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ABSTRACT

The impacts of wildfires on ecosystems and the factors contributing to their occurrence are increasingly receiving global attention. Advances in satellite remote sensing and information technology provide an opportunity to study these complex interrelationships. A Bayesian belief network (BBN) model was developed from a set of 12 biotic, abiotic and human variables to determine factors that influence wildfire activity in Swaziland using wildfire data from the Terra and Aqua satellites' Moderate Resolution Imaging Spectroradiometer (MODIS) for the period 2001–2007. These were geospatially integrated in the geographic information system (GIS) software ArcView and input into the software Netica for BBN analyses. Land cover, elevation, and climate (mean annual rainfall and mean annual temperature) were found to be strong predictors of wildfire occurrence, while aspect had the least influence on the wildfire occurrence. The model had a high predictive accuracy with an error rate of 9.62%, and an area under the receiver-operating characteristic (ROC) curve of 0.961. The study demonstrates how domain or field knowledge and limited empirical and GIS data can be combined within a BBN model to assist in determining key fire management interventions and lays the foundation for the future development of advanced and dynamic models.

1. Introduction

Natural and anthropogenic wildfires play an important role in the structure and functioning of many of world's ecosystems (Bond and Keeley, 2005). However, recent extreme wildfire activity such as the July 2007 Swaziland wildfire disaster (Dlamini, 2007) and other major wildfire incidents have increased the focus on how human activities affect fuel and vegetation dynamics, and the resultant dynamics and spatial distribution of wildfire occurrence and wildfire risk (Lavorel et al., 2007). Dwyer et al. (2000) and Eva and Lambin (2000) identified the need to understand the complex relationship between wildfires, climate, vegetation and human activities because the kind of wildfire activity or patterns that generally characterize a given area are expected to change with alterations in temperature and precipitation conditions under climate change. Moreover, there is also an increasing need to improve general ecosystem condition and to reduce the likelihood of catastrophic wildfires. Wildfire modeling, therefore, plays a crucial role in wildfire management especially in the evaluation of alternatives and future scenarios (Andrews and Queen, 2001; Lavorel et al., 2007).

Identifying areas that have a high risk of burning is an important component of wildfire management planning (Chou, 1992). The development of spatial models has greatly facilitated this process by allowing the mapping and analysis of variables contributing to wildfire occurrence across space and time. Numerous approaches and methodologies from various studies have emerged for predicting wildfire occurrence probability (e.g. Cardille et al., 2001; Kalabokidis et al., 2007; Maingi and Henry, 2007; Mouillot et al., 2003; and Vasconcelos et al., 2001). Understanding the strengths and limitations of different modeling approaches is important in ensuring that management objectives can be achieved with minimal computation and cost (Keane and Long, 1998). A description of burning patterns and determining the consequences at the landscape level is necessary for the precise characterization of an area's wildfire regime and the long-term effects on ecosystem processes. However, the modeling of wildfire occurrence on certain locations within a landscape can often mislead conclusions if this is based on large scale averaging of wildfire occurrence (Stratton, 2006). Conceptually and practically, wildfire processes are affected by topography, climate, and vegetation patterns (Mouillot et al., 2003; Trollope et al., 2004). In other locations where biotic and abiotic play a significant role in wildfire occurrence, researchers

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have examined the often complex relationships between these factors and wildfire occurrence (Maingi and Henry, 2007).

One of the primary challenges is that gaps persist in scientific knowledge about the interrelationships between human activities, climatic factors and wildfire frequency, extent and intensity and the sensitivity of wildfires to variations in these factors (Myers et al., 2004). This therefore points to the need for integrated research and modeling tools that provide new insights into the interactions between wildfire, biophysical and societal dynamics in order to aid decision making. When the biotic information is integrated with abiotic data with geospatially referenced data, particularly on human activities, a myriad of possibilities arise to create novel tools that may be useful for decision making and planning in wildfire-prone landscapes.

Researchers worldwide have used remote sensing to study recent wildfire occurrences in various ecosystems. Information technology advances such as the Internet, geographic information systems (GIS), and remote sensing technology offer both opportunities and challenges in the application of wildfire models to wildfire management (Andrews and Queen, 2001). This is particularly so with the emergence of special space-borne wildfire monitoring instruments such as the Moderate Resolution Imaging Spectroradiometer (MODIS) on-board NASA's Aqua and Terra satellites (Justice et al., 2002). The computer-based interpretation of remotely sensed data typically involves models and algorithms that are capable of combining evidence from what is being sensed with prior knowledge that exists on what is known about the surfaces, objects, and terrains being sensed (Kalácska et al., 2005). Analysing the wildfire occurrence for specific terrains from remotely sensed data is an example of such a complex task.

Graphical models and, in particular, Bayesian belief networks (BBNs) (Pearl, 1998; Lauritzen and Spiegelhalter, 1988) provide a useful way of dealing with complex problems because of their capability to combine the robust probabilistic methods with the lucidity of graphs that encode causal relationships between variables and, as such, offer a framework for handling uncertainty, unpredictability, imprecision and complexity in decision-support systems within a single model (Martin et al., 2005; McCann et al., 2006; Tremblay et al., 2004). BBN models consist of a directed acyclic graph (DAG) with the variables represented as nodes in the graph, and edges between the interacting variables and an associated set of conditional probability distributions used to represent the linkages (Pearl, 1988; Pollino et al., 2007). A BBN can, therefore, be used to represent dependencies among variables and to give a concise specification of a joint probability distribution. Specifically, BBN models represent the complex interactions and causal relationships between variables in terms of their individual probability densities and their dependencies as defined by conditional probability tables (CPTs), the information of which may come from empirical data, expert (domain) knowledge or predicted from bottom-up model outputs (Cain, 2001). Some evaluation of BBNs in comparison to other artificial intelligence approaches is given by Kalácska et al. (2005) and McCann et al. (2006). Essentially BBNs exploit the Bayes' theorem to create the conditional probabilities and, when necessary, to propagate uncertainties. BBN's allow for the revision and updating of prior beliefs with the provision of new evidence (field data) while at the same time allowing for a relative view about the state of knowledge rather than an absolute view because the beliefs can be continuously updated with increasing knowledge or evidence. The BBN propagation algorithm utilized by in the software used in this study is complex, and its implementation is explicitly explained in Neapolitan (1990) and Spiegelhalter et al. (1993).

BBNs are modeling tools have often been successfully applied in areas such as medical and forensic sciences, image processing, and particularly in the artificial intelligence community (Kalácska et al., 2005). Nevertheless, BBNs are also increasingly gaining popularity in environmental and ecological sciences where they have been used to model and depict the influence of environmental predictor variables on ecological-response variables and in adaptive natural resource management (e.g. Bromley et al., 2005; Henriksen et al., 2007; Kiiveri et al., 2001; Marcot et al., 2006; Martin et al., 2005; McCann et al., 2006; Pollino et al., 2007; Smith et al., 2007; Ticehurst et al., 2007). The versatility of BBNs has made them useful for facilitating many different forms of probabilistic reasoning in areas such as water and groundwater resources management (e.g. Castelletti and Soncini-Sessa, 2007; Henriksen et al., 2007; Olalla et al., 2007), coastal management (e.g. Ticehurst et al., 2007), and pollution monitoring (e.g. Dorner et al., 2007), among many environmental applications. BBNs are therefore appropriate for the modeling of geospatial data which can contain different kinds of uncertainties due to positional error, feature classification error, resolution, attribute error, data completeness, currency, and logical consistency (Kraak and Ormeling, 1996).

In this paper an approach for estimating the likelihood of wildfire occurrence in Swaziland, a 17,365 km^2 country located in southern Africa (Fig. 1), is introduced using a BBN, based on evidence from an archive of satellite-detected wildfires data and a set of geospatial data on biotic and abiotic factors. The objective of the study is to investigate the important factors influencing wildfire occurrence in Swaziland using a BBN model and to further assess the model's efficacy.

2. Methodology

2.1. Wildfire data collection

Data on daily MODIS active fires in Swaziland were obtained for the period January 2001–December 2007 from the MODIS Rapid Response System dataset (mapsftp.geog.umd.edu). The dataset is based on the contextual fire detection algorithm which uses the 4 μm and 11 μm thermal bands of the electromagnetic spectrum and classifies every pixel as missing data, cloud, water, fire, or unknown at a spatial resolution of 1 km (Giglio et al., 2003; Justice et al., 2002; Nishihama et al., 1997). Significant progress was made with the launch in 1999 and 2002 of the MODIS instrument on board the morning descending Terra and afternoon ascending Aqua polar orbiting earth observation satellites thus offering the opportunity to observe fire activity both day and night. MODIS Terra scans the Southern African region between 10:00 and 11:30 am and at night around 22:00 pm whereas MODIS Aqua scans in the afternoons between 14:00 and 15:30 pm and also in the early morning at 03:00 am (Giglio et al., 2003; Nishihama et al., 1997).

