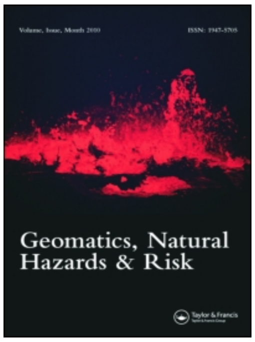

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Modelling the spatial variability of wildfire susceptibility in Honduras using remote sensing and geographical information systems

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ABSTRACT

Forests in Honduras are endangered as a result of the relentless occurrence of wildfires during the dry season, and their frequency and area burned have been gradually increasing, a pattern attributable to the numerous ignition sources. For this reason, there is a substantial need to identify the major drivers of wildfires and map the regions where they are most likely to occur. In this study, we integrated the wildfire occurrences throughout the 2010–2015 period with a series of variables using the random forest algorithm. We included variables related to human activities such as the continuous distances to infrastructure and settlements. Other variables included are satellite observations that reflect the seasonal vegetation change, climatic conditions over the country, and topographical variables. The analysis of the explanatory variables revealed that the dry fuel conditions and low precipitation combined with the proximity to non-paved and paved roads were the major drivers of wildfires in the region. The estimated area with high and very high wildfire susceptibility was 15% of the country, located mainly in the central and eastern regions. The proposed national-scale wildfire susceptibility map can lead to enhanced preventive measures to minimize risk and the impacts caused by wildfires.

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Wildfires; susceptibility; random forest; normalized multi-band drought index; MODIS; Honduras

1. Introduction

Forests are one of the most important natural resources for achieving environmental balance and provide a wide array of tangible and intangible benefits to populations (Pourtaghi et al. 2015). However, forests are being rapidly reduced by different causes, including the persistent occurrence of wildfires (Hernandez-Leal & Arbelo 2006; Martin et al. 2012). Wildfires are uncontrolled fires in an area of combustible vegetation that causes large ecological damage (Adab et al. 2013; Chowdhury & Hassan 2013), such as increased rates of soil erosion and sedimentation of rivers, release of large amounts of CO_2 into the atmosphere (Werf et al. 2004; Bowman et al. 2009), and abrupt changes in soil properties (Certini 2005; Akther & Hassan 2011). In addition to environmental damage, the economic loss caused by wildfires by evaluating only the tangible benefits such as wood, water, resin, and ecotourism is enormous (Barrantes 2006; Ojea et al. 2012).

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To define proper strategies for reducing the impacts caused by wildfires (Ferreira et al. 2015), many previous studies have focused on the analysis of the major drivers of wildfires and their spatial variability (Domínguez & Rodriguez Trejo 2008; Syphard et al. 2008; Martinez et al. 2009; Oliveira et al. 2012; Parisien et al. 2012; Arpaci et al. 2014; Moreno et al. 2014). Historically, wildfires are a hazard triggered as a result of natural processes, but their frequency has increased because of human interaction, making wildfires an increasing threat in the future (Bowman et al. 2009; Parisien & Moritz 2009; Adab et al. 2013). Climatic variables have also been found to be important for defining fuel conditions. Fuel conditions, a critical factor influencing fire ignition and the spread of fire (Li et al. 2014), can also vary depending on the species characteristics, topography, and environmental parameters (Rodrigues et al. 2016).

The spatial variability of fuel conditions must be considered when assessing or attempting to identify areas with high susceptibility for the occurrence of wildfires (Hernandez-Leal & Arbelo 2006). For this purpose, remote sensing-based data acquisition has recently become an important aid (Chowdhury & Hassan 2013). The use of remote sensing to assess the live fuel moisture conditions for this purpose is not new. For instance, the normalized difference vegetation index (NDVI) is the most commonly used vegetation index to assess live fuel moisture as a factor in estimating wildfire risk (Hernandez-Leal & Arbelo 2006; Fiorucci et al. 2007; Liu et al. 2010; Jurdao & Chuvieco 2012; Adab et al. 2013; Pourtaghi et al. 2015). Adab et al. (2013) mapped forest fire risk by using the normalized difference moisture index to assess the vegetation condition. Additionally, the enhanced vegetation index has been previously used for forest fire risk assessment (Bisquert et al. 2012). Akther and Hassan (2011) assessed the forest fire danger using a relatively new vegetation drought monitoring index, the normalized multi-band drought index (NMDI), and showed it to be useful to enhance the accuracy of estimating wildfire danger. This index, however, has not been used extensively for forest fire risk assessment (Chowdhury & Hassan 2013). The use of remote sensing-derived indexes instead of land cover maps is relevant as it can address the spatiotemporal variations of vegetation (Adab et al. 2013; Chowdhury & Hassan 2013). Additionally, the flammability of vegetation may vary even within the same forest type, depending on topographical factors and other soil characteristics (Robins 2006; Parisien et al. 2012).

Wildfire dynamics and a countrywide wildfire susceptibility map are difficult to obtain, hence its spatial variability is generally inaccurate or it is unknown in many specific areas. For this reason, modelling the spatial variability of wildfire susceptibility is essential (Parisien et al. 2012). For this task, a variety of methods can be applied. Many studies have used statistical methods such as logistic regression and multiple linear regression (Syphard et al. 2008; Martinez et al. 2009; Bisquert et al. 2012; Oliveira et al. 2012; Massada et al. 2013; Zhang et al. 2016). However, a number of studies have shown that machine learning algorithms can provide improved accuracy over statistical methods and are more likely to reduce the spatial autocorrelation effect (Bisquert et al. 2012; Oliveira et al. 2012; Massada et al. 2013). Machine learning algorithms previously used for forest fires probability risk mapping include maximum entropy (MaxEnt) (Parisien & Moritz 2009; Parisien et al. 2012), random forest (RF) (Oliveira et al. 2012; Arpaci et al. 2014), artificial neural networks (ANN) (Bisquert et al. 2012; Satir et al. 2015), and support vector machines (SVM) (Sakr et al. 2010). Of these algorithms, RF and MaxEnt have shown improved accuracy over ANN and SVM for spatial predictions (Oliveira et al. 2012; Massada et al. 2013; Olaya-Marín et al. 2013; Rodrigues & de la Riva 2014).

