Valuing Weather Observation Systems For Forest Fire Management

Nikolay Khabarov, Elena Moltchanova, and Michael Obersteiner

Abstract—**Weather information is an integral part of modern fire management systems. In this paper, we investigate, by means of simulation studies, how improvements in the weather observation systems help to reduce burned area by targeting and monitoring places ripe fires are likely to occur. In our model, the air patrolling schedule is determined by the Nesterov index, which is calculated from observed weather data. We use two weather data sets based on "rough" and "fine" grids. The reduction of the total burned area, associated with an air patrolling schedule based on the "fine" grid, indicates the benefits of using better weather observations. We, also, consider a stochastic model to simulate forest fires and explore the sensitivity of the model with respect to the quality of input data. Finally, we investigate the system of systems effect. We find the largest marginal improvement from the rough grid results when we increase the quality of observations in most critical areas.**

Index Terms—**Fires, forestry, meteorology, value of information, value of observations.**

I. 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. For this purpose, a comprehensive Global Earth Observation System of Systems (SoS) should be implemented.

The pathway of benefit generation for fire management, augmented by an Earth observation SoS, is achieved through better informed and, therefore, improved decision making processes resulting in overall reduced net losses. It is the matching of enhanced data streams with a joint knowledge base of fire management that finally results in fewer burned areas. There are many ways fire management can benefit from a global SoS.

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N. Khabarov and M. Obersteiner are with the International Institute for Applied Systems Analysis (IIASA), Laxenburg A-2361, Austria (e-mail: khabarov@iiasa.ac.at; oberstei@iiasa.ac.at).

E. Moltchanova is with the National Public Health Institute, Helsinki FIN-00300, Finland (e-mail: elena.moltchanova@ktl.fi).

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The first benefit that is created, which is, however, the least quantifiable one, is that over the next decades Global and Regional Earth Observation Systems will help revolutionize our understanding of the metabolisms and interrelations of Earth systems leading to fire calamities. In modern societies, knowledge is built in data-intensive evolutionary processes in an agent—information—artifact frame. Hence, at the heart of every good fire management practice lies an entire history consisting of proper data and sophisticated algorithms creating/coding/archiving useful information. Data per se does not have a value—only through its use can the value be generated. Time series of global fire occurrences, causes of ignition and associated fire management responses are currently non-existent. Today, mankind is not in the position to address risks emanating from forest fires on a global scale. Promises and political aspirations to build systems making the globe safer and better equipped to manage global fire risks lack both adequate knowledge and data. In many parts of the world, fire management is inefficient due to the lack of resources and basic knowledge on how to effectively use existing data and data products in all phases of a fire disaster cycle.

The second benefit of a global SoS is generated by *economies of scale*. The societal value of new global data streams increases (linearly or exponentially through network externalities) along with the number of people using it. This consideration is based on the idea of economies of scale and is motivated by the fact that global fire observing systems complementing national systems would lead to overall lower costs for individual countries.

The third benefit arises from *economies of scope*. An individual sub-system of a SoS might serve multiple purposes. In the case of fire management, remotely sensed images are used to detect fires and, at the same time, these images can help generate dynamic land cover maps. Likewise, weather information needed to delineate fire hazard zones garner many other purposes in sectors ranging from agriculture to tourism. Thus, sub-systems and, also, an SoS, have to be understood as information generators operating in a multifaceted production mode.

The fourth benefit we would like to investigate in greater detail in this paper relates to improvements in *efficiency and effectiveness*. The marginal reduction of burned forest area illuminates the benefits of finer resolved weather information used by application of forest patrolling rules to a specific geography.

Section II sets the stage by introducing a simple fire hazard model, relevant data, forest patrolling rules and probabilities' assessment composing together the forest fire fighting model. Then, we articulate the methodology to assess in a quantitative manner the benefits of improved weather observations. Further, in Section III, we focus on the sensitivity of the model with respect to the grid resolution, variation of the number of ground weather stations, and discuss the question of the optimal observation system design. Section IV concludes the paper.

