Value of Weather Observations for Reduction of Forest Fire Impact on Population

N. Khabarov [a,*], E. Moltchanova [a, b], M. Obersteiner [a]

[a] International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria – (khabarov, oberstei)@iiasa.ac.at
[b] National Institute for Health and Welfare, Helsinki, Finland – elena.moltchanova@thl.fi

Abstract – In this paper we investigate how improvements in the weather observation systems help to reduce forest fires impact on population by targeting and monitoring places where ripe fires are likely to occur. For the purposes of population impact assessment we suggest a relevant index. In our model the air patrolling schedule is determined by the Nesterov index, which is calculated from observed weather data sets at different spatial resolutions. The reduction of fire impact on population, associated with utilization of finer grid, indicates the benefits of more precise weather observations. We also explore the sensitivity of the forest fires model with respect to the quality of input data while taking into account the multitude of sources providing weather observations. Our model shows that approximately 90% of the feasible reduction of fire impact on population can be achieved by refining weather observations in 30% of the area of interest.

Keywords: forestry, fires, meteorology, population impact, societal benefits of Earth observations.

1. INTRODUCTION

Earth observation has been an integral part of managing human societies for millennia. In the 21st century mankind has substantially altered the major bio-geochemical cycles on global scales possibly augmenting risks emanating from changes in the behavior of the total Earth system. One of these new risks is linked to an increase in fire calamities, which possibly could cause negative feedbacks to the global carbon cycle, impair ecosystems functions, cause human casualties, and destroy valuable human assets. Thus, in order to attain sustainable development goals, the management of many observation subsystems in a coherent, efficient, and effective manner is needed. And for this purpose a comprehensive Global Earth Observation System of Systems should be implemented.

1.1 Motivation

The pathway of benefit generation for fire management, augmented by an Earth Observation System of Systems, is achieved through better informed and, therefore, improved decision making processes and more advanced fire management resulting in fewer burned areas and overall reduced net losses. Despite the practical importance of improved information for disaster prevention and response, the quantification of the "observation quality – benefits" relationship has not yet been performed with regard to the forest fires impact on population..

1.2 Aims

Our aim is to develop a model that would allow for a quantitative assessment of the value of improved observations for disaster response to forest fires. More specifically, we aim at obtaining quantitative results measuring the feasible reduction of forest fires-induced impact on population (including loss of life and property) that better Earth observations (EO) could contribute to. For that purpose we suggest an indicator measuring in an aggregated way the fire impact on population and perform an assessment of its reduction potential. Additional sub-goal is to explore the inter-dependence between the population impact and such natural indicator as burned areas. The research presented here is focused mainly on monitoring of the disaster-prone areas and early detection of fires. We employ simplified mathematical representation of other related processes, hence the detailed fire spread model and also fire extinguishing model are beyond the scope of this paper.

1.3 References to Related Work

The simplified forest fire index, which is at the core of the model we use, was originally suggested by Nesterov (1949). More sophisticated systems were developed with time, e.g. Van Wagner (1987). Nevertheless, Buchholz et al. (2000) show that application of simplified indices is still useful if the available information is limited to basic parameters. One of the applications of the Nesterov index to the Iberian Peninsula case study is presented by Venevsky et al. (2002). Fiorucci et al. (2004) explore a resource allocation problem for forest fire risk management. Khabarov et al. (2008) evaluate the importance of observations for reduction of burned areas. Some applications of remote sensing techniques to forest fire monitoring and risk assessment are presented in e.g. Saatchi et al. (2007), Yebra et al. (2008).

1.4 Overview

The next part of the paper sets the stage by introducing the fire impact on population index (FIPI) and a simple fire hazard model along with relevant data, forest patrolling rules and probabilities' assessment composing altogether the forest fire fighting model. Then, we articulate the methodology to assess in a quantitative manner the benefits of improved weather observations. Further, in the section 3, we focus on the sensitivity of the model with respect to the variation of the number of ground weather stations, and highlight the problem of the optimal observation system design. Section 4 concludes the paper.

