*Proceedings of the 2014 Winter Simulation Conference*
*A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.*

# A FOREST FIRE PROPAGATION SIMULATOR FOR BOGOTÁ

Gilberto A. Morales
Ridley S. Morales
Carlos F. Valencia
Raha Akhavan-Tabatabaei

Center for Optimization and Applied Probability (COPA)
Department of Industrial Engineering
Universidad de los Andes
Cra 1 # 18A- 12
Bogotá, D.C., COLOMBIA

## ABSTRACT

Forest fires are time evolving disasters that consume environmental and financial resources, endangering the rescue units that try to mitigate them. As such, a simulator that can predict the fire propagation is essential to locate control systems, in order to reduce the loss of natural resources without risking the firefighters. This paper proposes a simulator based on discrete representation of the selected areas where the velocity of fire propagation between neighbors depends on variables associated with locative or climatological characteristics. We consider discrete classification based on the spread in each direction. To validate our simulator we considered two scenarios: a theoretical area to test the algorithm considering complete information characteristics and a forest area near Bogotá, Colombia. The results show realistic propagation patterns compared to region real past forest fire events. For a better prediction we need more reliable data and relate the fire to both location and weather characteristics.

## 1 INTRODUCTION

Unlike many other natural disasters, forest fires do not happen within a confined time period, but they tend to evolve through time if not managed properly. Worldwide, there are at least 10,000 large forest fires annually; and between 2007 and 2009, 17,120 lives were lost in the 20 countries on the top of the list of fire management expenditures according to the World Fire Statistics Center. Additionally, there is an annual average of 13 millions burned acres due to wildfires only in North America. Forest fires in countries such as the United States can result in a cost of USD$17,000 millions per year, taking into account mitigation and fire control expenses (WFSC 2012).

Bogotá D.C.'s savannah and its surroundings are mixed forests that combine local vegetation with foreign introduced one. This creates a high-risk type of forest as the ecosystem is not well adapted to some of the non-native vegetation. The Eastern Forest Reserve of Bogotá has one of the largest urban limits in the world, causing the formation of many urban invasions in some of its 14,150 acres (CAR 2006). Forest fires are commonly produced by urban life activities happening in places surrounded by dense vegetation. On average, there are over 300 forest fires each year, from which at least the 5% are large scale fires of over 5.000$m^2$ (UAECOBB 2013a). In particular, the Eastern Reserve had at least one large scale fire every year, over the past 50 years. The latest fire before this text was written occurred in La Calera, Colombia, a town in the surroundings of Bogotá, which burned over 7 acres. In this case it was determined that the fire ignited next to a road between the two urban areas (UAECOBB 2013b).

Efficient fire mitigation policies may reduce both the natural and economic costs of such disasters. The Official Fire Fighters Department of Bogotá (UAECOBB) could perform more efficient attacks and have better ignition risk control strategies if they had a simulation tool that could predict the fire spread from a given point of origin. Such a simulator should consider how the fire spreads according to various location and weather conditions and show the final shape of the fire in a given time period. Our objective in this paper is to develop such a simulation model, considering the climate and location characteristics that affect the spread in the savannah of Bogotá, in order to efficiently predict the fire propagation based on the specific characteristics.

This paper is presented as follows: Section 2 describes some of the existing fire risk tools; Section 3 describes our proposed methodology and the mechanism of our proposed simulator; Section 4 presents results of the simulator in different scenarios and Section 5 presents conclusions on the results of the different simulations and our future work.

## 2 LITERATURE REVIEW

In this section we discuss the existing fire risk tools that could help design the fire mitigation policies, namely ignition risk models and prognostic propagation models. The first kind are models that consider the probability of each point to be the starting ignition point of a fire. The second kind predict the fire spread through time, from a given ignition area. They tend to relate either the ignition risk or the fire propagation (according to their objective) to a set of forest characteristics. These characteristics usually are location related (type of vegetation, height, nearby water bodies, vegetation coverage, etc.) and weather related (sun radiation, temperature, wind direction, wind speed, precipitation, etc.). In general, models tend to predict at least one of the three possible features: ignition risk, spread direction and spread speed. In the case of the ignition risk, Martínez et al. (2004) showed that factors as the temperature increase and changes in the type of vegetation were highly influential in forests near Barcelona, but the type of human activities near the event have little to no effect. Viegas et al. (2002) concluded that the wind direction and the slope are the most relevant characteristics to predict the spread direction and other characteristics like vegetation coverage and solar radiation are relevant depending on the type of forest. Summarizing both literature and the expert opinion of UAECOBB, in order to capture the fire spread speed, the most relevant factor is the wind speed (higher wind speed increases the spread rate) and type of vegetation (for example, bushes tend to need less heat to ignite than pine trees). Some factors like humidity and the amount of rain that falls during the days prior to the fire incidence are relevant depending on the type of forest for ignition risk, spread direction and spread rate.

