type of both seasonal scenarios. This coincides with the recreational activities in the park and may be related to the favorable weather conditions of Spring warming, conditions that promote fuel dryness which leads to higher ignition probability.

Considering the sensitivity of models to the ROADS and INFRA, as we observe in Fig 5 wildfire ignition patterns vary with time and distance (space). This finding confirms the novelty of the relationship between human activity and wildfire occurrence is not linear. In Winter Weekend response to both ROAD and INFRA, area between 100m and 200m have high influence to fire ignition and likelihood decreases as the distance increase. This might be explained by the reality that most distant areas are highly rugged topography and not accessible to humans. Similarly, in Spring Weekend higher ignition probability is observed in distance to INFRA of 100m to 200m. In Spring Weekday and Weekend wildfire is easily ignited by the human in a medium distance from the ROAD of 300m and Spring Weekend to INFRA (400m). The explanation might be illegal livestock shepherds' and arsonists seek remote areas to avoid capture. This finding shows how wildfire prevention or mitigation measures should proceed. Attention should be paid to areas directly adjacent to ROADS and INFRA during weekends in Winter and Spring Weekdays to INFRA. Distant zones should receive more attention during Spring Weekend to INFRA.

Nonetheless the drawbacks of MODIS active fire product including indistinguishable of its ignition sources, we use the MODIS data rather than the historical fire records in this study. Because of its accessibility, ability to assess the suitability of model and explore the variation of spatio-temporal pattern in the study area. Modelling human-caused ignitions probability by means of temporal dimension enhance our understanding of human activity to wildfire prevention. On average, the overall performance of our models is satisfactory (0.861). Our model outperform those other models based on intra-annual models. For example,**Arndt, et al. (2013)** study in modelling human-caused fire ignition for assessing fire danger in Austria the models created using logistic regression method reported 60.5% of model performance. Furthermore, the reported performance of dynamic model proposed, the highest prediction model process was 0.860 observed during summer months. It should be noted that their research considered the temporal dimension of human factors. The research was conducted in NE Spain using MaxEnt and wildfire data (2008-2012), they constructed eight fire occurrence data scenarios and assess their model accuracy using a cross-validation k-fold procedure. The reported performance of our models is clear low in Spring season particularly during weekdays, this might the explained by fewer fire occurrence experienced during this period. Our results have demonstrated that Winter fire occurrence data is more suitable for modelling and assessing the human-caused fire ignitions of the study area.

CONCLUSION

In this study, we used fire ignition data from MODIS spanning from 2007 to 2017 to construct four occurrence data scenarios. Considering the temporal dimension in modelling human-caused fire ignition is a foundation for efforts towards creation reliable and accurate predictions and explanation models. Application of MaxEnt method provided us with the mechanism for evaluating the performance of different temporal scenarios and the importance of the explanatory variables to the models. MaxEnt provided optimal opportunity to reflect distinct temporal distribution in different explanatory variables. Categorical MaxEnt proved to be a useful approach as it avoids problems of dealing with false, unreliable and pseudo-absences and it is relatively straightforward to implement and interpret. The study shows extend knowledge about the influence and the temporal patterns of human-caused fire ignition, which can aide the Park managers in developing sound fire prevention strategies, advising practical wildfire management and better allocation of the limited resources. Regardless of the overall performance of the model is satisfactory, improvement of the models would be achieved by introduction precise fire ignition or occurrence data that can identify source of ignition type, with lower omission error. Furthermore, the improvement of the model might achieve by parsing the explanatory variables, for instance, distance to main road, secondary road, hiking trails, distance to hotels, campsite).

REFERENCES

1. Adagbasa, G. E., Adelabu, S. A., & Okello, T. W. Spatio-Temporal Assessment of Fire Severity in a Protected and Mountainous Ecosystem. In IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium, (2018) 6572-6575. IEEE.
2. Adelabu, S. A., Adepoju, K. A., & Mofokeng, O. D. Estimation of fire potential index in mountainous protected region using remote sensing. Geocarto International, (2018), 1-18.

