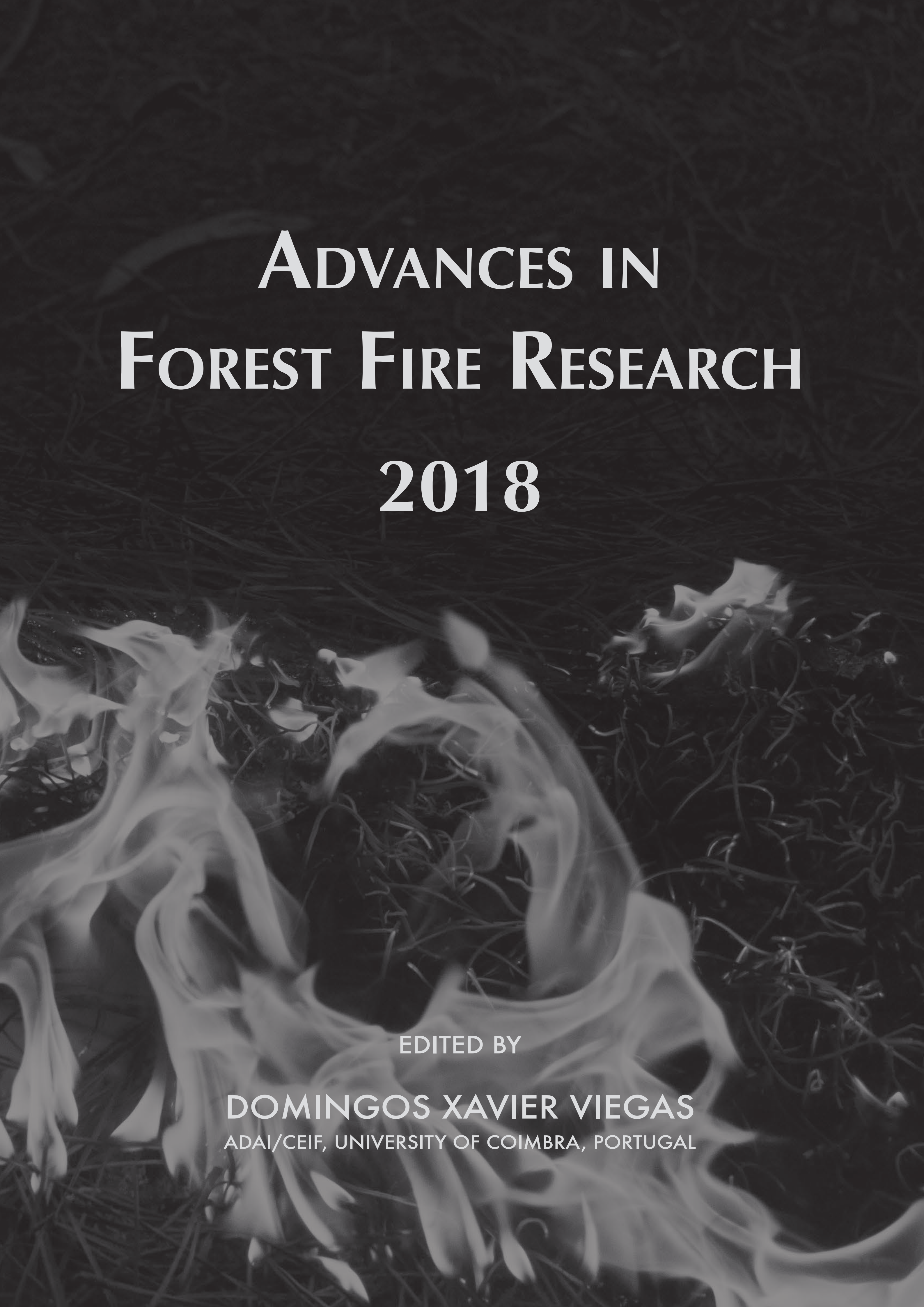

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Short contribution – Decision Support Systems and Tools

# Modelling the performance of forest and wildland fire aerial detection systems

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## 1. Introduction

Detection and initial attack systems are important components of response systems for forest and wildland fires, the primary objective of which is to contain potentially destructive fires quickly at a small size at a reasonable cost. Modern forest fire detection systems are large complex systems that often include fixed towers, fixed-wing aerial detection patrol aircraft and "loaded" patrols by rotary-wing aircraft carrying fire fighters and their equipment that can be dropped off to combat any fires that are detected along their flight path. Most forest fire management agencies also rely heavily on the public to report fires at little or no cost in or near heavily populated areas or along heavily used transportation corridors. Additionally, satellites sometimes serve as the first detector of fires in remote areas.