The ignition risk models are usually built from data of past fire events to predict the starting fire risk in a particular point. This fire ignition risk is estimated by the number of times this point has caught fire in a given time interval and try to relate it to a set of characteristics. These characteristics consider location (height, slope, type of vegetation, percentage of vegetation coverage, etc.) and weather conditions (wind speed and direction, temperature, solar radiation). Kalabokidis et al. (2007) used Linear and Logistic Regressions to reflect the influence of different features on fire ignition danger in Greek forests. On the other hand, Li et al. (2009) chose a methodology to measure the fire ignition risk based on Artificial Neural Networks. Both systems consider a weight for each characteristic, which represents the relevance of each of the variables in the model. This ignition risk varies according to season conditions or in some cases due to changes in the vegetation. Therefore, the ignition risk measurement must be recalculated continuously.

Propagation models mimic the fire spread given the initial ignition location. Thompson and Calkin (2011) presents two approaches for this type of modeling, probabilistic and non-probabilistic algorithms . In both approaches, the simulator must be trained first, that is necessary to calibrate an algorithm running with real fire data and determining the spread occurrence and speed. The probabilistic approach is divided into three types of modeling. The first one considers a pattern detection algorithm such as Logistic Regression or Continuous Artificial Neural Networks, relating the propagation probability to location and weather characteristics. With this probability, the event of propagation is simulated stochastically. An example of this approach is Preisler and Westerling (2007), who used Logistic Regression to generate large fires of over 400 acres for 1 month ahead, considering weather variables. The second approach uses various scenarios through a simulation software e.g., FARSITE (Finney 1998) or BEHAVE (Andrews 1986). Some examples of this type of modeling have been successfully applied in several places like Mt. Carmel, Israel (Carmel et al. 2009) and Central Brazil (Mistry and Berardi 2005). The third approach consists in simultaneously applying the first two. For example, Beverly et al. (2009) determined a point's fire probability considering multiple ignition locations and weather conditions to determine the Fire Susceptibility Index (FSI). Here not only the fire spread is considered but also the burn probability of each point according to historical fires in West Alberta, Canada. Finney et al. (2011) applied an FSI based model in various locations in the United States that considered burn probability maps. The model's first output is the Energy Release Component and through this, the fire spread probability was obtained.

The non-probabilistic approaches use algorithms to determine if a fire is propagated between contiguous locations and model the spread rate given particular values of independent predictors. This approach ensures a propagation instead of the probability in which the given case would happen. For example Hessburg et al. (2007) used a fuzzy logic algorithm to design a multi-criteria simulator which simultaneously determines the ignition risk and the spread characteristics (rate and length) in Wildfires in Utah, USA. Vakalis et al. (2004a) and Vakalis et al. (2004b) paired fuzzy logic and neural networks to estimate the fire spread according to location characteristics, vegetation and weather. The main 3 methodologies in non-probabilistic methods are Fuzzy Logic, Neural Networks and Support Vector Machines.

For both non-probabilistic and probabilistic models the available information is important and defines how the simulator works. There are two basic types of available information. In the first case, the model is trained with the real data characteristics, but does not have a live update of the current situation. Instead, the simulator considers various scenarios to determine the expected value of the spread taking into account the variation of the random variables (Denham et al. 2008). In the second case the information platform has live update of current conditions, which allows the simulator to consider a unique scenario for a limited time period before doing several scenarios for the stochastic variables (Kalabokidis et al. 2013).

We consider a probabilistic cellular automata model, in which location characteristics are constant at each point and weather characteristics are simulated accordingly in each of the given time intervals. Cellular automata modeling was introduced by Neumann and Burks (1966) to represent complex systems as a grid of cells with a finite state for each cell. The state of the grid evolves through time through the evolution of the states of each cell. The state of each cell depends on a set of rules and the state of the neighbor cells. Berjak and Hearne (2002), Ito (2005) and Yassemi et al. (2008) previously used cellular automata to model fire propagation. These characteristics are set to consider single fire spreads in each direction.