Improved knowledge of the driving forces of wildfires and spatial risk is essential for designing strategies to mitigate wildfire ignition (Finney 2005). In Central America, biodiversity is particularly rich, and the region includes the 'Meso-American biological corridor,' which has important environmental, social, cultural, and economic resources. Nevertheless, subsistence requirements of rural dwellers induce a high incidence of human-related wildfires (Domínguez & Rodriguez Trejo 2008; Barrantes 2006). Climatic and vegetation conditions strongly influence the increased rate of wildfires based on the region's fuel characteristics. The Central American environment is highly diverse in terms of climate, vegetation, and topographic characteristics, which leads to varying levels of wildfire susceptibility (Domínguez & Rodriguez Trejo 2008). In addition, Central America because of its unique location between two continental land masses and between the Pacific and Atlantic Oceans, has a demonstrated decline in precipitation rates and vegetation greenness during the El Niño-Southern Oscillation (ENSO) years (Chang et al. 2015), making the forests more prone to wildfires. Therefore, it is relevant to identify the geographic regions where wildfires are likely to occur and their major drivers.

Honduras, as a result of its climatic, physiographic, and socio-economic conditions in rural areas, is vulnerable to almost every global disaster category. Among these disasters, wildfires are present every year, and they are almost all related to human factors and activities. The Forest Institute of Honduras has reported that, for the most part, human negligence or malice is to blame for wildfires during the dry season. Despite the increased awareness and knowledge in Honduras about wildfire sources and the environmental loss, a reliable estimate of wildfire susceptibility remains a work in progress.

Based on the limitations that exist for data acquisition and the current situation of wildfires in Honduras, the purpose of this study was to explain and model areas with high susceptibility to wildfires and their spatial variability. We acquired historical wildfire data and linked the wildfires to a group of remote sensing-based variables representing the vegetation conditions and climatic variables and a series of Geographic Information Systems (GIS) layers representing human activities. These variables were selected from the literature and local experiences (Chuvieco 2003; Akther & Hassan 2011; Oliveira et al. 2012; Chowdhury & Hassan 2013; Arpaci et al. 2014; Zhang et al. 2016). We then used RF and the predictor variables to model the spatial variability of wildfire susceptibility. RF has shown similar or better accuracy than other machine learning algorithms when estimating forest fires spatial variability and susceptibility in previous research (Arpaci et al. 2014; Rodrigues & de la Riva 2014). Specifically, the main objectives of this research were threefold: (1) identify the most relevant driving forces leading to increased risk of wildfires in Honduras; (2) estimate the spatially explicit wildfire susceptibility by linking remote sensing and GIS data with historical wildfire data; and (3) evaluate the performance of the satellite-derived vegetation indexes for predicting wildfire susceptibility in Honduras. We expected the areas near population settlements and roads to have higher wildfire susceptibility and that the inclusion of the vegetation and drought indexes would improve the accuracy of the results. Predictions of forest fire risk and its spatial variability are important instruments for local authorities to use for forest management and conservation plans. This research is the first to map the spatial distribution of wildfire susceptibility and study the major drivers of wildfires in Honduras. The results can help the Forest Institute of Honduras and local environmental agencies implement localized strategies to reduce the damage and the impacts caused by wildfires in a vulnerable and climate change-prone region.

2. Study area

Honduras is located in the central part of the Americas surrounded by the Atlantic and Pacific oceans (Figure 1). The country has a territorial extension of 112,000 km^2. With an estimated 59% of its territory covered with forest (Vallejo Larios 2011), Honduras is considered a country with a forest vocation; however, the annual rate of deforestation has been variously estimated at 580 (Vallejo Larios 2011), 800 (SERNA 2005), and 1380 km^2 (Food and Agriculture Organization [FAO] 2010). One of the most relevant factors that contribute to forest degradation and loss in Honduras is the relentless occurrence of wildfires, caused mainly by human activities such as traditional agriculture, cattle grazing, and local incendiaries during the dry season.

The climate in Honduras is controlled by topography and latitude. A central mountain system in the central region separates the northern humid Atlantic region from the southern region, where a long dry season can result in intense drought and large wildfires (Birkel 2005). Most of the northern region has a tropical humid climate with an average precipitation of 2600 mm/yr and an average temperature of 27 °C. The central region has a tropical savannah climate with an average

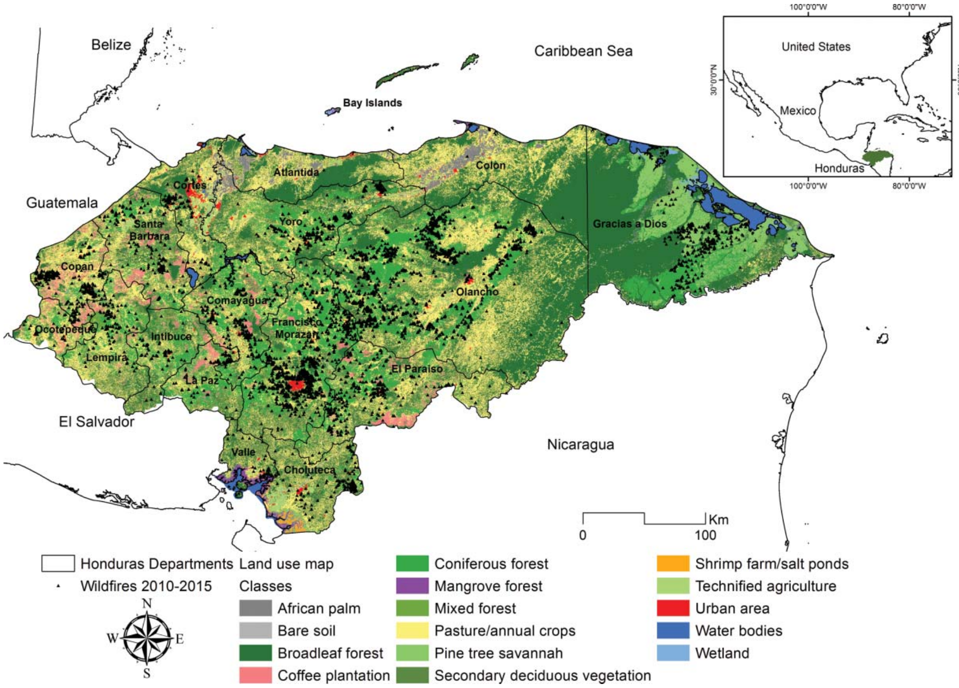

Figure 1. Location and land cover map of Honduras, located in Central America.

precipitation of 1600 mm/yr and an average temperature of 24 °C. In the south bordering the Pacific coast, the annual precipitation is less than 1000 mm/yr, and the average temperature is 29 °C (Valencia & David 2005).