The active fire detection algorithm uses specialized tests to reject potential false alarms caused by sun glint and desert boundaries, and along coastlines (Giglio et al., 2003). The University of Maryland provides a detailed description of the fire detection algorithm including the advantages and limitations of the derived data (http://maps.geog.umd.edu/products.asp). Extensive validation of the MODIS active fire data has been carried out and continues in various parts of the world, including southern Africa with varying degrees of accuracy. Giglio et al. (2003), Wang et al. (2003), Morisette et al. (2005), Schroeder et al. (2008), Frost and Vosloo (2006) and others have successfully used MODIS active fire data and have shown that MODIS location accuracy rates are as high as 90% whilst detection rates are of the order of 50% for smaller short-duration fires and higher for large long-lasting fires. Salomonson and Wolfe (2004) found that the geolocation of MODIS products is highly accurate, with surface location errors generally less than 70 m. This demonstrates the usefulness of MODIS active fire data in fire management and for the characterization of wildfire activity. The spatial distribution of the MODIS-detected fires in Swaziland is shown in Fig. 2.

The spatial prediction and analysis of wildfire ignition based on Bayesian or comparable modeling techniques requires a binary dependent variable (Vasconcelos et al., 2001; Kalabokidis et al., 2007). The dependent variable, fire, can be represented as a discrete binary variable indicating whether fire occurred at a point (1 = yes/true) or not (0 = no/false). Since no-fire points were available, control points that correspond to 'no fire' areas needed to be established. The MODIS active fire data includes an indication of the scan (east-west pixel size) and track (north-south pixel size) in kilometers because the pixel size is not always 1 km across the scan track, only along the nadir (exact vertical from the satellite). This is due to the orbital characteristics of the satellite platform and thus, the values shown for scan and track represent the actual spatial resolution of the scanned pixel (Justice et al., 2002). To avoid creating 'no fire' points that would be on the same or nearby location

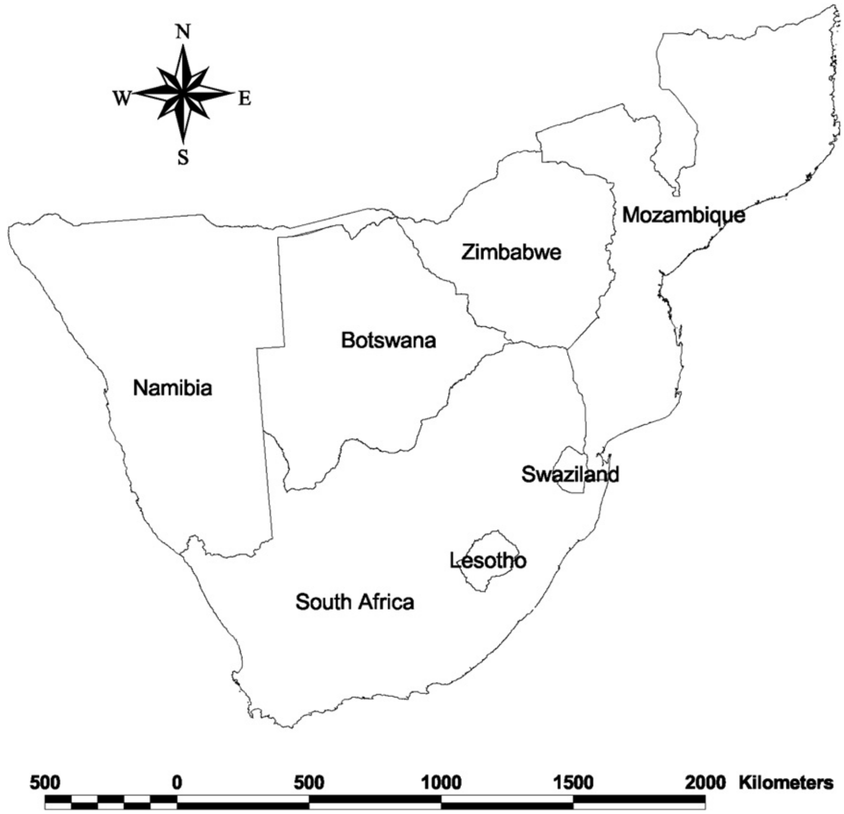

Fig. 1. Map showing the location of Swaziland.

to fire points, we applied a random sampling scheme excluding buffer zones of 1 km around the detected fire pixels. Using this buffer size and using the same procedure as Kalabokidis et al. (2007) and Koutsias et al. (2004), a set of 'no fire' points were randomly generated using the Random Point Generator ArcView extension (Jenness, 2005). Water and barren surfaces, from the land cover data, were also masked out and classified as non-fire even if fires were falsely detected by the MODIS sensor.

2.2. Independent explanatory variable selection

In the model, key applicable parameters that affect wildfire occurrence were determined from domain knowledge of Swaziland's ecosystems and conceptual models reviewed from various peer-reviewed wildfire literature (e.g. Brooks and Matchett, 2006; Cardille et al., 2001; Falk et al., 2007; Lavorel et al., 2007; Maingi and Henry, 2007; Malingreau, 1990; Ofren and Harvey, 1998). The selection of appropriate model variables for the analysis of wildfire occurrence ultimately depends on the objectives of the modeling effort and this requires the careful consideration of computational intensity, complexity, and parameterisation against accuracy (Keane and Long, 1998). In addition to the review of domain literature and conceptual models on wildfires, and using similar criteria as Borsuk et al. (2004) and Cardille et al. (2001), the focus of this study was on those factors or variables that:

a) were directly measurable and/or available for the entire study area;
b) could represent, as a single value in each cell, the average status of some biotic or abiotic variable;
c) varied substantially across the study area at the national/regional scale; and
d) were not highly correlated in the study area with any other factor.

A total of 12 explanatory variables including climatic (mean annual rainfall, mean annual temperature, winter relative humidity), topographic (elevation, slope, aspect), fuel (land cover/use), soil type and anthropogenic disturbances sources (human population density, distance to settlements, road density, and livestock density) met the above criteria and were included in the model. A brief description of the independent explanatory variables is given in Table 1. All independent explanatory variables were resampled to a grid resolution of 30 m to be compatible with other raster data that were available for the country. Road density, distance to human settlements, livestock density, human population density, elevation, slope and climatic data (mean annual temperature, relative humidity, and mean annual precipitation) were defined as continuous variables, while aspect, soil types and land cover types were defined as discrete or categorical.

The climatic data were from a 30-year (1971–2000) dataset from the Swaziland Meteorological Services obtained from a network of meteorological stations around the country and were found suitable for general climatic characterization or describing average climatic conditions for the country. The land cover classes, derived from orthorectified and pre-processed 30 m Landsat ETM data, were used as a proxy for fuel types because of the close relationship between fuel load and land cover (Kalabokidis et al., 2007; Van der Werf et al., 2006; Venkataraman et al., 2006). Land cover is also a good indicator of land use (Lavorel et al., 2007) and is also useful in masking out non-vegetated surfaces such as water surfaces (Tansey et al., 2004). The geographical database of all the variables was integrated using the ArcView 3.3 software (ESRI, 2002). All the explanatory variables were extracted at each point using ArcView's geoprocessing functions and exported into a Microsoft Excel® file for generating a case file of all the fire and no-fire points ($n = 13{,}792$) for input into the BBN software Netica 4.02 (Norsys Software Corporation, 2007). Some of the independent explanatory variables are shown in Fig. 3.

2.3. BBN construction

To build the BBN model, an influence diagram derived from the concept models and available datasets was developed into a BBN using the Netica software (Norsys Software Corporation, 2007). The concept of causality was used as the guiding principle whereby the causalities amongst the variables, as determined from the literature review, domain knowledge and views from local fire management practitioners, were graphically expressed by the direction of causation for directing arcs. To avoid over-fitting, it was necessary to construct a network with a simple and shallow topology but not compromising on the ability to infer wildfire occurrence with an acceptable error rate as suggested by Marcot et al. (2006). This required developing a model which best fits the data yet contains the fewest total parameters and therefore, the interest was not in a complex model that did not estimate a different topology or have significant effects on posterior probability estimates.

The number of states or the discretisation of the continuous variables was limited to a maximum of 3 states (e.g. low, medium, high) representing the ranges in Table 1 in order to improve the overall accuracy of the network (Kalácska et al., 2005; Marcot et al., 2006) whilst at the same time facilitating the parameterisation process (Pollino et al., 2007). The limit in the number of states was also done in order to keep manageable CPTs given the large number of explanatory variables as

Fig. 2. MODIS-detected fires in Swaziland (2001–2007).

proposed by Bromley et al. (2005). Using a combination of field knowledge of the study area coupled with the histogram examination and quantile discretisation functions in ArcView, the optimal state values for each variable were determined.