## 3 METHODOLOGY AND DATA PROCESSING

In this section we discuss how the proposed simulator works and detail the steps needed to achieve the final result of the fire simulation. The model is divided in 2 phases. In the data processing phase, the information is classified in various numerical attributes, relating each propagation speed (including speed 0 for no propagation) information data point to a set of characteristics. The second phase being the simulation, consists of using the previously processed data to determine the spread speed. The relation between each of the characteristics and the fire spread rate is based on expert opinion of the UAECOBB. The model was designed with the Risk Management department of the Official Fire Department of Bogotá, every theoretical result was also evaluated by them as a probable behavior of fire. The tool was made in Java Standard Edition 8, using each of the points of the map as an array of characteristics. Also each of the time periods is considered as an array corresponding to the weather conditions of each interval.

### 3.1 Data Processing

In this phase, the location and weather characteristics are organized accordingly. The simulator takes into account point to point dispersion. The fire is propagated at a different speed in each direction. The model does not propagate the fire when the propagation speed in a certain direction is not positive. To be able to create this simulation, we must have a spread rate obtained during a fire for each location considering both weather and location characteristics.To facilitate the point to point propagation estimation, we divide the endangered area into a grid, as shown in Figure 1. In this grid, we consider each location to be a square of $2m \times 2m$ and the distance from a location to the adjacent on the North, South, East and West is considered as $2m$ also. In the case of the North-West, North-East, South-West and South-East, the distance between location is $\sqrt{(2m)^2+(2m)^2}$, as that would be the distance between the center points of both locations. Figure 1 shows a graphical example of this grid, using $x$ as the length of the location.

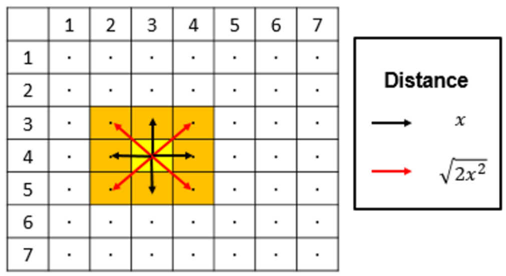



Figure 1: Distance calculation

One of the principal characteristics considered is the wind magnitude and direction. We model the wind direction by projecting its vector (red arrow) in the plane created from the span of the point simulation direction of the moment (green arrow), with an angular difference $\theta$. The wind projection vector is $v \cdot \cos(\theta)$, where $v$ is the total wind speed and $\cos(\theta)$ represents the projection from a given $\theta$ angle (purple arrow). Figure 2 shows a visual example of this rule.

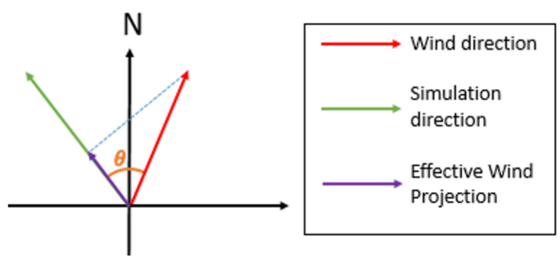



Figure 2: Wind Angle Projection

We consider a set of 5 variables to the model the spread rate function in each direction. The characteristics considered are: slope change, type of vegetation, percentage of vegetation coverage, projected wind vector and humidity. The location characteristics could be given in either text exported from GIS or in the image with a color label to process each point. To obtain the weight of each characteristic and the relations between them, we used the expert opinion of UAECOBB. All the weights were considered linearly related to the spread rate. Nevertheless, some additional rules were introduced to these weights considering conditions that may modify the behavior of the characteristic considering the location. This means, if the fire was individually evaluated by each characteristic, without considering the special cases, the spread rate $v$ of characteristic $c$ would be:

$$v(c) = \omega c + b, \qquad \omega, b \in \mathbb{R} \tag{1}$$

where $\omega$ corresponds to the weight and the effect of each characteristic on the fire speed. As the fire spread is considered in each direction, if the linear Equation 1 results in a negative speed, it is considered as 0. Therefore, the final spread rate, in the basic form of the formula, considering a set $C$ of different characteristics would be considered as:

$$v(c) = \max\left\{\sum_{i \in \mathrm{C}} \omega_i c_i + b\,,\,0\right\} \tag{2}$$

The first special case is considering when the fire reaches a barrier, for example, a river, a cliff or a wide road. In these cases, the absence of vegetation stops the fire spread. In these cases, if there is no vegetation (or the vegetation value is 0 in the propagation direction), the equation would be:

$$v(c) = 0 \tag{3}$$

The second special case considered is when the topology blocks or modifies the wind according to the direction. When the fire is ignited in a mount or hill, the wind is only considered if it goes uphill that means, if the mountain climbs to the North in an angle higher than $45^o$, only winds coming from the South, South-East or South-West are considered, in the rest, the weight of the wind projection is 0.