Most of the coniferous forests are located in the central and western regions of Honduras, with some patches in the eastern part. Northern Honduras and most of eastern Honduras are dominated by broadleaf forest. The southern region's dry forests have been largely substituted by shrubland and savannahs, with some remaining coniferous forests.

3. Materials and methods

To identify the spatial variability of wildfire susceptibility, the methodology designed for this study followed three main steps: (1) data collection and processing, (2) exploratory analysis of variables, and (3) spatial modelling and validation (Figure 2). Each of the steps is explained in detail in the following sections.

3.1. Data collection and processing

To prepare the variables used in this study, four different types of data-sets were collected: remote sensing data to derive vegetation condition variables, precipitation data, a digital elevation model to derive topographic factors, and a series of GIS layers to derive human driving predictors.

The moderate resolution imaging spectroradiometer (MODIS)/Terra surface reflectance 8-day version 7 (MOD09A3) data were acquired for the 2010–2015 period. The MOD09A3 surface reflectance has a spatial resolution of 500 m across the spectral bands of red (620–670 nm), near infrared (NIR) (841–876 nm), shortwave infrared ($SWIR_1$) (1628–1652 nm), and $SWIR_2$ (2105–2155 nm). MODIS surface reflectance data required the removal of clouds for estimating the NMDI for every

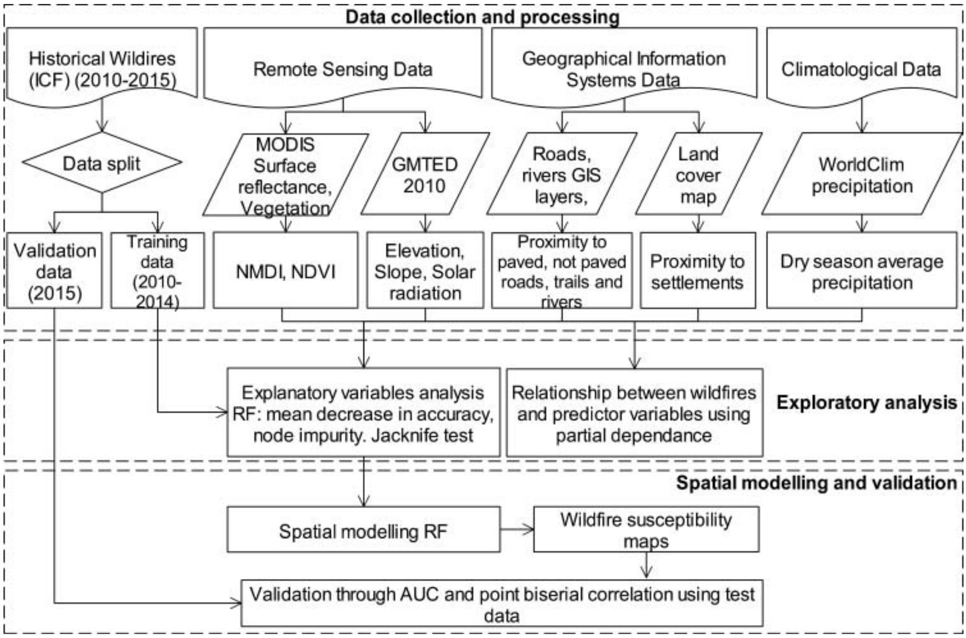

Figure 2. Methodology flowchart of the study.

month of the dry season (January–May). The NMDI combines the NIR and SWIR channels and therefore has improved sensitivity to detect drought and is well suited to estimate both soil and vegetation moisture (Wang & Qu 2007; Chen et al. 2014):

$$\mathrm{NMDI} = \frac{\mathrm{NIR} - (\mathrm{SWIR}_1 - \mathrm{SWIR}_2)}{\mathrm{NIR} + (\mathrm{SWIR}_1 - \mathrm{SWIR}_2)} \tag{1}$$

where $R_{0.86\ \mu\mathrm{m}}$, $R_{1.64\ \mu\mathrm{m}}$, and $R_{2.13\ \mu\mathrm{m}}$ are the reflectance's acquired by the sensor. The NMDI indicates dry conditions when it is near 0 and wet conditions when the values are near 1 (Wang & Qu 2007; Wang et al. 2008; Chen et al. 2014).

Another product used was the NDVI included in the Global MOD13A3 vegetation indices product with a spatial resolution of 1000 m. The NDVI was found to be an important factor in previous studies for assessing the live fuel moisture conditions (Chuvieco et al. 2004; Hernandez-Leal & Arbelo 2006; Renard et al. 2012). The NMDI and the NDVI values were averaged for all dry seasons during 2010–2015. The MOD13A3 data products are provided monthly at a 1 km spatial resolution as a gridded level-3 product in the sinusoidal projection. The two MODIS data-sets were projected to the Universal Transverse Mercator (UTM) coordinate system. The MODIS vegetation indices images were resampled to 500 m using the bilinear interpolation resampling method. We acquired the data for dry seasons (January–May) for the 2010–2015 period and calculated the dry season average.

In addition, to represent the climatic conditions, we used average monthly precipitation during the dry season from WorldClim, which has a spatial resolution of 1 km (Hijmans et al. 2005). These data was reprojected to UTM and resampled to 500 m.