The number of states for the variables was therefore, as is it often, a compromise between precision and parsimony (Kalácska et al., 2005) and also to reduce computational cost. A number of alternative parameterisations of the conditional probability tables (CPTs) are possible, but the most intuitive, according to Spiegelhalter et al. (1993), is the Dirichlet distribution, which reduces to a Beta distribution for binary variables (e.g. present/absent or yes/no). All the aforementioned parameters, which have direct/indirect influence on the occurrence of wildfire, were then integrated as shown in Fig. 4 using the Netica software (Norsys Software Corporation, 2007).

2.4. Training/calibration

Since BBNs allow for the propagation of information in the form of instantiated variable states forward or backward through nodes, and because the extent of past wildfires is not known, a train and test approach was used to quantitatively evaluate the model (as also used by Guisan and Zimmermann, 2000; Miller, 2005; and Rollins et al., 2004). This was achieved through the use of the empirical dataset using a k-fold partitioning ($k = 2$) in which the dataset was partitioned into a training and calibration portion (75%, $n = 10{,}479$) used to develop the model, and an evaluation dataset (25%, $n = 3493$), with which accuracy was assessed (Fielding and Bell, 1997; Hessl et al., 2007; Rollins et al., 2004).

The choice of a 2-fold partition was based on the need for simplicity and to avoid the large correlation associated with numerous training sets when the sample is small. The CPTs were then estimated from the data using the expectation–maximization (EM) algorithm because this algorithm updates initial parameter estimates by iteratively refitting the case file data to the final model till convergence and also accounts for missing data (as is the case with satellite-detected fires) and minimizes negative log likelihood (Lauritzen, 1995; Norsys Software Corporation, 2007; Watanabe and Yamaguchi, 2003). The two assumptions of the algorithm, which also apply in this study, are that the conditional probabilities that are being estimated are independent and the prior distributions are assumed to be multinomial (Korb and Nicholson, 2004).

2.5. Model assessment

The performance of the BBN model was evaluated in two ways. The first involved calculating the sensitivity of the wildfire occurrence node to findings in all the other nodes in Netica (Norsys Software Corporation). Through the process of sensitivity analysis, it was possible to identify variables or factors that have the most influence on wildfire occurrence and the causal relationships of importance using the mutual information (entropy reduction) values (Korb and Nicholson, 2004). The mutual information, is symmetric between two nodes, and is a measure of the magnitude with which a finding at one node (findings or explanatory node) is expected to alter the beliefs (measured as entropy reduction) at another node (the query node) (Pearl, 1998; Korb and Nicholson, 2004; Pollino et al., 2007). The Netica software calculates the entropy reduction for other variables in the network, expressed as a percentage of the total entropy of the query variable or node.

Secondly, the BBNs were also tested on the random subset of 3493 cases (25% of the case file) that were not used in the learning or training process. The error rate and scoring rules, which provide an evaluation of predicted probabilities of states over a set of variables, were calculated. The widely used scoring rules are the logarithmic loss, quadratic loss and spherical payoff (Kalácska et al., 2005; Marcot et al., 2006; Morgan and Henrion, 1990). The logarithmic loss is the only scoring rule whose value is determined solely by the probability of the outcome that actually

Table 1
Data sources and description of the explanatory/independent variables.

Variable (Node)	Type	Source	States (ranges)
Fire	Discrete	MODIS Rapid Response System (1 km resolution)	Present (Fire), Absent (No Fire)
Land cover	Discrete	Bob Smith, University of Kent at Canterbury, derived from Landsat 7 ETM+ (30 m resolution)	Bare soil/Water, Built-up, Cultivated, Forest and Woodland, Grasslands, Plantations, Sugarcane, Thicket and Bushland.
Mean annual temperature	Continuous	Swaziland Meteorological Services weather stations (1 km resolution)	$<19\,^\circ$C, 19–21 °C, $>21\,^\circ$C
Elevation	Continuous	Surveyor General's Office Digital Elevation Model (DEM) (20 m resolution)	<300 m, 300–800 m, >800 m above sea level
Mean annual rainfall	Continuous	Swaziland Meteorological Services weather stations (1 km resolution)	<750 mm/year, 750–900 mm/year, >900 mm/year
Livestock density	Continuous	Dipping tanks census data (1:50,000)	<0.3 livestock units/ha, 0.3–0.5 livestock units/ha, >0.5 livestock units/ha
Distance to settlements	Continuous	Calculated from digitised settlements from digital orthophotos (1:10,000)	<1 km, 1–5 km, >5 km
Soil type	Discrete	Soils map (1:50,000)	Five (5) soil suitability classes plus one (1) small unclassified piece.
Relative humidity	Continuous	Swaziland Meteorological Services (1 km resolution), weather stations	<36%, 36–39%, >39%
Road density	Continuous	Major and feeder roads map (1:10,000)	<2 km/km^2, 2–4 km/km^2, >4 km/km^2
Human population density	Continuous	Central Statistics Office Census Enumeration Areas (1:10,000)	<10 people/km^2, 10–100 people/km^2, >100 people/km^2
Aspect	Discrete	Derived from the DEM (20 m resolution)	North (0–45°, 315–360°), East (45–135°), West (225–315°), South (135–225°).
Slope	Continuous	Derived from the DEM (20 m resolution)	<5°, 5–15°, >15°

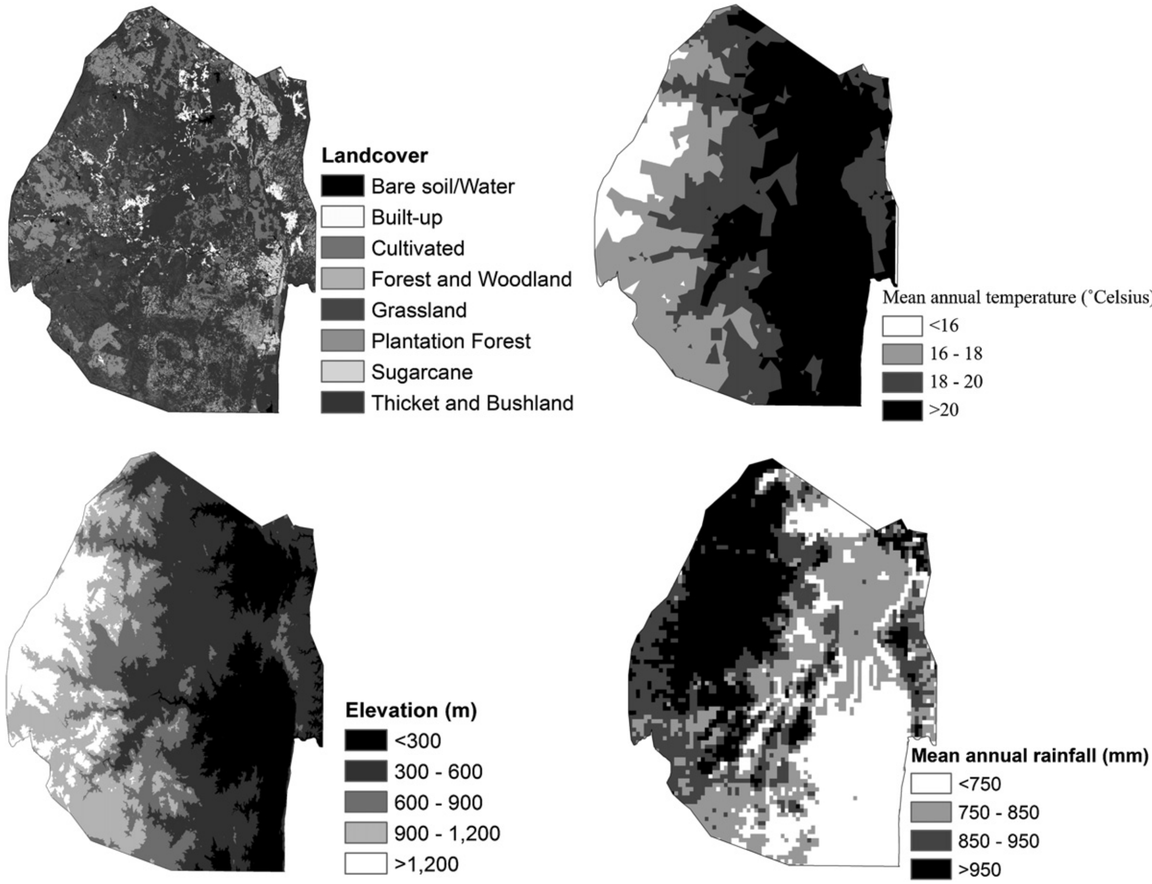

Fig. 3. Examples of the spatial explanatory variables used in the BBN model.

occurs (Colwell et al., 1993). For logarithmic loss (0 to infinity) and quadratic loss (0–2), scores close to zero are better whilst 1 indicates the best model performance for spherical payoff (0–1) (Korb and Nicholson, 2004).