2. MODEL AND DATA

The purpose of the model described below is to demonstrate how local population can benefit from the improvements to in-situ weather measurements. The effective use of air patrols for forest fire detection is at the model's core. As an example of the air patrolling rules, we utilize the rules developed in the Russian Federation, which are based on the Nesterov index. Some other forest fire danger assessment systems are presented in e.g. Van Wagner (1987) and Satoh et al. (2004). Nesterov index is used to assess fire danger on daily basis, and it is the basic indicator for

---

* Corresponding author.
** This research was performed in the framework of the EC project GEO-BENE (www.geo-bene.eu), led by IIASA.

decision making with regard to implementing particular measures to reduce possible losses due to forest fires. We calculate Nesterov index on two grids: (1) the original 'fine' grid and (2) the 'rough' grid with the spatial resolution decreased by factor 2. We pick up a small cell to represent weather data in bigger aggregated cell. Then we apply forest patrolling rules to calculate under otherwise equal conditions the losses in terms of the burned forest area and the total patrolled area for both 'fine' and 'rough' grids. After specifying the technical characteristics of an aircraft the total patrolled area can be easily converted into tons of fuel consumed for air patrol. The total cost of the burned area can be calculated based on the type of trees growing in the area, the distance from the roads/railways, the amount of CO_2 emissions caused by the fires, etc. Taking into account the population located in the area and possible damage caused by fires to the property and human health, including loss of life, we suggest to measure the fire impact on population by the following Fire Impact on Population Index (FIPI):

$$FIPI = BA / TA \times PD, \tag{1}$$

where *BA* is the yearly burnt area in a grid cell, *TA* is the total grid cell area, and *PD* is the population density in the grid cell (inhabitants per km^2). The FIPI reflects the number of people affected by fire per year per km^2.

For the calculations we chose the area covering parts of Spain and Portugal located approximately between -7.5W, 42.0N and -0.5W, 38.0N. The grid cell size is 50 x 50 km, see Figure 1. We have chosen this area only because of the availability of suitable weather data. We consider a simplified forest fire model aiming at developing an approach to assessment of the value of information for fighting forest fires. Using the same approach, the model constants and the set of forest fire patrolling rules can be adjusted to reflect real situation and practices in a particular region.

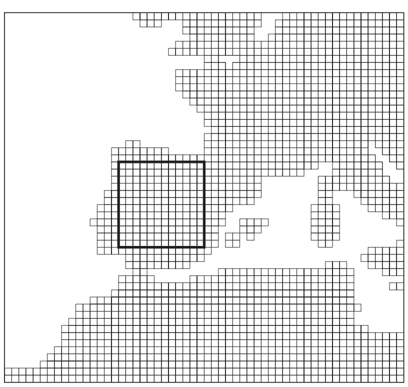

Figure 1. The dataset grid cells of the study area covering parts of Portugal and Spain.

We use a gridded weather dataset for the year 2000 containing daily temperature, precipitation, and vapor pressure (European Commission – Joint Research Centre (JRC) interpolated meteorological data source, JRC/AGRIFISH Data Base: http://mars.jrc.it/marsstat/datadistribution/). The formula for the calculation of the Nesterov index is

$$I(t) = \sum_{k=s}^{t} (t_k - t_k^d) \cdot t_k, \tag{2}$$

here t denotes day number since the start of observations, t_k is the daily temperature in Celsius degrees, t_k^d is the dew point temperature in Celsius degrees for the day k. If the precipitation is greater than 3 mm at a day number s-1, then the Nesterov index drops to zero and the summation restarts from the next day s.

2.1 Forest Fire Patrolling Rules

According to the actual value of the Nesterov index in a specific area the fire danger class is determined and corresponding air patrol frequency is applied to that area. Table A is officially used in Russia for that purpose. Below we show which implications that forest fires strategy coupled with observed weather data may have on the impact of forest fires on population in terms of FIPI.