To derive the topographic variables and solar radiation, we used the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010), a collection of elevation products with three different resolutions of approximately 1000, 500, and 250 m (Danielson & Gesch 2011). We chose the 500 m data to match the spatial resolution of MODIS and WorldClim data. We used the GMTED2010 to derive

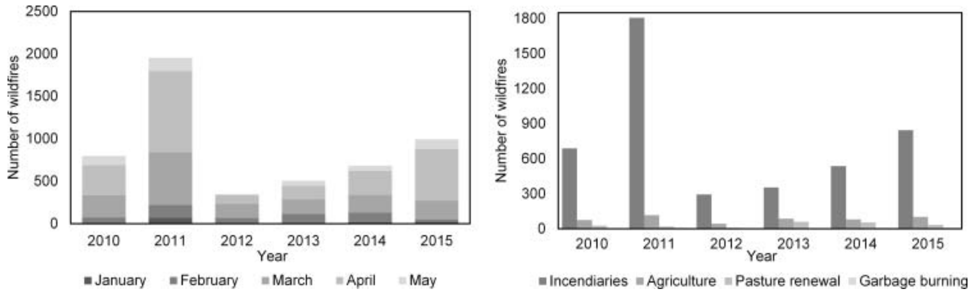

Figure 3. The number of wildfires occurred (a) per year and month, and (b) major causes of wildfires per year.

elevation (m a.s.l.), slope (degrees), and solar radiation (Wh/m^2) using the surface and solar radiation tools in ArcGIS.

The GIS data-sets were acquired from the National System of Territorial Information of Honduras (SINITHN in Spanish). We collected the GIS layers with three types of roads (paved roads, non-paved roads, and trails), main rivers, and secondary rivers. The settlements were extracted from the land cover map of Honduras, developed by the Forest Institute with the aid of Rapid-Eye satellite imagery (5 m spatial resolution). To signify the human imprint on the country, we estimated from the GIS data-sets the Euclidean distances (in meters) to paved roads, non-paved roads, and trails for accessibility variables, distances to main rivers and secondary rivers, and distances to the settlements.

Finally, the Forest Institute of Honduras provided the wildfires database for the 2010–2015 period. Wildfires in Honduras are identified by the Forest Institute with the aid of MODIS active fire location product (MCD14ML) and are used by local authorities to quickly reach wildfire sites; however, many are not wildfires but fires in agriculture areas where slash-and-burn farming is practiced. Additionally, this product cannot capture all wildfires because they may be blocked by clouds (Giglio 2007); hence, we used only the wildfires verified in the field by local authorities. The total number of wildfires in 2010–2015 was 5287, which, according to the reports from the Forest Institute, were mostly caused by human activities and had the highest frequency in April (Figure 3). Additionally, 50% of these wildfires occurred in coniferous forests, whereas only 8% occurred in broadleaf forests and 4% in mixed forests during this period. Wildfires in broadleaf forests are rare, but due to their understory condition and accumulated fuel, the fire intensity is usually higher than in coniferous forests. Pasture and savannahs also account for a large percentage (30%) of wildfires. In addition to the wildfire points, we randomly generated 4500 background points that we use as pseudo-absence data for the RF. We also assigned the values of the predictor variables for these background points in the same way as for the wildfire points.

In Honduras, acquiring updated information and data-sets is difficult; hence, the use of satellite information is needed to obtain a more accurate estimation of wildfire susceptibility.

Table 1 summarizes the data-sets acquired and processed in this study. We tested for multicollinearity among predictor variables to discard highly correlated ones that might produce biased variable importance results (Strobl et al. 2008; Nicodemus et al. 2010).

3.2. Random forest

RF modelling is an ensemble technique that averages the predictions of many single classification or regression trees, which are created using only a part of the training data (Breiman 2001). The algorithm also has higher prediction accuracy as it overcomes the uncertainty problem when using single trees. The main idea of RF is to combine many decision trees using a number of bootstrap samples and choosing some explanatory variables at every node (Arpaci et al. 2014). A certain amount of the original observations from the bootstrap sample is included at least once and the observations not

Table 1. Variables used for predicting the wildfire spatial variability and hotspots.

Variables	Resolution	Source	Description
Normalized multi-band drought index (NMDI)	500 m	MODIS surface reflectance MOD09A3	Monthly estimates (unitless)
Normalized difference vegetation index (NDVI)	1 km	MODIS MOD11A3	Monthly estimates (unitless)
Precipitation	1 km	WorlClim data	Monthly total precipitation (mm)
Elevation	500 m	GMTED 2010	Elevation (m a.s.l.)
Slope gradient	500 m	GMTED 2010	Degrees (°)
Solar radiation	500 m	GMTED 2010	(Wh/m^2)
Proximity to paved roads	500 m	SINITHN	Euclidean distance (m)
Proximity to non-paved roads	500 m	SINITHN	Euclidean distance (m)
Proximity to trails	500 m	SINITHN	Euclidean distance (m)
Proximity to settlements	500 m	SINITHN	Euclidean distance (m)
Proximity to primary rivers	500 m	SINITHN	Euclidean distance (m)
Proximity to secondary rivers	500 m	SINITHN	Euclidean distance (m)

included are called out-of-bag (OOB). The classification or regression trees are individually fit to a sample, and at the nodes, only a randomized subset of variables is used. The prediction is based on the majority results of all the trees. Additionally, because the OOB observations are used to estimate the error rate or mean squared error (MSE), an independent test data-set is not required.

Two critical parameters for the RF, the number of trees (*ntree*) and the number of variables to try at each split (*mtry*), were set to 1000 and 4, respectively, in this study. The *ntree* value of 1000 was reached after testing a series of values with an increment of 100 from 500 to 2000; more stable results were obtained with 1000 trees (Breiman 2001; Oliveira et al. 2012). The *mtry* was set to 4, a value derived by the *tuneRF* function, which finds the optimal number of variables by starting with a default in computation and then looks above and below the default to find the number of variables that provides the minimum error rate (Oliveira et al. 2012).

3.3. Variable importance analysis

The RF algorithm also incorporates a measurement of the variable importance, which displays the most relevant factors that contribute to wildfire susceptibility. Specifically, the variable importance is measured by the mean decrease in permutation accuracy and the mean increase in node purity (Rodrigues & de la Riva 2014; Wei et al. 2015). The first measure is calculated by estimating the MSE of individual trees and then comparing the prediction that is done using a subset of observations to the OOB observations prediction. For each variable, the OOB observations are permuted randomly and the MSE is recalculated (Strobl et al. 2008). The MSE difference for each tree is averaged and normalized by the standard deviation of the differences (Massada et al. 2013). A variable with a larger increase in MSE indicates a higher degree of its importance. As an alternative, the second measure is the total increase in node purity from splitting on each variable, averaged over all trees. A variable with a larger increase in the node purity indicates its higher degree of importance. Furthermore, we performed a jackknife test excluding one variable at a time to observe their decrease in area under the curve (AUC) of the receiver-operating characteristic plot. The variables that resulted in larger decreases in AUC were deemed to be more important. The jackknife test was also done by modelling using individual variables and then measuring their AUC (Massada et al. 2013). The variables with lower AUC values were considered to be less important.