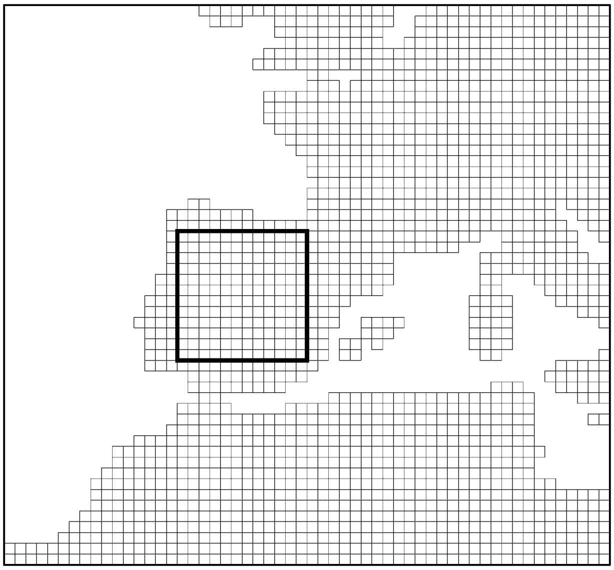

Fig. 1. Study area covering parts of Spain and Portugal.

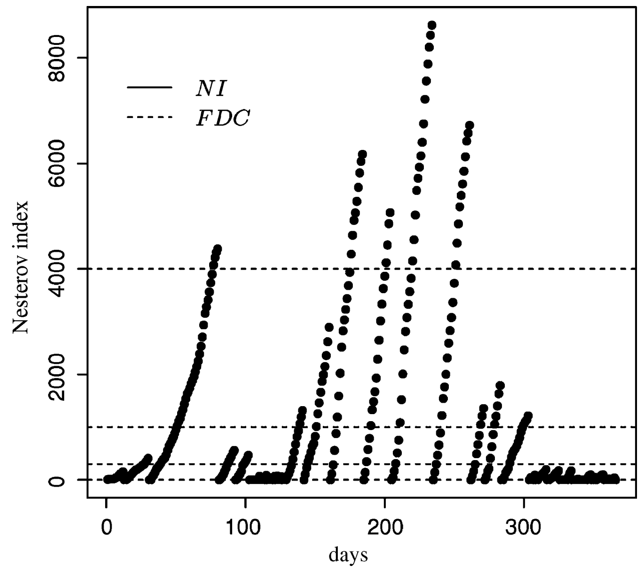

Fig. 2. Daily values of Nesterov index (NI) during the year 2000 for the cell (4,3) and thresholds (FDC) corresponding to fire danger classes.

II. Methods and Data

A. Model and Input Data Description

The purpose of the model described in the following is to demonstrate how fire management can benefit from the improvements to *in-situ* measurements and optimizing grid spacing in the application of Earth observations. 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., [1] and [2].

Nesterov index is used to assess fire danger on daily basis, and it is the basic indicator for decision making as 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 resolution decreased by factor 2 (the number of cells reduced by 2 times on the same area). Further these two grids are referred to as "fine" and "rough" grids. We pick up "small" cell to represent weather data in bigger "aggregated" cell.

We apply official aircraft forest patrolling rules based on Nesterov index, which are in force in Russian Federation and 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 taking into account 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. The difference between total losses associated with fine and rough grids indicates the benefits of better observations, i.e., using a fine grid for weather observations.

For the calculations we chose the area covering parts of Spain and Portugal located approximately between -7.5 W, 42.0 N and -0.5 W, 38.0 N. The grid cell size is 50 $\times$ 50 km, see Fig. 1. We have chosen this area only because of the availability of weather data. We consider a quite sketchy model with the sole purpose to present the approach of 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.