A receiver-operating characteristic (ROC) plot (Fielding and Bell, 1997; Pepe et al., 2006) was also used to evaluate the classification accuracy of the model because of the binary nature of the query (wildfire occurrence) node. The ROC plot determines how well an observer (the "receiver") can assign cases to dichotomous classes (Rollins et al., 2004) and is created by plotting true positives against false positives across a continuum of prediction thresholds (Marcot et al., 2006). The ROC therefore represents the probability that a positive outcome (wildfire occurrence) has a higher predicted probability than a negative outcome (no wildfire) (Zheng et al., 2006). The area under the curve (AUC) of the ROC function can be interpreted as a single measure of overall accuracy that is both threshold- and prevalence-independent (Manel, et al., 2001). The AUC varies from 0.5 (random guess or chance) to 1.0 (perfect performance). In general, values of 0.5–0.7 indicate poor discriminating ability, values of 0.7–0.9 indicate reasonable discriminating ability, and values above 0.9 indicate excellent discriminating ability (Gibson, et al., 2004; Hessl et al., 2007).

3. Results

The compiled model is shown in Fig. 4 and the beliefs are shown for each node in the form of the belief bars. These represent the initial beliefs (presented as probabilities) about the determinants of wildfire activity in Swaziland as evidenced by the data used. The probabilities in may be interpreted as the belief or likelihood that each variable is in a certain state. The sensitivity analysis results of this model are presented in Table 2 and the nodes are ranked in according to the degree of influence of their findings on the outcomes of the wildfire occurrence node calculated as a measure of mutual information or variance reduction (expressed as a percentage). Land cover is the most significant factor causing the largest entropy reduction in wildfire occurrence. Elevation and climatic variables (mean annual rainfall and mean annual temperature) also show a strong conclusive influence on wildfire occurrence with more than 5% entropy reduction values each. These are followed by road density, livestock density and proximity (distance) to human settlements each with more than 2% entropy reduction. Relative humidity, soil type, human population density and slope each result in less than 2% entropy reduction with aspect having the least influence with a value of 0.334%. The beliefs for the first four important factors when the finding on states of each model variable is entered are given in Table 3 and indicate the change in beliefs (from the initial beliefs) on the presence or occurrence of fires (i.e. fire = present). The changes in beliefs in reveal that the occurrence of wildfires is highly sensitive to and increased in sugarcane (29%), plantation forests (26.9%) and grasslands (26.8%) and, as expected, mainly reduced in water or bare ground (−29.4%). There is also a large change in belief (31.5%) for areas higher than 800 m above sea level (Table 3), particularly the western part (Highveld) of the country, indicating the influence of elevation on wildfire occurrences. Table 3 provides further evidence that areas with annual rainfall of more than 900 mm resulted in a 25.2% increase in belief for wildfire occurrence when the finding was entered. On the contrary, lower rainfall areas (<750 mm) had a reduced belief of wildfire occurrence (−16.7%).

The error rate was 9.65%, implying that the model had the majority of its predictions correct for wildfire observations. The scoring rule results are shown in Table 4 and they also confirm the model's strong predictive power. The logarithmic loss and quadratic loss scores were both closer to zero whilst the spherical payoff of 0.9177 thereby indicating excellent model performance. The model's ability to determine wildfire occurrences, i.e. its

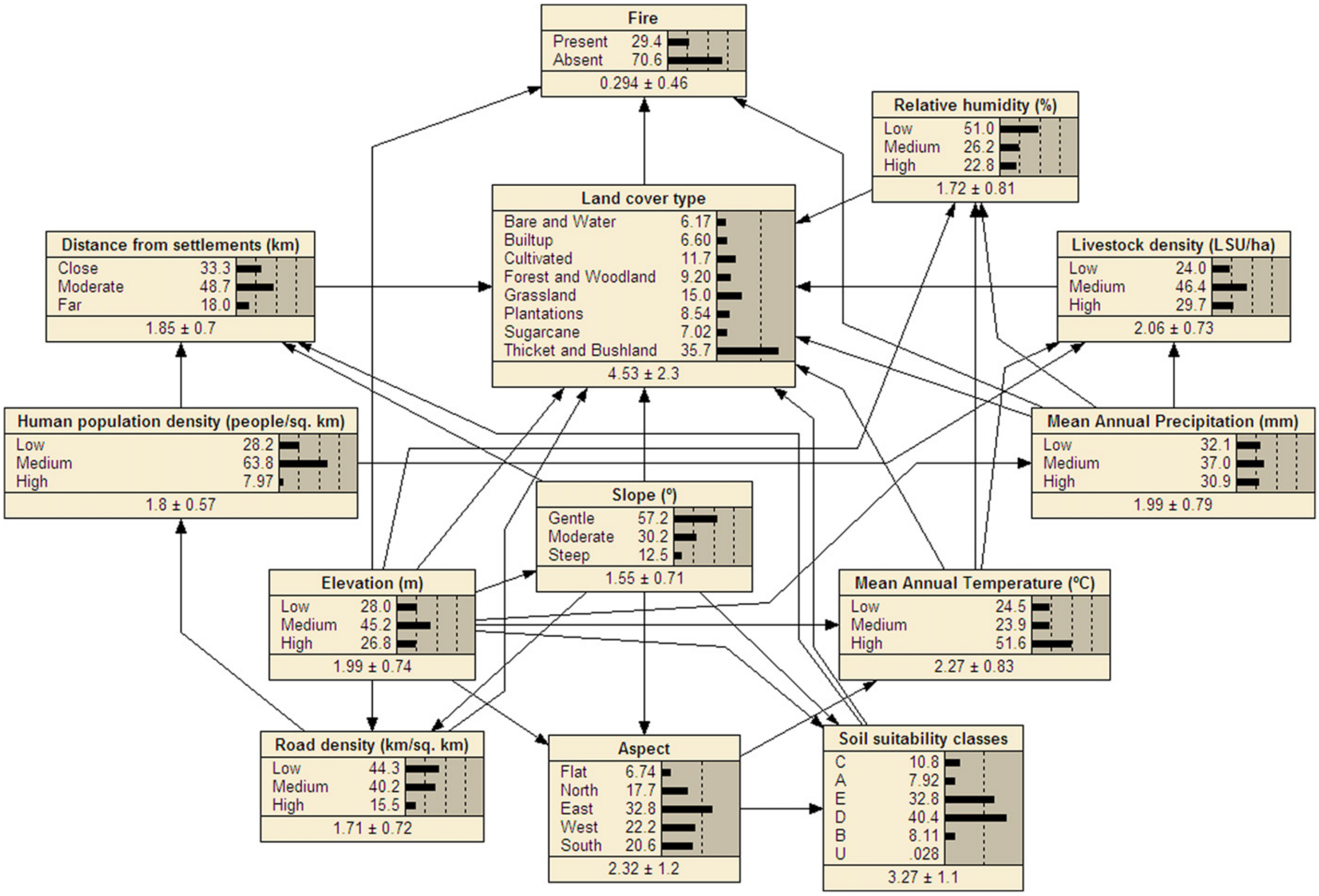

Fig. 4. The BBN model of wildfire occurrence in Swaziland.

sensitivity, is very high (0.963) and with a lower specificity value of 0.725. The area under the ROC curve (AUC) was 0.961 (95% confidence level: 0.950, 0.973), an additional evidence of the model's excellent predictive and discriminating ability (Fig. 5).

4. Discussion

The model generally manifests the complexity of the interactions between wildfire, vegetation, topography, and climate which can influence wildfire occurrence patterns (Falk et al., 2007). Land cover, which represents the fuel type, is the most influential factor on wildfire occurrence in Swaziland (Table 1) and this is due the fact that variations in fuel composition invariably lead to different wildfire activity in different land cover types since the vegetative content of land cover types affects the ignition potential

Table 2
Sensitivity analysis results ranked in decreasing order of influence on wildfire occurrence based on mutual information or entropy reduction (also expresses as a percentage in brackets).

Node (Variable)	Mutual info/Entropy reduction (%)
Fire	0.7577 (100)
Land cover	0.05243 (6.92)
Elevation	0.04512 (5.95)
Mean annual rainfall	0.04341 (5.73)
Mean annual temperature	0.04321 (5.7)
Road density	0.01939 (2.56)
Livestock density	0.01906 (2.51)
Distance to settlements	0.01687 (2.23)
July (winter) relative humidity	0.01509 (1.99)
Soil type	0.01408 (1.86)
Human population density	0.01149 (1.52)
Slope	0.01063 (1.4)
Aspect	0.00253 (0.334)

Table 3
Changes in belief for wildfire occurrence (fire = present) for the variable or node states.