Considering these special cases, the final spread rate function, considering the square length as $x$, is:

$$v(c) = \begin{cases} 0 & \text{if } c_{veg} = 0 \\ \max\left\{\sum_{i \in C \setminus \{\text{Wind}\}} \omega_i c_i + b\,,\,0\right\} & c_{wind} \cdot c_{slope} > 0 \text{ and } c_{slope} > \sqrt{2}x \\ \max\left\{\sum_{i \in C} \omega_i c_i + b\,,\,0\right\} & \text{other wise} \end{cases} \tag{4}$$

### 3.2 Point To Point Simulation

Once the weight of each characteristic is obtained, a new fire can be simulated by giving the simulator an ignition point, the 8 surrounding points (of the 8 basic directions) and the same characteristics initially used for training each pair of points (e.g., original and North, original and Northeast, ...). The fire spread speed is calculated in each direction and a list of points is created, in which the points are ordered by the time they catch fire. A location or point is not added to this list unless it has already been ignited. When a point that has previously been ignited is supposed to catch fire from another location, the fire and its position on the list is the minimum between the two times.

To describe the algorithm, first we define notation.

- $t_{max}$ is the maximum time the fire is going to be simulated to.
- $x$ is the length of each location.
- $\mathbb{A}$ is the set of point locations, with $A \in \mathbb{A}$.
- $\mathbb{B} = \{b_1, b_2, \cdots, b_n\}$ is the set of climate time periods considered, the climate is considered constant during each of this periods. $\left[\frac{t_{max}\cdot(i-1)}{n}, \frac{t_{max}\cdot i}{n}\right) = b_i \in \mathbb{B}$
- $t(A) = \begin{cases} t & \text{if } t \text{ is the minimum moment when point } A \text{ was ignited} \\ \infty & \text{if the point was never ignited before} \end{cases}$
- $P$ is the organized set of points that have been ignited during the fire. The set is organized according to the moment of ignition, with $(A_i, t(A_i)) \in P, i$ the position that the point has in the array.
- $L_A$ is the set of local characteristics of point $A$

- $W_{b_i}$ is the set of weather characteristics of time period $b_i \in \mathbb{C}$.
- $A'$ is a neighbor of $A$ if there is no point location $A''$ (in the grid) between $A$ and $A'$. For the next definitions, let $A' \in \mathbb{A}$ be a neighbor of $A \in \mathbb{A}$.
- $C_{A,A',t} = (L_{A'} - L_A) \times W_t$ is the set of characteristics of both local and weather conditions in a given set of points $A, A'$ at moment $t$. For the local conditions, each coordinate is the difference between the new ignited point $A'$ to the original point $A$. The weather corresponds to that of the $t \in b_i \in \mathbb{B}$.
- $v(C_{A,A',t})$ is the spread rate corresponding to the set of characteristics $C_{A,A',t}$.
- $d_{A,A'}$ is the distance between points $A$ and $A'$, $d_{A,A'} \in \{x, \sqrt{2}x\}$.

Considering this notation and having an ignition point $A_0$ for the fire at a moment $t_0$, the algorithm for the simulation is:

**Data**: Location characteristics $L_A, A \in \mathbb{A}$, Climate characteristics for time periods $W_b, b \in \mathbb{B}$, First ignition point and moment $(A_0, t_0)$, the maximum time of observation $t_{max}$
**Result**: Organized list of ignited points according to moment of ignition
Create the organized array $P = ((A_0, t_0))$
Let $k = 0$ ;
**while** *P has points to simulate and the time of simulation does not exceed* $t_{max}$ **do**
  **for** $A'$ *neighbour of* $A_k$ **do**
    Let $v = v(C_{A_k,A',t_k})$ ;
    **if** $v > 0$ **then**
      Let $\Delta t = \frac{d(A_k,A')}{v}$ ;
      **if** $t + \Delta t < \min\{t_{max}, t(A')\}$ **then**
        Change $t(A') \leftarrow t + \Delta t$ ;
        Add $(A', t(A'))$ to $P$ ;
        Sort $P$ according through time ;
      **end**
    **end**
  **end**
  $k = k + 1$
**end**

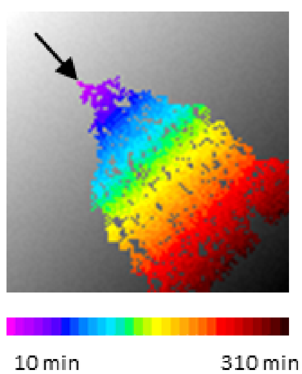
## 4 RESULTS

To demonstrate the performance of our proposed algorithm, we apply it on three scenarios. All simulations were run on a ASUS R401V with Intel®Core™i7 running at 2.3 GHz and 8 GB of RAM under a Windows 7 Professional x64. The first scenario serves as a theoretical test of the model for validation purposes. For the second scenario, we took the information characteristics from a forest in Bogotá surrounding savannah to test the simulator with real inputs. The third scenario compares a real fire from Cota, Cundinamarca, a town located North-West of Bogotá that occurred on January 2013. In all cases we took the weight information given by the UAECOBB, according to their experience in Bogotá's savannah. The Bogotá weather stations report weather conditions in 10 minute time periods, the conditions reported are the maximum, minimum and average of each characteristic in this period. Because the original training information is given in this 10 minute intervals, we consider constant conditions during 10 minute time intervals for the simulation. All scenarios presented a computational time of under 200 milliseconds.