Table A. Fire danger classes and air patrol frequency depending on Nesterov index

Nesterov index	Fire danger	Fire danger class	Air patrol frequency
≤ 300	—	I	No patrol
> 300	Low	II	Once in 2–3 days
> 1 000	Medium	III	Once daily
> 4 000	High	IV	Twice daily
> 10 000	Extreme	V	Three times a day

2.2 Probabilities Assessment

To assess the forest fire occurrence probability, we use the formulas proposed by Venevsky et al. (2002). The probability of a fire provided that there is an ignition in the area is calculated as

$$P(I) = 1 - e^{-aI}, \tag{3}$$

where I is the Nesterov index, and the value of the parameter a is set to 0.000337. The average number of ignitions during a day is expressed in the form

$$N(PD) = (w(PD)\, PD\, b + l)\, S, \tag{4}$$

where PD is the population density, b=0.1 is the average number of ignitions in a day produced by one human scaled to one million hectares, l is the probability of a fire in some area caused by natural reasons (e.g. lighting), S is the total area of the grid cell in millions of hectares, the function $w(PD)$ describes the human ignition potential

$$w(PD) = 6.8\, PD^{-0.57}. \tag{5}$$

The probability of at least one fire in the area given certain population density PD and Nesterov index I can be expressed in the form:

$$P_1(I,PD) = 1 - (1 - P(I))^{N(PD)}, \tag{6}$$

where probability $P(I)$ and the number of ignitions $N(PD)$ are calculated using the formulas (3) and (4) – (5) respectively.

2.3 Simplifying Assumptions and Constants

We made some assumptions to simplify the assessment of possible forest fires consequences: (a) the whole area under consideration is covered with a homogeneous forest so that the fire conditions in a cell are solely determined by the weather conditions; (b) there are no extreme winds in the area so that we do not account for wind conditions in the model; (c) for the calculations we set the fire spread rate $v = 0.3$ m/min, which is approximately equal to 0.02 km/h. Under the assumption of constant fire spread rate the total area burned during the time t is calculated as the area of the circle of radius vt. We also pose the maximum limit of 24 hours for undetected forest fire assuming that satellite observation system will make it possible to detect the fire within this time frame. In addition we allow 2 hours to extinguish the fire and take this time into account to calculate the burned area.

2.4 Calculation Methodology

In the suggested simplified model the only stochastic variable is the occurrence of fire. The probability of fire occurrence depends on Nesterov index and population density. This rather rough assumption allows us to assess the value of better weather observations in a straightforward way.

Based on the air patrol frequency from the Table A one may estimate the fire detection times and daily patrolled areas depending on the fire danger class. Then the calculation of the total expected FIPI for a full 12x12 cell set can be performed as follows:

$$FIPI = \sum_{i,j=1}^{12} \left(PD_{ij} \sum_{t=1}^{365} S_{ij}^{t} \right),$$

where PD_{ij} is the population density in the grid cell (i,j), and S_{ij}^{t} is the expected relative burned area in the grid cell (i,j) in day t implicitly depending on both Nesterov index and population density. The difference in values of total expected FIPI calculated for 'rough' and 'fine' grids is due to different fire danger classes assigned to each cell (i,j) on a daily basis using 'rough' and 'fine' weather data.

3. RESULTS

In order to simulate the usage of coarse weather information, a cell from a fine grid should be selected to represent weather information for each cell of a rough grid. There are several options to choose a 'small' cell within an 'aggregated' cell. For the illustration purposes we choose the upper left cell. The Table B summarizes the results.

Table B. Total expected FIPI, burned area (% of total area) and cumulative patrolled area (times of the total area) for rough and fine grids and respective improvement ratios

	Rough grid	Fine grid	Improvement
FIPI	0.4496	0.3807	15 %
Burned area	0.5261 %	0.3910 %	26 %
Patrolled area	295.2	300.8	-2 %

Here, we observe the decrease of both total expected FIPI and burned area at the expense of a slight increase in cumulative patrolled area.