Variable and states	Change in belief (Fire = Present)
Land cover type	
Sugarcane	0.29008
Plantations	0.26872
Grassland	0.26811
Built-up	−0.02216
Forest and woodland	−0.02487
Thicket and bushland	−0.12672
Cultivated	−0.13931
Bare soil/water	−0.29409
Elevation (m)	
High (>800)	0.31451
Low (<300)	−0.10028
Medium (300–800)	−0.12471
Mean annual precipitation (mm)	
High (>900)	0.2515
Medium (750–900)	−0.06514
Low (<750)	−0.16671
Mean annual temperature (°C)	
Low (<19)	0.31915
Medium (19–21)	−0.08546
High (>21)	−0.11174

Table 4
Confusion matrix and performance measurements of the BBN model.

Observed		Predicted		
		Fire	No fire	Total
	Fire	2524	96	2620
	No Fire	240	633	873
	Total	2764	729	3493
Error rate	9.62%			
Logarithmic loss	0.2562			
Quadratic loss (Brier Score)	0.1397			
Spherical payoff	0.9255			
Sensitivity	0.963			
Specificity	0.725			

and spreading characteristics of wildfires (Korontzi et al., 2004; Venkataraman et al., 2006). Moreover, land cover is an important variable in wildfire modeling, hence its consideration in most wildfire danger rating systems worldwide (Mouillot et al., 2003). The high influence of land cover to wildfire activity is also a result of the significant effect on and close association with land use (Lavorel et al., 2007), patch overgrazing by livestock (Fuls, 1992), local rainfall variation (Wiens, 1985), and/or variation in topography and soil fertility (Scholes, 1990). Fuel availability in the different land cover types is also influenced by people who collect fuel for domestic energy (Frost, 1999), which is a common practice in Swaziland. The changes in beliefs (Table 3) are a result of the use fire in sugarcane harvesting, the extreme fire hazard of plantation forests and the natural fire regimes in grassland. This implies that any land use or land cover transformation to sugarcane, plantations, or grasslands is likely to increase the occurrence of wildfires. Hence, wildfire management must pay particular attention to these land cover and/or land management types. Land cover changes or changes in the status of land cover types due to factors such as land use change will significantly modify the spatial patterns of wildfires in Swaziland. A description of the spatial distribution of land cover characteristics is therefore fundamental to the assessment of wildfire hazard and risk across a landscape for wildfire and land management purposes.

The findings also indicate that the spatial distribution of wildfires is also largely explained by elevation in line with observations from other areas where topography has been found to be a major determinant of wildfire activity (e.g. Maingi and Henry, 2007 and Mouillot et al., 2003) and, coupled with local weather elements, has a direct effect on the wildfire through its effect on both fuel

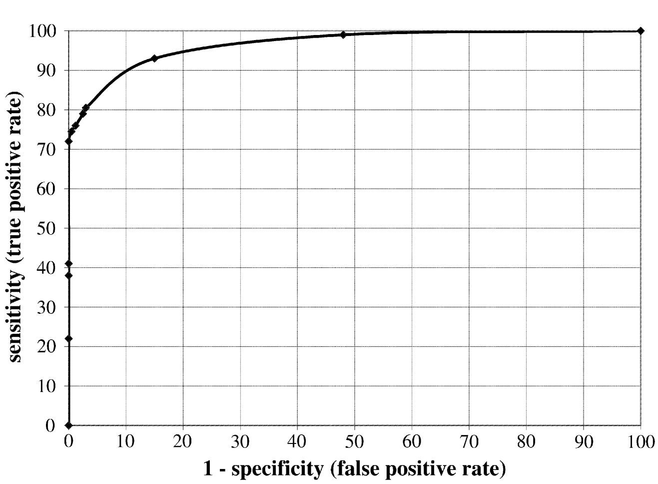

Fig. 5. The receiver-operating characteristic (ROC) curve of the BBN model.

moisture and fuel type (Andrews and Queen, 2001). At the spatial scale of this study, elevation gradients may also generate persistent local climate variation, inducing variation in vegetation and fuel productivity as suggested by Gavin et al. (2003) and such variations in Swaziland have also been observed to influence moisture conditions and tree species composition (Remmelzwaal, 1993; Sweet and Khumalo, 1994). The extreme altitudinal variability that is characteristic of the Swaziland landscape may help to explain the extent and pattern of most wildfires by either inhibiting or enhancing wildfire activity.

The influence of rainfall on wildfire occurrence in Swaziland in notable and corroborates observations by Malingreau (1990) and Ofren and Harvey (1998) that annual rainfall is an important factor in wildfire occurrence and frequency in the tropics, due to its influence on fuel moisture and loading. During the July 2007 fire disaster, Dlamini (2007) observed that the fires were mainly concentrated in the Highveld and Middleveld, the wetter eco-climatic zones in the country. However, the analyses to evaluate relationships between wildfire occurrence and rainfall requires long-term data that may span many decades to over a century in order to capture the full range of conditions necessary to infer trends for different vegetation or land cover types (Brooks and Matchett, 2006). Future changes in rainfall regimes nevertheless have the potential to affect wildfire regimes in Swaziland considering that predictions that the country may be entering a multi-decade period of relatively low rainfall in the early 21st century (Matondo et al., 2004) may have implications for vegetation and fuel conditions.

Mean annual temperature is the fourth most influential factor determining the incidence of wildfires in the country. Several studies investigating trends over the past century have found that wildfire activity and frequency (Clark, 1990; Dwyer et al., 2000) and the area burned (Flannigan and van Wagner, 1991; Riaño et al., 2007) correlated well with air temperature, leading to increased concern over the potential impact of climate change on wildfire severity. The findings in this study (Table 3) clearly show that areas with low mean annual temperature have a higher likelihood of wildfire incidence. Clearly, this corresponds to the Highveld and parts of the Upper Middleveld of Swaziland which, as already mentioned, are susceptible to extreme wildfire incidents examples of which are the 2007 extreme wildfires. While the exact nature of the changes in temperature and extreme events is not known, climate change scenarios for Africa indicate future warming across the continent ranging from 0.2 °C per decade for the low scenario to more than 0.5 °C per decade for the high scenario (Hulme et al., 2001) whilst Matondo et al. (2004) predict higher temperatures to the year 2075 and as such wildfire activity is likely to change in the country under these future conditions. This opens up the exciting possibility of using such observations in helping to predict wildfire regimes under changing climate conditions.

The influence of roads is also notable, indicating the possible impact of road developments in increasing human access to wild areas, thereby increasing the interaction of humans and the natural environment through fire. Thus, road construction could influence overall fire activity, through determining the access to areas prone to such fires (Cardille et al., 2001; Maingi and Henry, 2007), thereby confirming findings of other studies such as Chou (1992) and Nepstad et al. (2001) which refer to the importance of roads to the origin of wildfires.

Similar to the findings by Kalabokidis et al. (2007), the livestock density is also observed to have a notable effect on wildfire occurrence in Swaziland mainly as a result of the complex but very significant relationship between the availability of fuel and herbivory (Van Wilgen and Scholes, 1997). Walker (1985) also concluded that wildfire and herbivores are the two most important variable determinants which modify the inherent structure imposed on savannas by climate and soil type. A study by Roques et al. (2001) also revealed that shrub/thicket cover on communal grazing land in Swaziland increased from approximately 3% to over 40% in 50 years as a result of high grazing pressure through grass fuel removal and the concomitant reduction in fire frequency. This is particularly interesting because the Swazi people are largely livestock rearers supported by various government policies (Sweet and Khumalo, 1994).

The strong link between wildfires and the location of human settlements is consistent with findings by Cardille et al. (2001) and Maingi and Henry (2007) who concluded that areas that had higher population density or human influence are more likely to burn. In this study, however, wildfire occurrence was less sensitive to human population density than the proximity to human settlements, reinforcing the assertion that most of the fires are a result of human activity. Thus human settlements pose risks because forests and other vegetation that is closer to these areas are more likely to burn due to a higher concentration of humans, and their activities such as arson, smoking, and deliberate burning of vegetation. Conversely, wildfires are also a significant threat to human settlements with the increase in the wildland-urban interface and the encroachment of settlements into forested areas or areas with high fuel content.

Relative humidity is also not a very strong factor in this study, although it is important because of its recorded influence particularly on the occurrence of spot wildfires and its influence on fuel flammability (Weir, 2007). The influence of soil types of wildfire activity is also weaker, even though soil types affect the amount of moisture retained in the soil profile which also determines aboveground primary productivity and nutrient status (DeBano et al., 1998; Wan et al., 2001). Aspect had the least influence on wildfire occurrence and this is likely due to the smaller scale of the analysis which may obscure local variations. In their analysis, Ofren and Harvey (1998) also observed that slope and aspect had the least influence on wildfire occurrence. The widespread detection of fires in the flat Lowveld sugarcane-growing areas and in the more rugged Highveld grasslands and plantations could have further minimized any relation with slope in the country. Moreover, the differences in the spatial resolution of the active wildfire data (1 km) and the topographic variables (30 m) may have further obscured such relationships.