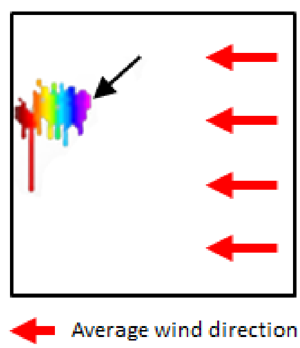
### 4.1 Theoretical Scenario

The first scenario consists only in a theoretical test of the model and the algorithm in which an information database was created with 6 characteristics: 3 deterministic and 3 random. The deterministic characteristics are related to the location. The location conditions do not change during the fire, but remain constant for each point. The first deterministic characteristic is related to the height, as positive slopes increase the chances of fire propagation. The second characteristic is related to the type of vegetation, considering a discrete classification with 5 possible classes related to combustion capacity (temperature at which the vegetation ignites) which move from lowest to highest fire temperature that can generate. The third characteristic is related to the vegetation coverage, which is the proportion of land that has vegetation in the given area.

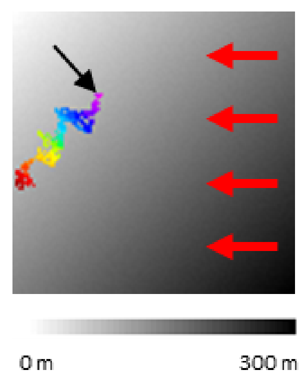
The random characteristics are related mostly to weather conditions: factors like wind speed, wind direction, solar radiation and temperature tend to change even in short time periods, and as such they are not constant during the duration of the fire. The first characteristic would be related to the wind angle, considering the most common angle during the simulation period, as fire tends to move in the same direction of the wind. The second random characteristic is related to the wind speed, as it tends to give a close approximate to the spread speed in most cases. Through the combination of the first two characteristics, we find a projected wind speed according to each pair of points to simulate, as explained in the Section 3.1. The last weather condition considered is related to the solar radiation, as higher radiation tends to dry the vegetation and slightly modify the spread speed and in extreme cases of dryness, also the direction. In the validation, we consider 3 different cases regarding the input information, the first one considering only the location information (altitude), the second one using only weather random variables and the third one combining both sets. The location information set was planned in order to spread the fire to the lower left direction. On the other hand, the weather information was set in order to spread the fire to the left direction. In all 3 cases, the simulation ran through 310 minutes, color coded as in 10 minute periods as shown in Figure 3. Both the length between locations and time intervals are given in generalized units, considering the proportions. In all three cases, the ignition point is marked by the tip of the black arrow and was the same for all cases.




(a) Theoretically created fire with location characteristics




(b) Theoretically created fire with weather characteristics



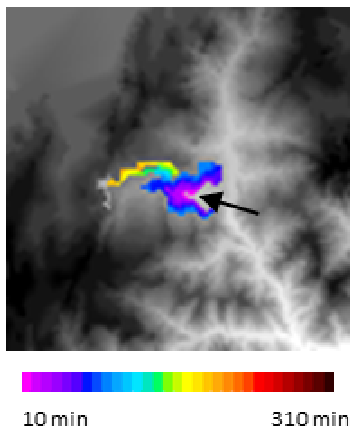

(c) Theoretically created fire with both location and weather characteristics

Figure 3: Simulation of the theoretical scenarios

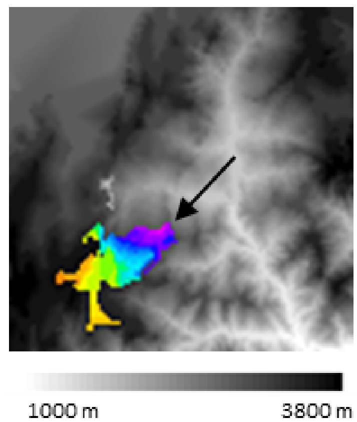
For the first case, Figure 3a shows the resulting spread which ignited almost through the whole image, showing a slow spread rate. Figure 3b shows the results of this simulation using only the weather characteristics (i.e. wind direction), in this case the fire spread only to the left, at a fast spread rate, with some not common dispersion as the one given in the minute 250 (red) in which the course was modified downwards unlike the rest of the simulation, due to a significant instant speed in that period which was strictly downward. The third case, presented in the Figure 3c presents the combination of both weather and location characteristics. The spread rate is given in a speed that is in between the two previous cases and the spread direction tends to move diagonally, to the lower left direction, giving most of the predilection weight to the weather characteristics, but still considering the location as relevant information.