3.1 Sensitivity Analysis

We have considered so far just two grid resolutions – 'rough' and 'fine'. The more precise measurement of the sensitivity of the model to the amount of data used to feed it is still of great practical interest. In this section, we adjust the amount of information containing in the input data set by refining the 'rough' data set in most critical sub-areas.

We consider a network of weather stations supplying weather data on a 'rough' grid, and we increase the number of weather stations in most critical 'small' cells. The term *critical* means that the contribution of a particular cell to the total FIPI is maximal among other cells. The FIPI is recalculated for modified (improved) data set and, then, the procedure is repeated to select the next cell where better information should be used. Since we do not specify any further technical details, the suggested approach may, also, be considered as a model of combination of rough and fine data sets representing the integration of two systems, one of which provides relatively rough information at a low cost and the other system supplies relatively costly, but more precise information (this could be e.g. satellite observations and in-situ measurements respectivly).

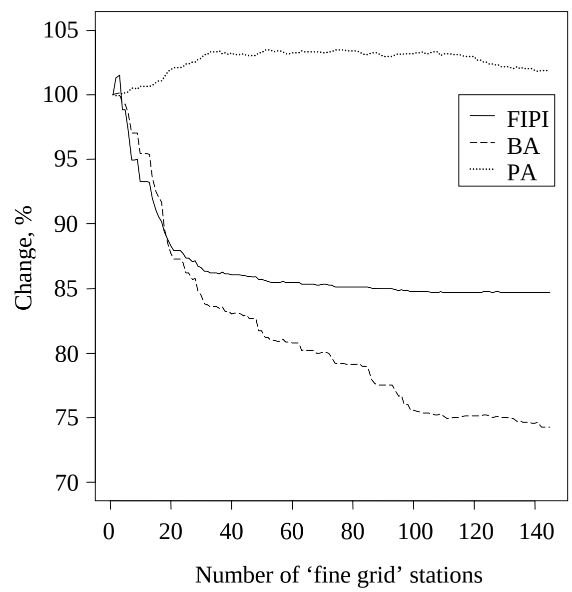

Figure 2. Dependence of the FIPI, burned (BA) and patrolled (PA) areas on the number of 'added' weather stations.

Figure 2 illustrates the reduction of FIPI and respective change in burned and patrolled areas depending on the number of added weather stations. The important point to emphasize here is that the introduction of a relatively small number of more precise stations in critical areas could immensely improve the overall performance of the system. So, about 40 precise stations covering only 30% of the territory could provide about 90% of the feasible improvement of FIPI (attainable by placing the weather stations everywhere). At the same time, that still leaves a big potential for improvement in terms of burned area. The optimal combination should take into account the trade-off between the costs for improved information and possible losses caused by fire. Another important implication of the results presented in Figure 2 is the high importance of the model's performance indicator: if one is just minimizing FIPI they would stop after adding about 40 precise stations (since marginal reduction of FIPI becomes negligible at that point), where those minimizing burned area would still continue improving observation capacity.

Figure 3 shows that the patterns of population density and expected burned areas look quite similar, emphasizing that the population is the main driver of forest fires. At the same time, as we mentioned before in the comment to the Figure 2, the population density alone or even integrated into FIPI cannot be used as the only fire impact measure, since it becomes quite insensitive to burned areas.

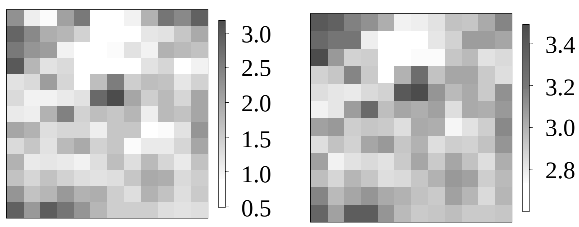

Figure 3. Population density (left figure, inhabitants/km^2) and expected yearly burned areas (right figure, hectares) patterns – both on $\log_{10}$ scale.