5. Synthesis

The influence of the major governing mechanisms (climate, land cover, elevation) on wildfire occurrence varies across spatial and temporal scales and in specific ways. Similar to the findings of this study, Cardille et al. (2001) also found that land cover, temperature and precipitation were significant wildfire determinants. Altitude and rainfall, among other variables, have been observed to play important factors in determining vegetation structure in southern Africa where wildfire frequency and intensity are largely governed by rainfall and herbivory (Von Maltitz and Scholes, 2006). However, the results of this model may not be generalized to other ecosystems because as Kalácska et al. (2005) observe, differences in land cover or vegetation structure and climate will pose unique challenges that are particular to each type of ecosystem.

The BBN model used is relatively highly accurate in analyzing wildfire occurrence when considering the low error rate and the scoring results presented in Table 4. Nevertheless, Rollins et al. (2004) observe that it is possible to have a high overall accuracy, while having a high probability of false negatives or false positives because overall accuracy does not necessarily account for commission and omission errors (Congalton and Green, 1998). The results of the BBN model, however, reveal a high sensitivity and good but lower degree of specificity. While the model had the greatest confidence in its predictions in areas where wildfire was present the confidence in its predictions in areas with no wildfire relatively lower. The increased confidence in areas with wildfire, hence the high sensitivity, is partly due to the training data in which the majority of the cases had wildfire because almost two-thirds of the total study area was affected by wildfire whilst only the remaining third did not experience wildfires. This also indicates that most of the errors were due to Type II errors (false positives) which may be tolerable because having greater certainty over factors controlling the occurrence of an event (wildfire in this case) is preferable rather than having greater certainty over those factors controlling its absence (Marcot et al., 2006). The lower confidence in predictions for non-wildfire did not, however, affect the accuracy or predictive power of the BBN. The complexity of the model, including the choice of predictor variable states or discretisation can also influence its accuracy more especially its specificity (Yuen and Mila, 2003).

Notwithstanding the findings of the study, it is important to mention that the precision, accuracy, robustness and reliability of Bayesian models rely on both the strength of the pattern inherent in the training data and the quality of such data (Taroni et al., 2004). The variability in the predictions of the model can also be viewed as a measure of the model's strength in representing the inherent uncertainty in the represented spatial relationships. Some of these uncertainties, although not quantified, could also be attributed to common geospatial data errors such as positional errors and logical consistency described in Kraak and Ormeling (1996). Similar to all satellite-based fire datasets, the MODIS fire product is also affected by undetected fires (omission errors) due to obscuration by clouds, smaller fire sizes and misses between satellite overpasses in addition to false alarms (commission errors) (Chuvieco et al., 2008). The detectability of wildfires by the MODIS sensor is mainly affected by its orbital and sensor characteristics, thus compromising the ability to characterize wildfire activity. Chefaoui and Lobo (2008) also observe that the pseudo-absence selection method (random generation of 'no fire' points), as used in this study in the creation of 'no fire' data from sites where wildfires were highly likely to be absent, can greatly influences the percentage of explained variability, the scores of the accuracy measures and, most importantly, the degree of constraint in the distribution estimated.

Another constraint stems from the fact that the data used to parameterise the model was from different sources and collected at different temporal and spatial scales. Hence, the results of this study could also be interpreted as a pilot for further in-depth investigations. Marcot et al. (2006) suggest that building BBNs strictly from empirical datasets for models of wildlife and natural resource management tends to overfit the data, creating a model that is pertinent only to the specific dataset used. Also, strictly using rule induction or empirical data ignores a wealth of expert knowledge, which could be quite helpful for building more robust predictive models. Other possible sources of error may also include natural randomness, model parameters and model structure (Melching, 1995). However, given the geographical scale of this study, the resolution of the data used and the robustness of Bayesian analysis, it is not expected that the above mentioned errors and limitations can significantly affect the results or conclusions.

6. Conclusion

In this analysis, we have demonstrated a novel approach to analyse wildfire occurrence from satellite and GIS data. A BBN model was developed in the assessment framework for the ranking and selection of biotic, abiotic and human factors influencing wildfires patterns as detected by MODIS within Swaziland. Sensitivity analysis was used to identify key parameters or key management interventions that need to be determined accurately and from a monitoring and adaptive management perspective. Land cover, together with elevation, mean annual rainfall and mean annual temperature, were the most influential factors explaining wildfire occurrence in Swaziland. The findings points to the significance of climate and land use (as manifested by the different land cover types) on the occurrence of fires. Of particular importance is that the BBN approach provides the means of combining and reasoning about data from different sources and scales. Despite the inherent limitations and errors, the model was highly accurate and has enabled the complex wildfire processes to be conceptualized and integrated in order to identify key factors specific to Swaziland. The BBN can still be developed further into a dynamic model that takes into account temporal variations in climate and land use/land cover which could be useful in dynamic wildfire risk assessment. The inclusion of other variables such as lightning risk (whose data is not yet available for the country), could also improve the predictive power of the future models. Improvement can also be made by increasing the time scale through assimilating other wildfire products such as the Advanced Very High Resolution Radiometer (AVHRR) and Along Track Scanning Radiometer (ATSR)/ Advanced Along Track Scanning Radiometer (AATSR) to further refine the model.