3.4. Partial dependence plots

To observe the behaviour of each individual variable, we prepared the partial dependence plots to have a graphical representation of the relationship between individual variables and the predicted probability of wildfires estimated from RF (Hastie et al. 2009).

The partial dependence plots are generated by incorporating the effects of all variables besides the variable of interest. Partial dependence data are constructed by selecting points evenly spaced along the distribution of the X variable of interest. For each value ($X = x$), the average RF prediction over all other variables in X is calculated by using the following equation:

$$\tilde{f}(x) = \frac{1}{n} \sum_{i-1}^{n} \hat{f}\left(x, x_{i,o}\right), \tag{2}$$

where $\hat{f}$ is the predicted response from the RF and $x_{i,o}$ is the value of all other predictors except $X = x$ for the observation i (Friedman 2000). Basically, an average of the predictions for each observation in the training set at the value of $X = x$ is estimated (Ehrlinger 2015).

The average predictions obtained from this method are more than just marginal relationships between the wildfires and the variables. Each of the predictions is made using the information from all the other predictors of an observation; hence, the method gives the partial dependence rather than the marginal dependence. The relationship displayed in a partial dependence plot contains the link between $X = x$ and $\hat{f}$, and it also includes the averaged effects with all the other predictors X.

3.5. Spatial modelling and validation

We ran the model using all 12 non-correlated explanatory variables, and the variables that showed least importance were removed. The model was then rerun using only the most relevant explanatory variables, and after the model was fitted, we performed the prediction of the wildfire susceptibility on the whole study site. After the prediction, we validated our results using MSE, the internal validation used by the RF. The wildfire database acquired from the Forest Institute was separated for training and validation. We used wildfires from 2010 to 2014 for training the model and wildfires in 2015 for validation. We conducted an independent validation using the 2015 wildfires as the independent test data-set and measured the model's fitness by the AUC (Fielding & Bell 1997). An AUC value of 0.5 indicates the prediction is not better than random, values below 0.5 worse than random, and higher than 0.5 better than random (Fielding & Bell 1997). Finally, the non-threshold dependent point-biserial correlation was estimated using the independent test data (Kraemer 2006).

4. Results and discussion

4.1. Variable importance analysis

Before the variable importance analysis, we tested for multicollinearity among predictor variables, and based on the results, we removed proximity to trails, which had high correlation (>0.6) with proximity to paved roads, non-paved roads, and settlements. Based on the permutation accuracy test of variable importance (Figure 4), the variables related to accessibility, drought conditions of vegetation and precipitation were the strongest predictors of wildfire ignitions. From the node impurity in RF, precipitation, proximity to non-paved and paved roads, NMDI, and elevation were the most relevant explanatory variables. The least important variables were proximity to main rivers, proximity to secondary rivers, and slope.

From the jackknife measures of the variable importance (Figure 5), the variables that resulted in large decreases of the AUC when removed were proximity to non-paved roads, NMDI, precipitation, and elevation. When used alone, precipitation, proximity to non-paved roads and NMDI showed the highest AUC. The least important variables were proximity to main and secondary rivers, and slope.

In these tests, the ranking of variables showed some variation on the highest ranked variables; however, in general, the precipitation, accessibility variables, NMDI, and elevation showed the highest importance. By averaging the rankings from all variable importance tests, precipitation was the most important variable in the study site, followed by proximity to non-paved roads, the MODIS-derived

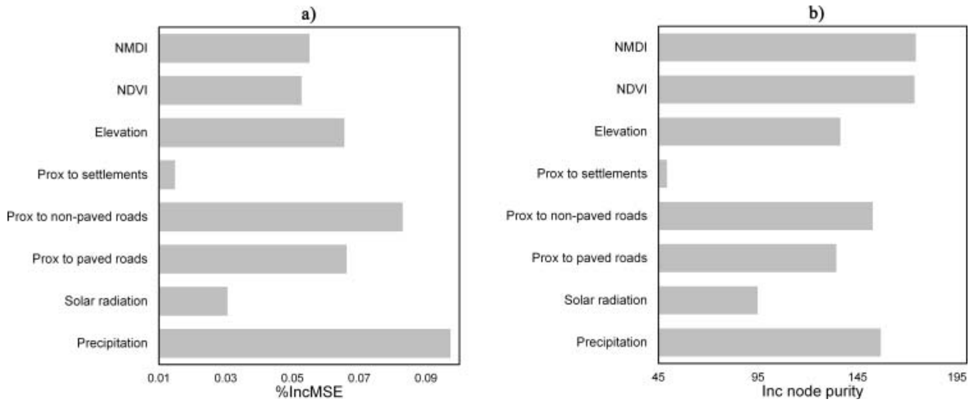

Figure 4. Native RF variable importance analysis: (a) % increase in mean square error, (b) increase in node purity.

NMDI, and elevation. Proximity to paved roads also showed to be an important variable in all tests (Table 2). The variables, proximity to main and secondary rivers, and slope, were consistently the least important in both native variable importance tests and the two jackknife tests; hence, they were removed from the model for the final analysis of variable importance, partial dependence, and the estimation of wildfire susceptibility in Honduras. The findings in the variable importance analysis indicate that the accessibility from rural areas to the forested areas and shrublands is an important factor for wildfire susceptibility in Honduras if the fuel conditions are highly flammable due to strong drought conditions in the summer. Similar results have been found in other regions where proximity to human-made features is the most important predictor for wildfire susceptibility, particularly proximity to roads (Parisien et al. 2012; Massada et al. 2013). In Honduras, however, proximity to non-paved roads showed a higher degree of importance compared to proximity to paved roads, a different result from studies by Nepstad et al. (2001) and Zhang et al. (2016) in which main roads and paved roads show higher degrees of importance than non-paved roads. This indicates that most wildfires in Honduras occur mostly in rural areas and in the outskirts of large cities. The variable importance analysis also showed that NMDI is an important variable to include in a wildfire model and the rankings support the assertion by Akther and Hassan (2011) that, by including the NMDI in the forest