### 4.2 Realistic Scenario - Savannah of Bogota

The second case consisted of the simulation of fires in a location nearby Bogotá D.C., Colombia taking into account real Bogotá weather conditions from the September 21 of 2013 at 13:00. For the simulation, we restricted the fire to 310 minutes, with each class representing a 10 minute period. The wind speed was between 0.1 and 5 $m/s$, the lowest point was at 1000m and the highest at 3800m above sea level. There were two different fires generated as shown in Figures 4a and 4b. The ignition point in Figure 4 is represented as the tip of the black arrow.




(a) Bogotá D.C. Simulation 1




(b) Bogotá D.C. Simulation 2

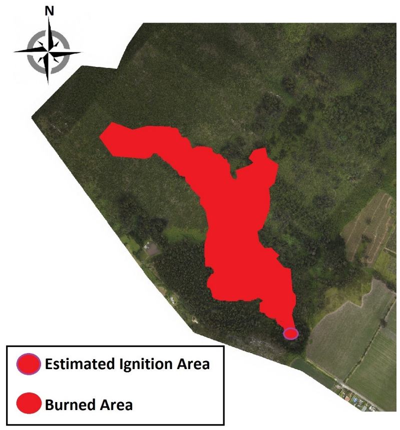
Figure 4: Bogotá D.C. Case Simulation

Both Figures 4a and 4b show that the fire tends to move according to topography instead of the weather characteristics, as both fires had the same weather conditions and the spread direction had a considerable variance between both cases. Figure 4a presents a fire that spread in all directions but east during the first 120 minutes, then it spread to the northwest direction and Figure 4b shows a fire that spread southwest during the duration of the simulation. In both case the fire spread almost exclusively uphill, giving most of the predilection weight to the slope characteristics, but still considering the weather as relevant information. The computational time presented a similar time of calculation between the fire spread made from each ignition point. Both scenarios took under 1 second to simulate.

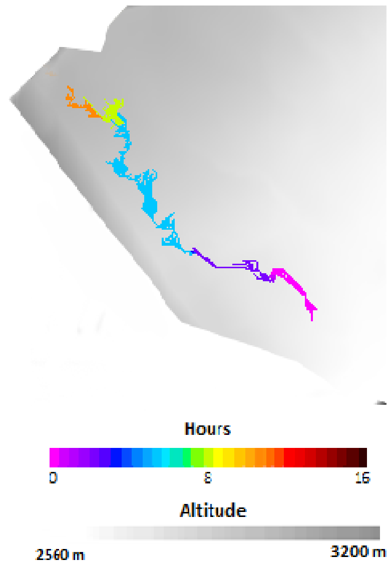
### 4.3 Real Scenario - Cota, Cundinamarca

On this simulation, we compared our simulator with a real fire that occurred on January 11 of 2013. This fire propagated during 9 hours to be contained and took over 15 days to be extinguished in a joint effort of several fire departments of the region. Due to the propagation duration, our simulator considered a 16 hour length. The considered altitude in area had a minimum of 2560 m and a maximum of 4020 m, the topography of the specific mount in which the fire started climbed to the North-West direction. The wind speed varied from $2m/s$ to $20m/s$ and focused mostly on the North, North-East and North-West direction.

On our results presented on Figure 5b the fire propagated only in one of the directions in which the original fire moved presented on Figure 5a and continued until the $12^{th}$ hour completed. In this case all the climate information was randomly generated instead of using the real weather of the moment, this in




(a) Cota, Cundinamarca Real Fire




(b) Cota, Cundinamarca Simulation

Figure 5: Cota, Cundinamarca Case Simulation

order to test the simulator compared to the real purpose, which is to simulate live fires in which we do not have life update.

## 5 CONCLUSIONS AND FUTURE WORK

We proposed a discrete event simulation model to reproduce the fire propagation given an ignition point and other locative and weather characteristics. To determine the relevance of these characteristics we interviewed various firefighters from the UAECOBB. Then we demonstrated the performance of our model on three scenarios, a theoretical one to validate the proposed model, another based on real data from savannah of Bogotá and a third one to repeat a real fire occurring in Cota, Cundinamarca, North of Bogotá in January of 2013.