Decisions concerning when what detection patrol aircraft should fly what routes should be informed by estimates of the probability that the on-board detection observers will detect any undetected fires near their planned flight paths. The estimation of that probability is complicated by the fact that although we know about a detection observer's successes - the fires he or she found and reported, it's impossible to identify all the fires the fires that were "missed". In this paper we describe how we used aircraft tracking technology and lightning stroke counter technology to overcome that obstacle.

## 2. Methods

In order to develop an aerial detection probability model we had to identify a set of fires, their locations, when they were ignited, when aerial detection patrol aircraft flew nearby and whether or not the detection observer detected and reported the fire. We used lightning-caused fire ignition data on the assumption that it's difficult to confirm the ignition time of many human-caused fires.

We began by compiling a sample of lightning-caused fires that occurred in the province of Ontario, Canada during the years 2008-2015. We used lightning strike data collected by Ontario's lightning strike counter system, along with fire report dates, to estimate which day each lightning ignited fire occurred and when during the day that lightning occurred. Fire report data was used to determine when each of those fires was detected and reported and the detection agent.

The detection aircraft tracking system data is available in the form of a single "heartbeat" file for each aircraft. Each heartbeat datum includes the registration, datetime, latitude and longitude of the aircraft that was recorded every two minutes while the aircraft was powered up. Unfortunately, the raw heartbeat data for each detection aircraft does not indicate the type of flight that was taking place at that time. A subset of the heartbeat data might for example, be associated with a planned detection patrol, a training flight, or the ferrying of the detection aircraft from one airport to another.

We developed heartbeat parsing rules to partition each aircraft's stream of heartbeat data into discrete flights and estimated the purpose of each of those flights. Our parsing rules were based on flight durations and patterns (e.g., the number and magnitudes of turning angles) that are characteristic of planned detection flights that have been flown in Ontario in the past.

Our next task was to identify "looks", namely points in time and space when a detection aircraft on a planned patrol flew a straight line segment of a patrol near an undetected fire. We began by creating a 25 km radius circle around each fire and identified all the flight segments that passed through that circle between the time the fire was estimated to have been ignited and when it was known to have been detected. Each such look was characterized with respect to several attributes including the shortest distance from the flight segment to the fire, the type of fuel in which the fire was burning, the fire danger rating conditions and whether or not each look was successful. A successful look is defined as the fire being detected and subsequently reported.

Logistic regression methods were then used to relate the probability that an aerial detection observer will detect an undetected fire to the distance of the fire from the detection aircraft's flight path, the fire weather conditions, the time of day the look took place and the forest fuel in which the undetected fire was burning.

## 3. Potential use of the detection probability model

Each day the detection planner must decide upon the departure time and the flight path of each of his or her detection patrol aircraft. Suppose the fire management area has been partitioned into a large number of small grid cells and that he or she has access to a spatially explicit fire occurrence prediction system that provides probabilistic predictions of the number of undetected fires burning in each cell. One can then specify a proposed detection patrol route, determine when and how close that flight will pass by each grid cell and estimate the expected number of fires detected by that patrol. If one can estimate the values at risk in each cell one can estimate the expected values at risk "found" by that patrol.

The routing of aerial detection patrols is a very complex variant of the traditional vehicle routing problem with multiple vehicles, multiple depots with uncertainty concerning the time required to complete each flight due in part to uncertainty concerning the time required to asses any fires detected en route. Our plan is to eventually incorporate our new detection probability model in a detection patrol routing optimization model.

## 4. Acknowledgements

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