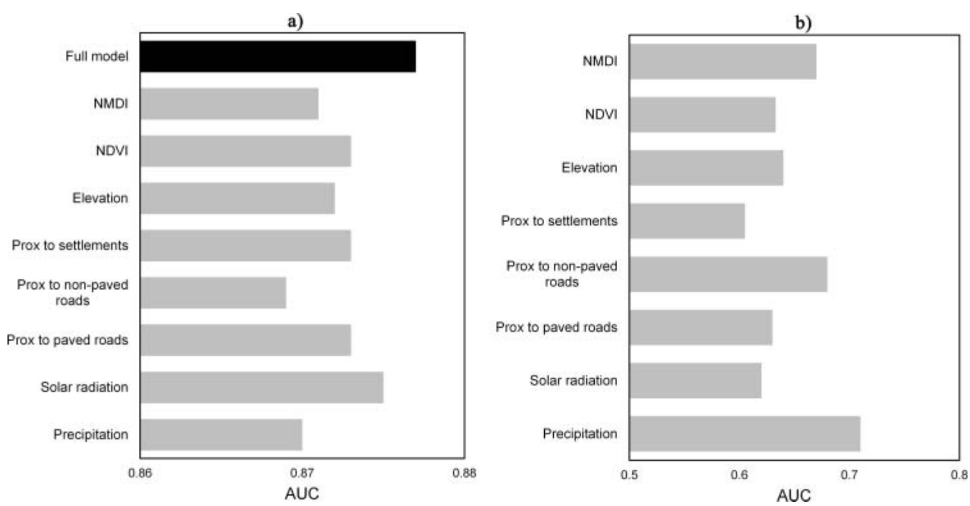

Figure 5. Jackknife test results for variable importance: (a) model excluding one variable at a time, (b) model including only one variable.

Table 2. Variable importance measures, their corresponding rankings, and the majority rank for each variable.

Explanatory variable	%IncMSE	Increase in node purity	Jackknife test without variable	Jackknife test with only one variable	Majority rank values
NMDI	5	1	3	3	3
NDVI	6	2	5	5	5
Elevation	4	5	4	4	4
Proximity to settlements	8	8	6	8	8
Proximity to non-paved roads	2	4	1	2	2
Proximity to paved roads	3	6	5	6	6
Solar radiation	7	7	7	7	7
Precipitation	1	3	2	1	1

fire danger estimation, the accuracy would be improved. Additionally, most studies related to wildfire risk mapping and probability estimation include the NDVI as a predictor to assess the live fuel moisture conditions (Hernandez-Leal & Arbelo 2006; Pourtaghi et al. 2015; Zhang et al. 2016). In this study, however, it proved to be less important when compared to the NMDI, demonstrating the NMDI's higher potential for wildfire susceptibility mapping in Central America. Elevation was another relevant variable in our variable importance analysis. In Honduras, most wildfires occur in the central region where most of the pine tree forests are located, and the central region is mainly in mid to high elevations. By linking forest fires with the land cover, we also observed that most wildfires occurred in coniferous forest, which has a more flammable understory than broadleaf forests (Ellair & Platt 2013) and drier fuel during the dry season compared to other types of forest.

4.2. Relationship between variables and prediction using partial dependence plots

The partial dependence plots depict the range of values from each predictor at which there is a higher probability of success (Figure 6). For proximity variables, the probability of predicting wildfires is higher near roads and settlements and drops dramatically with distance. Specifically, the partial dependence of non-paved roads on wildfire occurrence is high when the distance is below 10,000 m and decreases rapidly when the distance is higher than 20,000 m. The non-paved roads variable has the largest overall influence on the spatial distribution of wildfires when compared with all the other variables used. The paved roads also show high partial dependence when the distance is below 10,000 m. The overall influence of roads on the wildfire prediction confirms the variable importance analysis results acquired in this study and findings in other regions (Massada et al. 2013; Zhang et al. 2016).

The partial dependence of precipitation on wildfire occurrence, as expected, is large when precipitation is between 50 and 20 mm/month during the dry season. The partial dependence drops dramatically when precipitation is higher than 50 mm/month but also when it is below 20 mm/month. This is because the southern region, which is the region with lowest precipitation rates in the country, does not have a high incidence of wildfires during the dry season, and the area, in general, does not have high wildfire susceptibility as it can be seen in the prediction. Furthermore, in the northern region, the wildfire susceptibility is greatly minimized as a result of high precipitation rates, high relative humidity, and the overall non-usage of slash and burn practice for agriculture, due to its economic activity. This is also confirmed by observing the non-collinear interaction between elevation and precipitation in which high susceptibility is observed in mid-range elevation and low precipitation values.

The partial dependence of elevation on wildfire occurrence is high on specific elevation ranges. A high mountain range in the central region, where the majority of wildfires occur, has elevations of 500 m a.s.l. or higher, the altitude where major partial dependence is observed. Solar radiation shows high partial dependence when the values are high, consistent with what was expected; however, it was ranked one of the least important variable in our variable importance analysis.

As anticipated, the variables used to assess live fuel moisture conditions and drought condition, NDVI and NMDI, are shown to have high partial dependence when values are between 0.6 and 0.4,