We use a gridded weather dataset for the year 2000 containing daily temperature, precipitation, and vapor pressure (European Commission—Joint Research Center (JRC) interpolated meteorological data source, JRC/AGRIFISH Data Base: http://mars.jrc.it/marsstat/datadistribution/). The formula for calculating Nesterov index according to [3] is

$$\begin{aligned} &I(t)=\sum_{k\in[T_0(t),t]}\left(t_k-t_k^d\right)\cdot t_k\\ &T_0(t):p(k)<3 \quad \forall k\geq T_0(t) \quad p\left(T_0(t)-1\right)\geq 3\\ &I\left(T_0(t)-1\right)=0\\ &I(0)=0 \end{aligned} \tag{1}$$

here t denotes day number since the start of observations (discrete time) for which the Nesterov index is calculated, t_k is the daily temperature in Celsius degrees, t_k^d is the dew point temperature in Celsius degrees for the day k, and $p(k)$ is a daily precipitation in millimeters. The left point of the summing interval $T_0(t)$ is defined such that the interval contains all days with the precipitation less than 3 mm after a day with precipitation of more or equal to 3 mm. The Nesterov index was originally introduced in [4]. The description and applications of Nesterov index, as well as comparison with other similar indices can also be found in [5] and [6]. Fig. 2 shows an example of how Nesterov index depends on time for the cell (4,3) of the area under consideration.

B. Data Preprocessing

In order to convert the vapor pressure, which is provided by the weather data set into the dew point temperature required for Nesterov index calculation we use the conversion formulas as follows.

The calculation of saturated water vapor pressure $P(t)$ in $\mathrm{hPa} = 100$ Pa depending on temperature t in Celsius we use the Goff-Gratch equation as per [7]

$$\begin{aligned}\tilde{t} &= t + 273.15\\ c_0 &= 373.15\\ c_1 &= 1013.25\\ \tilde{p}(t) &= -7.90298 \cdot (c_0/\tilde{t} - 1) + 5.02808 \cdot \log_{10}(c_0/\tilde{t})\\ &\quad - 1.3816 \cdot 10^{-7} \left(10^{\left(11.344 \cdot (1-\tilde{t}/c_0)\right)} - 1\right)\\ &\quad + 8.1328 \cdot 10^{-3} \left(10^{\left(-3.49149 \cdot (c_0/\tilde{t}-1)\right)} - 1\right)\\ &\quad + \log_{10}(c_1)\\ P(t) &= 10^{\tilde{p}(t)}.\end{aligned}$$

The calculation of the dew point temperature $\tilde{t}^d(t,h)$ based on temperature t in Celsius and relative humidity h is performed according to the following formula:

$$\begin{aligned}a &= 17.27\\ b &= 237.7\\ \gamma(t) &= a \cdot t/(b+t) + \ln(h)\\ \tilde{t}^d(t,h) &= b \cdot \gamma(t) / (a - \gamma(t)).\end{aligned}$$

This formula is based on Magnus–Tetens formula for the vapor pressure according to [8]. The final calculation of the dew point temperature $t^d(t,p)$ based on temperature t in Celsius and vapor pressure p (hPa) is done through

$$t^d(t,p) = \tilde{t}^d(t,h), \quad h = p/P(t).$$

C. Forest Fires Patrolling Rules

According to the actual value of Nesterov index in a specific area the fire danger class is determined and corresponding air patrol frequency is applied to that area. Table I is officially used in Russia for that purpose (see [9]). In the following, we show which implications the previously mentioned forest fires strategy coupled with weather data may have on the consequences of forest fires.