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References

Andrews, P.L., Queen, L.P., 2001. Wildfire modeling and information system technology. International Journal of Wildland Wildfire 10, 343–352.
Bond, W.J., Keeley, J.E., 2005. Fire as a global 'herbivore': the ecology and evolution of flammable ecosystems. Trends in Ecology and Evolution 20, 387–394.
Borsuk, M.E., Stow, C.A., Reckhow, K., 2004. A Bayesian network of eutrophication models for synthesis, prediction and uncertainty analysis. Ecological Modelling 173, 219–239.
Bromley, J., Jackson, N.A., Clymer, O.J., Giacomello, A.M., Jensen, F.V., 2005. The use of Hugin® to develop Bayesian networks as an aid to integrated water resource planning. Environmental Modelling & Software 20, 231–242.
Brooks, M.L., Matchett, J.R., 2006. Spatial and temporal patterns of wildfires in the Mojave Desert, 1980–2004. Journal of Arid Environments 67, 148–164.
Cain, J., 2001. Planning Improvements in Natural Resources Management: Guidelines for Using Bayesian Belief Networks to Support the Planning and Management of Development Programmes in the Water Sector and Beyond. Centre for Ecology and Hydrology, Natural Environment Research Council, Wallingford, UK.
Cardille, J.A., Ventura, S.J., Turner, M.G., 2001. Environmental and social factors influencing wildfires in the upper midwest, USA. Ecological Applications 11 (1), 111–127.
Castelletti, A., Soncini-Sessa, R., 2007. Bayesian networks in water resource modelling and management. Environmental Modelling & Software 22 (8), 1073–1074.
Chefaoui, R.M., Lobo, J.M., 2008. Assessing the effects of pseudo-absences on predictive distribution model performance. Ecological Modelling 210, 478–486.
Chou, Y.H., 1992. Management of wildfires with a geographical information system. International Journal of Geographical Information Systems 6 (2), 123–140.
Chuvieco, E.W., Giglio, L., Justice, C., 2008. Global characterization of fire activity: toward defining fire regimes from Earth observation data. Global Change Biology 14, 1488–1502.
Clark, J.S., 1990. Effect of climate change on wildfire regimes in northwestern Minnesota. Nature 334, 233–235.
Colwell, R.G., Dawid, A.P., Speigelhalter, D.J., 1993. Sequential model criticism in probabilistic expert systems. IEEE Transactions on Pattern Analysis and Machine Intelligence 15 (3), 209–219.
Congalton, R.G., Green, K., 1998. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. Lewis, Boca Raton, Florida, USA.
DeBano, L.F., Neary, D.G., Folliott, P.F., 1998. Wildfire's Effects on Ecosystems. John Wiley and Sons, New York.
Dlamini, W.M., 2007. A review of the July 2007 Swaziland fire disaster using GIS and MODIS data. PositionIT, September/October 2007, 61–65.
Dorner, S., Shi, J., Swayne, D., 2007. Multi-objective modelling and decision support using a Bayesian network approximation to a non-point source pollution model. Environmental Modelling & Software 22 (2), 211–222.
Dwyer, E., Gregoire, J.M., Pereira, J.M.C., 2000. Climate and vegetation as driving factors in global wildfire activity. In: Innes, J.L., Beniston, M., Verstraete, M.M. (Eds.), Biomass Burning and its Inter-Relationships with the Climate System. Springer, New York, pp. 171–191.
ESRI, 2002. ArcView: Release 3.3. Environmental Systems Research Institute, Redlands, California.
Eva, H., Lambin, E.F., 2000. Fires and land-cover change in the tropics: a remote sensing analysis at the landscape scale. Journal of Biogeography 27, 765–776.
Falk, D.A., Miller, C., McKenzie, D., Black, A.E., 2007. Cross-scale analysis of wildfire regimes. Ecosystems 10, 809–823.
Fielding, A.H., Bell, J.F., 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24, 38–49.
Flannigan, M.D., van Wagner, C.E., 1991. Climate change and wildfire in Canada. Canadian Journal of Forestry Research 21, 66–72.
Frost, P.G.H., 1999. Wildfire in southern African woodlands: origins, impacts, effects, and control. In: Proceedings of an FA0 Meeting on Public Policies Affecting Forest Wildfires, FAO Forestry Paper 138, pp 181–205.
Frost, P., Vosloo, H., 2006. Satellite-based early warnings of fires: reducing fire flashovers on transmission lines. ESI Africa 2, 48–51.
Fuls, E.R., 1992. Ecosystem modification created by patch-overgrazing in semi-arid grassland. Journal of Arid Environments 23, 59–69.
Gavin, D.G., Brubaker, L.B., Lertzman, K.P., 2003. An 1800-year record of the spatial and temporal distribution of fire from the west coast of Vancouver Island, Canada. Canadian Journal of Forest Research 33, 573–586.
Gibson, L.A., Wilson, B.A., Aberton, J.G., 2004. Landscape characteristics associated with species richness and occurrence of small native mammals inhabiting a coastal heathland: A spatial modeling approach. Biological Conservation 120, 75–89.
Giglio, L., Descloitres, J., Justice, C.O., Kaufman, Y.J., 2003. An enhanced contextual fire detection algorithm for MODIS. Remote Sensing of Environment 87, 273–282.
Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. Ecological Modelling 135, 147–186.
Henriksen, H.J., Rasmussen, P., Brandt, G., von Bulow, D., Jensen, F.V., 2007. Public participation modeling using Bayesian networks in management of groundwater contamination. Environmental Modelling and Software 22, 1101–1113.
Hessl, A., Miller, J., Kernan, J., Keenum, D., McKenzie, D., 2007. Mapping paleowildfire boundaries from binary point data: comparing interpolation methods. The Professional Geographer 59 (1), 87–104.
Hulme, M., Doherty, R.M., Ngara, T., New, M.G., Lister, D., 2001. African climate change: 1900–2100. Climate Research 17, 145–168.
Jenness, J., 2005. Random point generator (randpts.avx) extension for arcview 3.x, v.1.3 [Online URL]. <http://www.jennessent.com/arcview/random_points.htm> (accessed 17.07.07).
Justice, C.O., Giglio, L., Korontzi, S., Owens, J., Morisette, J.T., Roy, D., Descloitres, J., Alleaume, S., Petitcolin, F., Kaufman, Y., 2002. The MODIS fire products. Remote Sensing of the Environment 83, 244–262.
Kalabokidis, K.D., Koutsias, N., Konstantinidis, P., Vasilakos, C., 2007. Multivariate analysis of landscape wildfire dynamics in a Mediterranean ecosystem of Greece. Area 39 (3), 392–402.
Kalácska, M., Sánchez-Azofeifa, G.A., Caelli, T., Rivard, B., Boerlage, B., 2005. Estimating leaf area index from satellite imagery using Bayesian belief networks. IEEE Transactions on Geoscience and Remote Sensing 43 (8), 1866–1873.
Keane, R.E., Long, D.G., 1998. A comparison of coarse scale wildfire effects simulation strategies. Northwest Science 72 (2), 76–90.
Kiiveri, H.T., Caccetta, P., Evans, F., 2001. Use of conditional probability networks for environmental monitoring. International Journal of Remote Sensing 22, 1173–1190.
Kraak, M., Ormeling, F., 1996. Cartography, Visualization of Spatial Data. Addison Wesley Longman Limited, Essex, England.
Korb, K.B., Nicholson, A.E., 2004. Bayesian Artificial Intelligence. Chapman and Hall/ CRC Press, London.
Korontzi, S., Roy, D.P., Justice, C.O., Ward, D.E., 2004. Modeling and sensitivity analysis of wildfire emissions in southern Africa during SAFARI 2000. Remote Sensing of Environment 92, 255–275.
Koutsias, N., Kalabokidis, K.D., Allgöwer, B., 2004. Wildfire occurrence patterns at landscape level: beyond positional accuracy of ignition points with kernel density estimation methods. Natural Resource Modeling 17, 359–375.
Lauritzen, S.L., 1995. The EM algorithm for graphical association models with missing data. Computational Statistics and Data Analysis 19 (2), 191–201.