In our theoretical scenario, we found that considering only location or weather characteristics is not enough for an exact simulation, therefore both sets of characteristics must be considered. The fire cannot be related to only one variable, even when it is one of the most relevant factors such as wind direction or height. In order to create an accurate simulation, the user must feed at least 3 variables that would affect the fire spread most, considering both climate and location: vegetation coverage, altitude (which can be translated into slope) and wind direction.

In our particular interest case of Bogotá, the combination of a mountain topography and slow wind activity produces fires that depend much more on the slope between locations than the weather characteristics, therefore the higher the precision of the height curves data bases, the more accurate the simulation can be.

In our case of Cota, Cundinamarca, the precision of the height curves data bases helped us in a better estimation of the slope. Even though the fire did not propagated in the two directions the original fire went, the direction which followed considered the same time progress as the real fire that occurred in January 2013.

Our future work can be separated in two different phases. The first one consists on the tracking of real fires to be able to produce a mixed model that considers not only the experts opinion, but a pattern detection according to historical data. This historical data can be obtained through thermal imaging. The second phase consists of a multiple scenario simulation, in which the random variables adopt different values in order to obtain an exact real time simulation, instead of a unique scenario of just one of the possible propagation cases that can occur.

## ACKOWLEDGEMENTS

This study was supported by the Official Fire Department of Bogotá D.C. (UAECOBB) and its research division. The authors would like to thank them for their information and collaboration.

## REFERENCES

Andrews, P. 1986. "BEHAVE: Fire behavior prediction and fuel modeling system - BURN subsystem, Part 1". USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-194, 130 pp.

Berjak, S. G., and J. W. Hearne. 2002. "An improved cellular automaton model for simulating fire in a spatially heterogeneous Savanna system". *Ecological Modelling* 148 (2): 133–151.

Beverly, J. L., E. P. Herd, and J. R. Conner. 2009. "Modeling fire susceptibility in west central Alberta, Canada". *Forest Ecology and Management* 258 (7): 1465 – 1478.

CAR 2006. "Plan de Ordenamiento y Manejo Ambiental de la Reserva Forestal Protectora - Bosques Orientales de Bogotá D.C.". Technical report, Corporación Autónoma Regional de Cundinamarca.

Carmel, Y., S. Paz, F. Jahashan, and M. Shoshany. 2009. "Assessing fire risk using Monte Carlo simulations of fire spread". *Forest Ecology and Management* 257 (1): 370 – 377.

Denham, M., A. Cortés, T. Margalef, and E. Luque. 2008. "Applying a Dynamic Data Driven Genetic Algorithm to Improve Forest Fire Spread Prediction". In *Computational Science – ICCS 2008*, edited by M. Bubak, G. Albada, J. Dongarra, and P. Sloot, Volume 5103 of *Lecture Notes in Computer Science*, 36–45. Springer Berlin Heidelberg.

Finney, M., C. McHugh, I. Grenfell, K. Riley, and K. Short. 2011. "A simulation of probabilistic wildfire risk components for the continental United States". *Stochastic Environmental Research and Risk Assessment* 25 (7): 973–1000.

Finney, M. A. 1998. "FARSITE: Fire Area Simulator—Model Development and Evaluation". *Evaluation*.

Hessburg, P. F., K. M. Reynolds, R. E. Keane, K. M. James, and R. B. Salter. 2007. "Evaluating wildland fire danger and prioritizing vegetation and fuels treatments". *Forest Ecology and Management* 247 (1–3): 1 – 17.

Ito, A. 2005. "Modelling of carbon cycle and fire regime in an east Siberian larch forest". *Ecological modelling* 187 (2): 121–139.

Kalabokidis, K., N. Athanasis, F. Gagliardi, F. Karayiannis, P. Palaiologou, S. Parastatidis, and C. Vasilakos. 2013. "Virtual Fire: A web-based GIS platform for forest fire control". *Ecological Informatics* 16 (0): 62 – 69.

Kalabokidis, K. D., N. Koutsias, P. Konstantinidis, and C. Vasilakos. 2007. "Multivariate analysis of landscape wildfire dynamics in a Mediterranean ecosystem of Greece". *Area* 39 (3): 392–402.

Li, L.-M., W.-G. Song, J. Ma, and K. Satoh. 2009. "Artificial neural network approach for modeling the impact of population density and weather parameters on forest fire risk". *International Journal of Wildland Fire* 18 (6): 640–647.