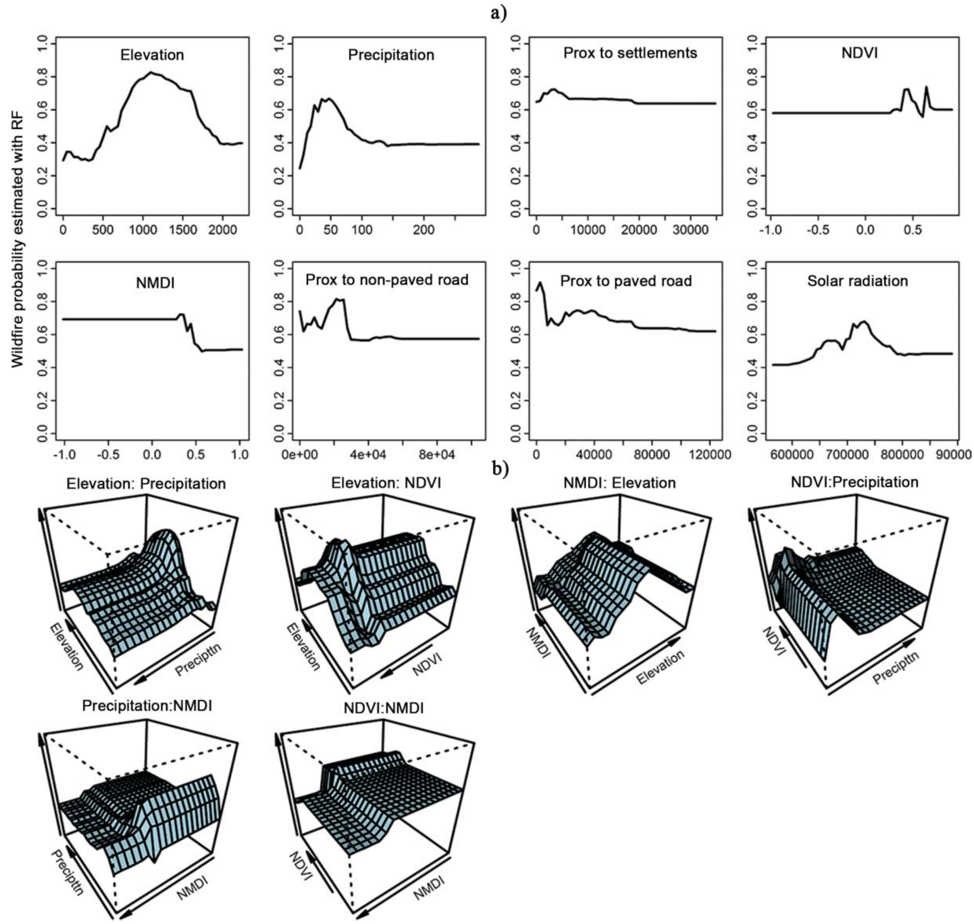

Figure 6. (a) Partial dependence plots on the explanatory variables selected for the final modelling; (b) variable interaction plots on the explanatory variables selected for the final modelling.

and 0.6 and 0.5, respectively. The partial dependence plots of these two variables exhibit a similar pattern to that of precipitation, suggesting a strong link between climate, fuel moisture, and drought condition. The largest partial dependence is observed within the mid-range values corroborating that in the southern region even though there are low precipitation rates, which affects the vegetation drought condition, does not indicate that there will be more wildfire events. This is also confirmed by observing the variable interaction between precipitation, NDVI, and NMDI. This is a strong indication that the human activity present plays a major role in the wildfire incidence in Honduras when the vegetation is highly flammable and the drought conditions are favourable for the occurrence of wildfires. The type of vegetation also plays an important role in the wildfire occurrence; however, as indicated in previous studies (Parisien et al. 2012; Hernandez-Leal & Arbelo 2006; Akther & Hassan 2011), the flammability condition may vary also within the same type of vegetation, justifying in this way the use of vegetation indices for a better assessment of wildfire susceptibility.

4.3. Spatial modelling and validation

Figure 7 presents the wildfire susceptibility results showing areas with very high, high, low, and very low susceptibility for wildfire occurrence by the class intervals of 0.8–1.0, 0.6–0.8, 0.4–0.6, 0.2–0.4, and 0.0–0.2, respectively. The model thus identifies 5% of the country with very high, 10% with

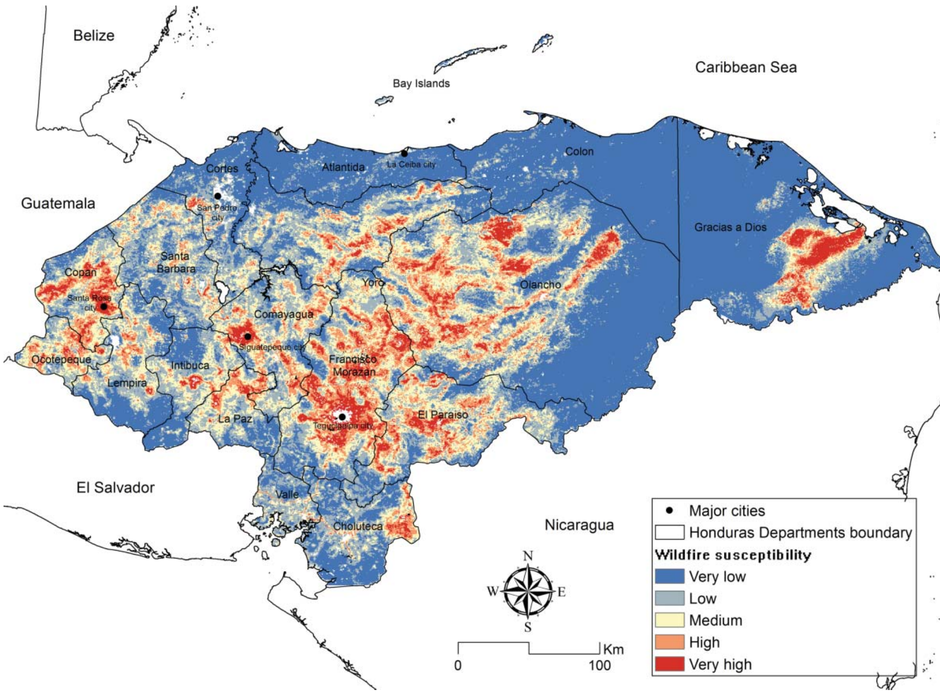

Figure 7. Predictive map of wildfire susceptibility for Honduras using the random forest model. The values represent the susceptibility of each pixel for having a wildfire occurrence.

high, 19% with moderate, 24% with low, and 42% with very low wildfire susceptibility. From the results acquired, the spatial patterns of wildfire susceptibility throughout the country tend to be higher near the central and western regions of the country, which correspond to areas where coniferous forests and mixed forests are mostly located.