4. CONCLUSION

In this paper we analyzed the influence of data quality on the forest fires management model. For the purposes of generality, we did not specify the way the weather parameters are measured. The forest fire detection model presented in this paper is based on the Nesterov fire danger index. The Nesterov index is a natural candidate for simplified fire danger rating, since it is an easily computable function of a few parameters. However, the model can be modified to use similar indices, such as KBDI, see e.g. Buchholz (2000) or more sophisticated systems, e.g. Canadian FFWI, see Van Wagner (1987). The comparison of the sensitivity of different fire danger rating systems to the quality of input weather data with the application to the model presented in this paper could be an interesting direction for further research.

We presented a methodology to assess the benefits of improved weather observations with the application to forest fire management. The results of the modeling could be refined by taking into account other parameters important for forest fire management, such as e.g. fuel load in the forest, type of the forest, age of the forest, resources availability in terms of fire fighters and equipment for fire extinguishing, aircrafts and fuel for forest patrols. We assume that Nesterov index is suitable for the local conditions under consideration. Using more sophisticated systems for the analysis would require much more detailed data, which are usually not freely available. Although the presented analysis is quite basic, we believe that the conclusions will remain valid and that other indices would produce the results in the same direction, although not necessarily to the same extent.

The analysis of the optimal stations' location problem shows that the total system performance can be optimized, and, at the same time, the costs for implementation, operation, and maintenance can be reduced thanks to better overall systems design. A possible interpretation of this result in terms of integration of two systems ('precise-expensive' and 'rough-cheap') leads to the conclusion that an optimal combination of systems (System of Systems) is able to deliver a significant improvement in the overall system's performance as well as improved cost-effectiveness. This conclusion is close to the Global Earth Observation System of Systems concepts, which imply benefits from integration of different observation systems.

REFERENCES

G. Buchholz and D. Weidemann, The use of simple fire danger rating systems as a tool for early warning in forestry, International Forest Fire News, no. 23, pp. 32–36, 2000.

P. Fiorucci, F. Gaetani, R. Minciardi, R. Sacil, and E. Trasforini, Dynamic resource allocation for forest fire risk management, Proceedings of the 15th International Workshop on Database and Expert Systems Applications, pp. 603--607, 2004.

N. Khabarov, E. Moltchanova, M. Obersteiner, Valuing Weather Observation Systems for Forest Fire Management, Systems Journal, IEEE, Volume 2, Issue 3, pp. 349–357, 2008.

V. Nesterov, Forest fires and Methods of fire risk determination, Goslesbumizdat, Moscow, 1949.

S. Saatchi, K. Halligan, D. G. Despain, and R. L. Crabtree, Estimation of forest fuel load from radar remote sensing, IEEE Transactions on Geoscience and Remote Sensing, vol. 45, no. 6, pp. 1726–1740, 2007.

K. Satoh, S. Weiguo, and K. T. Yang, A study of forest fire danger prediction system in Japan, Proceedings of the 15th International Workshop on Database and Expert Systems Applications, pp. 598--602, 2004.

C. E. Van Wagner, Development and structure of the Canadian Forest Fire Weather Index System, Forestry technical report 35, Canadian Forestry Service, Ottawa, 1987.

S. Venevsky, K. Thonicke, S. Sitch, and W. Cramer, Simulating fire regimes in human-dominated ecosystems: Iberian peninsula case study, Global Change Biology, vol. 8, no. 10, pp. 984–998, 2002.

M. Yebra, E. Chuvieco, and D. Riaño, Estimation of live fuel moisture content from MODIS images for fire risk assessment, Agricultural and Forest Meteorology, vol. 148, no. 4, pp. 523–536, 2008.

ACKNOWLEDGMENTS

Authors thank Anatoly Shvidenko for helpful discussions, Steffen Fritz and Ian McCallum for their support with data conversion. The authors acknowledge JRC concerning the supplied data.