Martínez, J., J. Martínez, and P. Martín. 2004. "El factor humano en los incendios forestales: Análisis de factores socio-económicos relacionados con la incidencia de incendios forestales en España". In *Nuevas tecnologías para la estimación del riesgo de incendios forestales*, 101–142.

Mistry, J., and A. Berardi. 2005. "Assessing Fire Potential in a Brazilian Savanna Nature Reserve1". *Biotropica* 37 (3): 439–451.

Neumann, J. v., and A. W. Burks. 1966. "Theory of self-reproducing automata".

Preisler, H. K., and A. L. Westerling. 2007. "Statistical model for forecasting monthly large wildfire events in western United States". *Journal of Applied Meteorology and Climatology* 46 (7): 1020–1030.

Thompson, M. P., and D. E. Calkin. 2011. "Uncertainty and risk in wildland fire management: a review". *Journal of Environmental Management* 92 (8): 1895–1909.

UAECOBB 2013a. "Investigación Incendios Forestal - Compilado Incendios 2012 - 2013". Technical report, Unidad Administrativa Especial - Cuerpo Oficial de Bomberos de Bogotá.

UAECOBB 2013b. "Investigación Incendios Forestal - La Calera, Cundinamarca - 23 de Septiembre de 2013". Technical report, Unidad Administrativa Especial - Cuerpo Oficial de Bomberos de Bogotá.

Vakalis, D., H. Sarimveis, C. Kiranoudis, A. Alexandridis, and G. Bafas. 2004a. "A GIS based operational system for wildland fire crisis management I. Mathematical modelling and simulation". *Applied Mathematical Modelling* 28 (4): 389 – 410.

Vakalis, D., H. Sarimveis, C. Kiranoudis, A. Alexandridis, and G. Bafas. 2004b. "A GIS based operational system for wildland fire crisis management II. System architecture and case studies". *Applied Mathematical Modelling* 28 (4): 411 – 425.

Viegas, D., M. Cruz, L. Ribeiro, A. Silva, A. Ollero, B. Arrue, R. Dios, F. Gómez-Rodríguez, L. Merino, A. Miranda et al. 2002. "Gestosa fire spread experiments.". In *Forest fire research and wildland fire safety: Proceedings of IV International Conference on Forest Fire Research 2002 Wildland Fire Safety Summit, Luso, Coimbra, Portugal, 18-23 November 2002.* Millpress Science Publishers.

WFSC 2012. "WFSC Newsletter". Accessed Mar. 21, 2013. http://www.wfsc.info/.

Yassemi, S., S. Dragićević, and M. Schmidt. 2008. "Design and implementation of an integrated GIS-based cellular automata model to characterize forest fire behaviour". *Ecological Modelling* 210 (1): 71–84.

## AUTHOR BIOGRAPHIES

**GILBERTO A. MORALES** received his BSc degree in industrial engineering in March 2013 at Universidad de los Andes, Colombia. He is currently finishing his BSc degree in Mathematics in the same university. His main area of interest is mathematical modelling and stochastic processes. His e-mail address is ga.morales413@uniandes.edu.co

**RIDLEY S. MORALES** is an instructor at the Department of Industrial Engineering, Los Andes University in Bogotá, Colombia. He received his M.Sc. degree in Industral Engineering with emphasis in Operations Research. He received his BSc degree in the same department in 2011 and his undergraduate final project was part of winters simulation conference that year. His main area of interest is disaster operation management and the uses of geographic information system. His e-mail address is rs.morales64@uniandes.edu.co.

**CARLOS F. VALENCIA** is a PostDoctoral research Fellow at the Engineering School, Los Andes University in Bogota, Colombia. He received his Ph.D. degree in Industral Engineering with emphasis in Applied Statistics and minor in Mathematics form the H. Milton Stewart School of Industrial & Systems Engineering at Georgia Institute of Technology, Atlanta, USA. Prior to that ha has been Instructor at Los Andes Uniersity. His research interest is Applied Statistical Models in general, and in particular, statistical learning algorithms for high dimensional models used in classification and prediction. His e-mail address is cf.valencia@uniandes.edu.co.

**RAHA AKHAVAN-TABATABAEI** is an assistant professor at the Department of Industrial Engineering, Universidad de los Andes in Bogotá, Colombia. Prior to this position she was a senior industrial engineer at Intel Corporation, Chandler, AZ, USA. She has received her Ph.D. degree in industrial engineering with minor in operations research from the Edward P. Fitts Department of Industrial and Systems Engineering, North Carolina State University, Raleigh, USA. Her research interests include stochastic processes and stochastic dynamic optimization with applications in health and humanitarian logistics, transportation and manufacturing. Her e-mail address is r.akhavan@uniandes.edu.co.