D. Probabilities Assessment

We use the formula proposed by Venevsky *et al.* [10] to assess the probability of the fire occurrence in a forest provided that there is an ignition in the area

$$\tilde{P}(I) = 1 - e^{-\alpha I} \tag{2}$$

where I is the Nesterov index, and the value of the parameter α is set to 0.000337. The average number of ignitions during a day according to [10] is expressed in the form

$$N(P_D) = (\kappa(P_D) P_D a + l)\, S \tag{3}$$

TABLE I
FIRE DANGER CLASSES AND AIR PATROL FREQUENCY DEPENDING ON NESTEROV INDEX

Nesterov index	**Fire danger**	**Fire danger class**	**Frequency of the air patrol**
0 ... 300	—	I	No patrol
301 ... 1000	Low	II	Once in 2–3 days
1001 ... 4000	Medium	III	Once daily
4001 ... 10000	High	IV	Twice a day
more than 10000	Extreme	V	Three times a day

where P_D is the population density, $a = 0.1$ is the average number of ignitions in a day produced by one human scaled to one million hectares, l is the probability of 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 coefficient κ describes the human ignition potential with respect to population density according to [11]

$$\kappa(P_D) = 6.8 P_D^{-0.57}. \tag{4}$$

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

$$P(I, P_D) = 1 - \left(1 - \tilde{P}(I)\right)^{N(P_D)} \tag{5}$$

where probability $\tilde{P}(I)$ and number of ignitions $N(P_D)$ are calculated using the formulas (2)–(4), respectively.

E. Simplifying Assumptions and Constants

The following is the list of assumptions we made to simplify the assessment of possible forest fires consequences.

1) The whole area under consideration is covered with a homogeneous forest (the fire conditions in a cell are fully determined by weather conditions).
2) The whole area is populated with constant density (the ignition potential is uniformly distributed in the area).
3) There are no extreme winds in the area (we do not account for wind conditions in the model).

In order to be able to calculate the actual outcome of the application of the forest fire fighting policy under certain amount of information, we need to set several constants discussed as follows.

For the calculations, we set the fire spread rate v equal to 0.3 m/min, which is approximately equal to 0.02 km/h. Under assumption of constant fire spread rate the total area S burned during the time Δt is calculated as the area of the circle of radius $v \cdot \Delta t$

$$S(\Delta t) = \pi(v \cdot \Delta t)^2.$$

For the sake of simplicity, we assume the fire duration times to be constants depending solely on the fire danger class. We also pose the maximum limit of 24 h 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 h to extinguish the fire and take this time into account to calculate the burned area in Table II. Here, for the sake of simplicity,

TABLE II
FIRE DETECTION TIME, BURNED AREA, AND DAILY PATROLLED AREA DEPENDING ON FIRE DANGER CLASS (S_0 IS THE AREA OF A GRID CELL)

Fire danger class, ν	**Frequency of air patrol**	**Fire detection time, $\Delta t(\nu)$, h**	**Burned area, $d(\nu)$, km^2**	**Area patrolled daily, $c(\nu)$**
I	no patrol	24	0.85	0
II	once in 2 days	12	0.36	$S_0/2$
III	once daily	6	0.08	S_0
IV	twice a day	3	0.03	$2S_0$
V	three times a day	2	0.02	$3S_0$

TABLE III
BURNED AND PATROLLED AREAS FOR ROUGH AND FINE GRIDS AND IMPROVEMENT RATIOS

	Rough grid	Fine grid	Improvement
Burned area, S_b, ha	74 899	55 887	25.38%
Patrolled area, S_p, km^2	112 305 000	108 237 500	3.62%

we do not consider any limitations that might exist with respect to fire fighting resources. One of the possible approaches to dynamic resource allocation is presented in [12].

F. Benefits Calculation Methodology

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

Based on the fire detection times and daily patrolled areas both depending on the fire danger class ν as per Table II the calculation of total expected burned S_b and patrolled S_p areas for a 12×12 cell set for one year (365 days) can be performed as follows:

$$\begin{aligned} S_p &= \sum_{t=1}^{365} \sum_{i,j=1}^{12} c\left(\nu_{ij}^t\right) \\ S_b &= \sum_{t=1}^{365} \sum_{i,j=1}^{12} p\left(I_{ij}^t\right) \cdot d\left(\nu_{ij}^t\right) \\ p(I) &= P(I, P_D) \end{aligned} \tag{6}$$

where the fire probability $P(I, P_D)$ is defined in (5). The difference in values of burned area S_b and patrolled area S_p calculated for "rough" and "fine" grids is due to different values of fire danger classes ν_{ij}^t calculated for each cell (i, j) on a daily basis t using "rough" and "fine" weather data, respectively. As we mentioned before, the costs associated with the areas S_b and S_p may be expressed in monetary units.