3. Archibald, S. Managing the human component of fire regimes: lessons from Africa. Philosophical Transactions of the Royal Society B: Biological Sciences, (2016), 371 (1696), 20150346.
4. Archibald, S., Roy, D. P., WILGEN, V., Brian, W., & SCHOLES, R. J. What limits fire? An examination of drivers of burnt area in Southern Africa. Global Change Biology, (2009), 15 (3), 613-630.
5. Arndt, N., Vacik, H., Koch, V., Arpaci, A., & Gossow, H. Modeling human-caused forest fire ignition for assessing forest fire danger in Austria. iForest-Biogeosciences and Forestry, (2013), 6 (6), 315.
6. Bowman, D. M., Balch, J., Artaxo, P., Bond, W. J., Cochrane, M. A., D'antonio, C. M., DeFries, R., Johnston, F. H., Keeley, J. E., & Krawchuk, M. A., et al The human dimension of fire regimes on Earth. Journal of biogeography, (2011), 38 (12), 2223-2236.
7. Brown, J. L. SDM toolbox: a python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. Methods in Ecology and Evolution, (2014), 5 (7), 694-700.
8. Carmona, A., González, M. E., Nahuelhual, L., & Silva, J. Efectos espacio-temporales de los factores humanos en el peligro de incendio en Chile mediterráneo. Bosque (Valdivia), (2012), 33 (3), 321-328.
9. Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, M. P., Vilar, L., Martínez, J., Martín, S., P.:, I., de la Riva, J., Baeza, J., Rodríguez, F., Molina, J. R., Herrera, M. A., & Zamora, R. et al Development of framework for fire risk assessment using remote sensing and geographic information system technologies. Ecological Modelling, (2010), (221), 46-58.
10. Clarke, H., Gibson, R., Cirulis, B., Bradstock, R. A., & Penman, T. D. Developing and testing models of the drivers of anthropogenic and lightning-caused wildfire ignitions in south-eastern Australia. Journal of Environmental Management, (2019), 235, 34-41.
11. Costafreda-Aumedes, S., Comas, C., & Vega-Garcia, C. Human-caused fire occurrence modelling in perspective: a review. International Journal of Wildland Fire, (2018), 26 (12), 983-998.
12. Davies, D. K., Ilavajhala, S., Wong, M. M., & Justice, C. O. Fire information for resource management system: archiving and distributing MODIS active fire data. IEEE Transactions on Geoscience and Remote Sensing, (2008), 47 (1), 72-79.
13. Del Hoyo, L. V., Isabel, M. P. M., & Vega, F. J. M. Logistic regression models for human-caused wildfire risk estimation: analysing the effect of the spatial accuracy in fire occurrence data. European Journal of Forest Research, (2011), 130 (6), 983-996.
14. Elith, J., Phillips, S. J., Hastie, T., Dudik, M., Chee, Y. E., & Yates, C. J. A statistical explanation of MaxEnt for ecologists. Diversity and distributions, (2011), 17 (1), 43-57.
15. Eskandari, S., & Chuvieco, E. Fire danger assessment in Iran based on geospatial information. International Journal of Applied Earth Observation and Geoinformation, (2015), 42, 57-64.
16. Fawcett, T. (2006). An introduction to ROC analysis. Pattern recognition letters, 27 (8), 861-874.
17. Food and Agricultural Organisation, F. Fire management-global assessment 2006. In. FAO, Rome. (2007).
18. Genton, M. G., Butry, D. T., Gumpertz, M. L., & Prestemon, J. P. Spatio-temporal analysis of wildfire ignitions in the St Johns River water management district, Florida. International Journal of Wildland Fire, (2006), 15 (1), 87-97.
19. Mancini, L. D., Corona, P., & Salvati, L. Ranking the importance of Wildfires' human drivers through a multi-model regression approach. Environmental Impact Assessment Review, (2018), 72, 177-186.
20. Mansuy, N., Miller, C., Parisien, M.-A., Parks, S. A., Batllori, E., & Moritz, M. A. Contrasting human influences and macro-environmental factors on fire activity inside and outside protected areas of North America. Environmental Research Letters, (2019), 14 (6), 064007.
21. Martín, Y., Zúñiga-Antón, M., & Rodrigues Mimbrero, M. Modelling temporal variation of fire-occurrence towards the dynamic prediction of human wildfire ignition danger in northeast Spain. Geomatics, Natural Hazards and Risk, (2019), 10 (1), 385-411.
22. Martínez-Fernández, J., Chuvieco, E., & Koutsias, N. Modelling long-term fire occurrence factors in Spain by accounting for local variations with geographically weighted regression. Natural hazards and earth system sciences, (2013), 13 (2), 311.
23. Martínez, J., Vegan-García , C., & Chuvieco, E. Human-caused wildfire risk rating for prevention planning in Spain. Journal of Enviornmental Management (2009), (90), 1241-1252.
24. Massada, A. B., Syphard, A. D., Stewart, S. I., & Radeloff, V. C. Wildfire ignition-distribution modelling: a comparative study in the Huron–Manistee National Forest, Michigan, USA. International Journal of Wildland Fire, (2013), 22 (2), 174-183.
25. Molaudzi, O. D., & Adelabu, S. A. Review of the use of remote sensing for monitoring wildfire risk conditions to support fire risk assessment in protected areas. South African Journal of Geomatics, (2018), 7 (3), 222-242.
26. Parisien, M.-A., Miller, C., Parks, S. A., DeLancey, E. R., Robinne, F.-N., & Flannigan, M. D. The spatially varying influence of humans on fire probability in North America. Environmental Research Letters, (2016), 11 (7), 075005.
27. Pereira, P., Mierauskas, P., Úbeda, X., Mataix-Solera, J., & Cerda, A. Fire in protected areas-the effect of protection and importance of fire management. Environmental Research, Engineering and Management, (2012), 59 (1), 52-62.
28. Ricotta, C., Bajocco, S., Guglietta, D., & Conedera, M. Assessing the Influence of Roads on Fire Ignition: Does Land Cover Matter? Fire, (2018), 1 (2), 24.
29. Taru, P., & Chingombe, W. Geoheritage and the potential of Geotourism in the Golden Gate Highlands National Park, South Africa. African Journal of Hospitality, Tourism and Leisure, (2016), 5 (2), 1-10.
30. Vacchiano, G., Foderi, C., Berretti, R., Marchi, E., & Motta, R. Modeling anthropogenic and natural fire ignitions in an inner-alpine valley. (2018).
31. Vilar, L., Gómez, I., Martinez-Vega, J., Echavarría, P., Riaño, D., & Martín, M. P. Multitemporal modelling of socio-economic wildfire drivers in central Spain between the 1980s and the 2000s: comparing generalized linear models to machine learning algorithms. PLoS One, (2016), 11 (8).
32. Ye, J., Wu, M., Deng, Z., Xu, S., Zhou, R., & Clarke, K. C. Modeling the spatial patterns of human wildfire ignition in Yunnan province, China. Applied Geography, (2017), 89, 150-162.
33. Zhang, Y., Lim, S., & Sharples, J. J. Modelling spatial patterns of wildfire occurrence in south-eastern Australia. Geomatics, Natural Hazards and Risk, (2016), 7 (6), 1800-1815.
34. Zhou, X.-H., McClish, D. K., & Obuchowski, N. A. Statistical methods in diagnostic medicine (2009), (Vol. 569). John Wiley & Sons.