Additionally, high probability areas are also found near the capital city, Tegucigalpa, the most populated city in Honduras, Siguatepeque in the Comayagua department, and Santa Rosa in the Copan department. In the eastern part of the country, the region corresponding to the Gracias a Dios department is a special case of high wildfire susceptibility. This region is mostly covered by pine tree savannah and, although no major roads are within the region, there are many small settlements surrounding it. The departments that show the highest wildfire susceptibility are Francisco Morazán, Olancho, Copan, and Comayagua, in addition to Gracias a Dios.

The validation using independent test data-set aside from the wildfire database was conducted using AUC and point-biserial correlation. Predictive accuracy based on the independent test data was good for the model acquired, with an AUC of 0.87 (Figure 8) and a point-biserial correlation of 0.62 ($p < 0.01$).

The wildfire susceptibility map showed areas of high susceptibility near some of the major cities such as Tegucigalpa, Santa Rosa de Copan, and Siguatepeque, cities surrounded by coniferous forests. The capital city also receives a large number of migrants from rural areas, and this may add to the wildfire problem in the outskirts (Meza 2006). The wildfire susceptibility results are in agreement with the relative variable importance analysis, which showed proximity to non-paved roads to have the highest degree of importance. The northern part of the country has high temperatures year round; however, the probability of wildfire ignition is almost non-existent due to high precipitation rates. This region, however, cannot be neglected in its entirety, as the intensity of the occasional wildfires that occur tends to be very high, due to the accumulation of combustible vegetation.

The results from the variable importance analysis and the susceptibility mapping indicate that for an accurate estimate of wildfire susceptibility and for a better assessment, it is necessary to

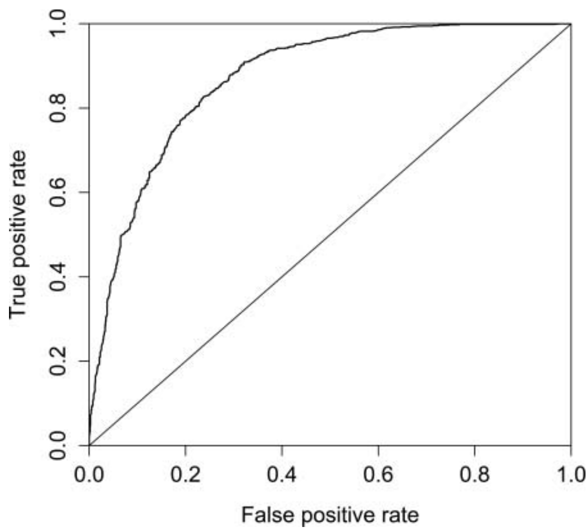

Figure 8. Receiver-operating characteristic curve for the independent test data.

incorporate all the fire components: the ignition source, which is mainly constituted by human activities, proper climatic conditions with low precipitation combined and higher than average temperature, and dry vegetation conditions for a wildfire to expand.

The identification of variables that enhance fire susceptibility is complicated, as it can vary significantly through sub-continents (Parisien & Moritz 2009; Oliveira et al. 2012), and in the Central American tropical countries, where the orographic effect on climate and the effect of sea surface temperature (SST) variations on vegetation greenness and climate are large (Waylen & Quesada 2002; Brenes et al. 2003; Chang et al. 2015), these variables can even vary at the local level. This variation could be observed during the 1998 El Niño event in Central America and Mexico where wildfire events increased greatly (Domínguez & Rodriguez Trejo 2008). The results acquired in this study also give us a better understanding of the spatial distribution of wildfires throughout the country. Fire management strategies such as controlled burning to reduce fuels and fire intensity should be developed in areas with high wildfire susceptibility. Other actions such as the construction and maintenance of permanent or temporary firebreak lines should be conducted before the wildfire season in localized areas, especially near non-paved roads because proximity to non-paved roads is the most relevant spatial variable that contributes to wildfire occurrence in Honduras. Such actions should focus also on specific areas where the climatic and drought conditions are suitable for the occurrence of wildfires. These actions are also needed in areas where livestock and traditional agriculture activity is present, near paved roads, and especially in areas where coniferous forest areas and mixed forests prevail in mid-range elevations. Another measure such as controlled fires should be included in areas near roads and settlements as well in areas where the wildfires are not so frequent and the areas with medium susceptibility to avoid accumulation of combustible vegetation that may trigger high-intensity wildfires. Preventive measures such as education and legislation have been implemented with varying degrees of intensity in most rural regions every year (Domínguez & Rodriguez Trejo 2008); however, the effect of these prevention actions seems questionable. It is clear that more sustainable practices are required with higher intensity in the high wildfire susceptibility areas.

5. Conclusions

Identifying the spatial variables that influence the occurrence of wildfires in a highly vulnerable region like Honduras is a challenging task because of the complex interaction that exists among variables such as vegetation conditions, climatic variables, and human activities. In this research, we analysed recent wildfire information from the Forest Institute of Honduras by using a series of spatial variables known to increase the risk of wildfires and the RF algorithm capable of capturing the nonlinear relationships between the variables. Moreover, the RF method ranked the variables according to their relative contribution to the model and their significance in explaining wildfire distribution in Honduras. Specific variables related to climatic and vegetation conditions were deemed relevant, particularly the use of MODIS-derived data, such as NMDI. In addition, the variables that represent the human activity resulted in key variables to predict the wildfire spatial variability in Honduras. The wildfire susceptibility map estimated from the final model represents a spatially refined estimate within the country, as shown by the high accuracy of the model when validated with independent data-sets. Our results indicate that the central region of the country has the highest wildfire susceptibility, especially in rural areas and the outskirts of some major cities. Our results also indicate that the combination of human-driven factors with physical variables is relevant when defining the strategies to reduce the susceptibility to wildfires and their impacts. The results also have important inferences for developing effective wildfire strategies to minimize the environmental degradation caused by the increasing amount of wildfires in Honduras.

This research is the first to study the spatial distribution of wildfire susceptibility in Honduras using the historical observations acquired; however, the predictions in this study are specific to the actual physical conditions and the changes in human driving factors, which may vary through time. Additional efforts to improve the prediction in future works may include using future climate change scenarios and increasing the time frame for evaluating the influence of the known teleconnection patterns (e.g. ENSO, north atlantic oscillation [NAO]) in the spatial variability of vegetation greenness or climatic variables.

Disclosure statement

No potential conflict of interest was reported by the authors.

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