Lauritzen, S.L., Spiegelhalter, D.J., 1988. Local computations with probabilities on graphical structures and their application to expert systems. Journal of the Royal Statistical Society 50 (2), 157–224.
Lavorel, S., Flannigan, M.D., Lambin, E.F., Scholes, M.C., 2007. Vulnerability of land systems to wildfire: interactions among humans, climate, the atmosphere, and ecosystems. Mitigation and Adaptation Strategies for Global Change 12, 33–53.
Maingi, J.K., Henry, M.C., 2007. Factors influencing wildfire occurrence and distribution in eastern Kentucky, USA. International Journal of Wildland Wildfire 16, 23–33.
Malingreau, J.-P., 1990. The contribution of remote sensing to the global monitoring of fires in tropical and subtropical ecosystems. In: Goldammer, J.G. (Ed.), Fires in the Tropical Biota, Ecosystem Processes and Global Challenges. Springer-Verlag, Berlin, pp. 337–370.
Manel, S., Williams, H.C., Ormerod, S.J., 2001. Evaluating presence–absence models in ecology: the need to account for prevalence. Journal of Applied Ecology 38, 921–931.
Marcot, B.G., Steventon, J.D., Sutherland, G.D., McCann, R.K., 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. Canadian Journal of Forestry Research 36, 3063–3074.
Martin, T.G., Kuhrnet, P.M., Mengersen, K., Possingham, H.P., 2005. The power of expert opinion in ecological models using Bayesian methods: impact of grazing on birds. Ecological Applications 15, 266–280.
Matondo, J.I., Peter, G., Msibi, K.M., 2004. Evaluation of the impact of climate change on hydrology and water resources in Swaziland: part II. Physics and Chemistry of the Earth 29, 1193–1202.
McCann, R.K., Marcot, B.G., Ellis, R., 2006. Bayesian belief networks: applications in ecology and natural resource management. Canadian Journal of Forestry Research 36, 3053–3062.
Melching, C.S., 1995. Reliability estimation. In: Singh, V.P. (Ed.), Computer Models of Watershed Hydrology. Water Resources Publication, Highlands Ranch, Colorado, pp. 69–118.
Miller, J., 2005. Incorporating spatial dependence in predictive vegetation models: residual interpolation methods. The Professional Geographer 57, 169–184.
Morgan, M.G., Henrion, M., 1990. Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge Press, New York.
Morisette, J.T., Giglio, L., Csiszar, I., Justice, C.O., 2005. Validation of the MODIS active fire product over southern Africa with ASTER data. International Journal of Remote Sensing 26 (19), 4239–4264.
Mouillot, F., Ratte, J.-P., Joffre, R., Moreno, J.M., Rambal, S., 2003. Some determinants of the spatio-temporal wildfire cycle in a Mediterranean landscape (Corsica, France). Landscape Ecology 18, 665–674.
Myers, B., Allan, G., Bradstock, R., Dias, L., Duff, G., Jacklyn, P., Landsberg, J., Morrison, J., Russell-Smith, J., Williams, R., 2004. Wildfire Management in the Rangelands. Tropical Savannas CRC, Darwin, Australia.
Neapolitan, E., 1990. Probabilistic Reasoning in Expert Systems. Wiley, New York.
Nepstad, D., Carvalho, G., Barros, A.C., Alencar, A., Capobianco, J.P., Bishop, J., Moutinho, P., Lefebvre, P., Lopes da Silva Jr., U., 2001. Road paving, fire regime feedbacks and the future of Amazon forests. Forest Ecology and Management 154, 395–407.
Nishihama, M., Wolfe, R., Solomon, D., Patt, F., Blanchette, J., Fleig, A., Masuoka, E., 1997. MOD28 Algorithm Theoretical Basis Document: Level 1A Earth Location V3.0. Technical Report. August 1997. [Online URL]. NASA, GSFC, Washington, USA. modis.gsfc.nasa.gov/data/atbd/atbd mod28 v3.pdf (accessed 21.04.07).
Norsys Software Corporation, 2007. Netica verison 4.02 [Online URL]. <http://www.nosys.com> (accessed 09.06.07).
Ofren, R.S., Harvey, E., 1998. A multivariate decision tree analysis of biophysical factors. In: Tropical Forest Wildfire Occurrence. Integrated Tools Proceedings, pp. 221–227. Boise, Idaho, USA, 16–20 August 1998.
Olalla, F.M., Dominguez, A., Ortega, F., Artigao, A., Fabeiro, C., 2007. Bayesian networks in planning a large aquifer in Eastern Mancha, Spain. Environmental Modelling & Software 22 (8), 1089–1100.
Pearl, J., 1988. Probabilistic Reasoning in Intelligent Systems. Morgan Kaufmann, San Mateo, California.
Pearl, J., 1998. Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. Morgan Kaufmann, San Mateo, California.
Pepe, M.S., Cai, T., Longton, G., 2006. Combining predictors for classification using the area under the receiver operating characteristic curve. Biometrics 62 (1), 221–229.
Pollino, C.A., Woodberry, O., Nicholson, A., Korb, K., Hart, B.T., 2007. Parameterisation and evaluation of a Bayesian belief network for use in an ecological risk assessment. Environmental Modelling and Software 22 (8), 1140–1152.
Remmelzwaal, A., 1993. Physiographic Map of Swaziland. FAO/UNDP/GOS Land Use Planning for Rational Utilization of Land and Water Resources, Project SWA/89/001 Field Document 4. Mbabane, Swaziland.
Riaño, D., Moreno Ruiz, J.A., Barón Martínez, J., Ustin, S.L., 2007. Burned area forecasting using past burned area records and southern oscillation index for tropical Africa (1981–1999). Remote Sensing of Environment 107, 571–581.
Rollins, M.G., Keane, R.E., Parsons, R.A., 2004. Mapping fuels and wildfire regimes using remote sensing, ecosystem simulation, and gradient modeling. Ecological Applications 14 (1), 75–95.
Roques, K.G., ÓConnor, T.G., Watkinson, A.R., 2001. Dynamics of shrub encroachment in an African savanna: relative influences of wildfire, herbivory, rainfall and density dependence. Journal of Applied Ecology 38, 268–280.
Salomonson, V.V., Wolfe, R.E., 2004. MODIS geolocation approach, results and the future. IEEE Geoscience and Remote Sensing Letters (2003 IEEE Workshop on Advances in Techniques for Analysis of Remote Sensing Data), 424–427.
Scholes, R.J., 1990. The influence of soil fertility on the ecology of southern African dry savannas. Journal of Biogeography 17, 415–419.
Schroeder, W., Prins, E., Giglio, L., Csiszar, I., Schmidt, C., Morisette, J., Morton, D., 2008. Validation of GOES and MODIS active fire detection products using ASTER and ETM data. Remote Sensing of Environment 112, 2711–2726.
Smith, C.S., Howes, A.L., Price, B., McAlpine, C.A., 2007. Using a Bayesian belief network to predict suitable habitat of an endangered mammal – the Julia Creek dunnart (Sminthopsis douglasi). Biological Conservation 139, 333–347.
Spiegelhalter, D.J., Dawid, A.D., Lauritzen, S.L., Cowell, R.G., 1993. Bayesian analysis in expert systems. Statistical Science 8, 219–283.
Stratton, R.D., 2006. Guidance on spatial wildland wildfire analysis: models, tools, and techniques. General Technical Report RMRS-GTR-183. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO: U.S.
Sweet, R.J., Khumalo, S., 1994. Range Resources and Grazing Potentials in Swaziland. Ministry of Agriculture and Cooperatives/United Nations Development Programme, Mbabane.
Tansey, K., Grégoire, J.M., Stroppiana, D., Sousa, A., Silva, J., Pereira, J.M.C., Boschetti, L., Maggi, M., Brivio, P.A., Fraser, R., Flasse, S., Ershov, D., Binaghi, E., Graetz, D., Peduzzi, P., 2004. Vegetation burning in the year 2000: global burned area estimates from spot vegetation data. Journal of Geophysical Research 109, D14S03.
Taroni, F., Biedermann, A., Gabolino, P., Aitken, C.G.G., 2004. A general approach to Bayesian belief networks for the interpretation of evidence. Forensic Science International 139, 5–16.
Ticehurst, J.I., Newham, L.T.H., Rissik, D., Letcher, R.A., Jakeman, A.J., 2007. A Bayesian network approach for assessing the sustainability of coastal lakes in New South Wales, Australia. Environmental Modelling and Software 22 (8), 1129–1139.
Tremblay, J.-P., Hester, A., Mcleod, J., Huot, J., 2004. Choice and development of decision support tools for the sustainable management of deer–forest systems. Forest Ecology and Management 191, 1–16.
Trollope, W.S.W., de Ronde, C., Geldenhuys, C.J., 2004. Wildfire behavior. In: Goldammer, J.G., de Ronde (Eds.), Wildland Wildfire Management Handbook for Sub-Saharan Africa. Global Wildfire Monitoring Centre (GFMC), pp. 27–59.
Van der Werf, G.R., Randerson, J.T., Giglio, L., Collatz, G.J., Kasibhatla, P.S., Arellano Jr., A.F, 2006. Interannual variability of global biomass burning emissions from 1997 to 2004. Atmospheric Chemistry and Physics Discussions 6, 3175–3226.
Van Wilgen, B., Scholes, R., 1997. The vegetation and wildfire regimes of southern hemisphere Africa. In: In van Wilgen, B.W., Andreae, M.O., Goldammer, J.G., Lindesay, J.A. (Eds.), Wildfire in Southern Afn'can Savannas. Witwatersrand University Press, Johannesburg, pp. 27–46.
Vasconcelos, M.J.P., Silva, S., Tomé, M., Alvim, M., Pereira, J.M.C., 2001. Spatial prediction of fire ignition probabilities: comparing logistic regression and neural networks. Photogrammetric Engineering and Remote Sensing 67, 73–81.
Venkataraman, C., Habib, G., Kadamba, D., Shrivastava, M., Leon, J.-F., Crouzille, B., Boucher, O., Streets, D.G., 2006. Emissions from open biomass burning in India: integrating the inventory approach with high-resolution Moderate Resolution Imaging Spectroradiometer (MODIS) active-wildfire and land cover data. Global Biogeochemical Cycles 20, GB2013.
Von Maltitz, G.P., Scholes, R.J., 2006. Vulnerability of Southern African Fauna and Flora to Climate Change. AIACC Working Paper No. 24. Assessments of Impacts and Adaptations to Climate Change (AIACC), Washington, DC.
Walker, B.H., 1985. Structure and function of savannas: an overview. In: Tothill, J.C., Mott, J.J. (Eds.), Ecology and Management of the World's Savannas. Australian Academy of Science, Canberra, pp. 83–91.
Wan, S., Hui, D., Luo, Y., 2001. Wildfire effects on nitrogen pools and dynamics in terrestrial ecosystems: a metaanalysis. Ecological Applications 11, 1349–1365.
Wang, S., Zhou, Y., Wang, L., 2003. A Research On Fire Automatic Recognition Using MODIS Data. IEEE International Geoscience and Remote Sensing Symposium (IGARSS03), Toulouse, France, July 21–25, 2003. 4, 2502–2504.
Watanabe, M., Yamaguchi, K., 2003. The EM Algorithm and Related Statistical Models. Marcel Decker, New York.
Weir, J.R., 2007. Using relative humidity to predict spotwildfire probability on prescribed burns. In: Sosebee, R.E., Wester, D.B., Britton, C.M., McArthur, E.D., Kitchen, S.G. (Eds.), Proceedings: Shrubland Dynamics—Wildfire and Water; 2004 August 10–12; Lubbock, TX. Proceedings RMRS-P-47. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO: U.S., pp. 69–72.
Wiens, J.A., 1985. Vertebrate responses to environmental patchiness in arid and semiarid ecosystems. In: Pickett, S.T.A., White, P.S. (Eds.), The Ecology of Natural Disturbance and Patch Dynamics. Academic Press, New York, pp. 169–193.
Yuen, J.E., Mila, A., 2003. Are Bayesian approaches useful in plant pathology? In: Van Boekel, M.A.J.S., Stein, A., Van Bruggen, A.H.C. (Eds.), Proceedings: Bayesian Statistics and Quality Modelling in the Agro-food Production Chain. Springer-Verlag, Wageningen, Netherlands/New York, pp. 95–103.
Zheng, Y., Cai, T., Feng, Z., 2006. Application of the time-dependent ROC curves for prognostic accuracy with multiple biomarkers. Biometrics 62 (1), 279–287.