III. 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. Just for illustration purposes, we choose the bottom right cell. Table III summarizes the results. Here, we observe the decrease of both total patrolled area and burned forest.

TABLE IV
SUMMARY OF SIMULATION RESULTS (AVERAGE VALUES)

	Rough grid	Fine grid	Improvement
Burned area, ha	107 417	85 248	20.64%
Number of patrols	45 404	43 772	3.62%
Total fire duration, h	64 650	49 405	23.58%

A. Simulation Approach

In order to investigate the model dynamics in more detail, we have conducted a simulation study, in which we have simulated 1000 fire histories conditional on the weather history observed for the year 2000 for the fine and rough grids, respectively. In each case, the patrolling regime was set up based on the Nesterov index observed by the corresponding grid of weather stations and according to the rules stated in Table I. The fire probability was in both cases evaluated based on the fine-grid Nesterov index, and the daily number of fires was then randomly sampled from a Poisson distribution. The starting times of those fires for each day were sampled uniformly between 06.00 and 18.00, i.e., assuming that no ignition is possible during night. The fire, then, burned either until the arrival of the patrol and was subsequently extinguished, or during the maximum allowed time for detection (24 h) plus extinguishing time.

Two quantities of particular interest were evaluated: the yearly total burned area and the yearly total patrols number. The burned area was estimated under the assumption that the fire spread is circular with a rate of 0.02 km/h. The simulation results for the whole area are summarized in Table IV. The difference between the two models with respect to the estimation of burned area as shown in Tables III and IV is due to the following features of the simulation-based model: 1) it allows for two or more fires during one day in the same area; 2) it calculates the estimation of the burned area in a more accurate way consistent with the inequality $\mathbb{E}(\xi^2) \neq (\mathbb{E}\xi)^2$, which holds for any nontrivial random variable ξ; 3) it simulates (random) fire detection time based on the patrolling schedule. The simulation-based model additionally allows us to analyze the burned area distribution.

There is a correlation between the yearly total burned area and the average Nesterov index (see Fig. 3). The change from the fine to the rough grid generally caused both the total duration and the total squared duration distributions to move to the right

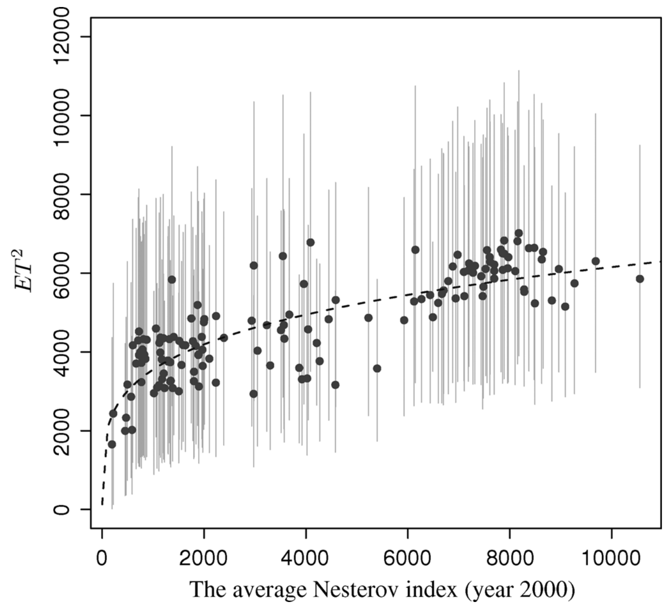

Fig. 3. Dependence of average quadratic fire duration on the average yearly Nesterov index, the gray lines demarcate the 95% confidence intervals, the gray points are the respective means.

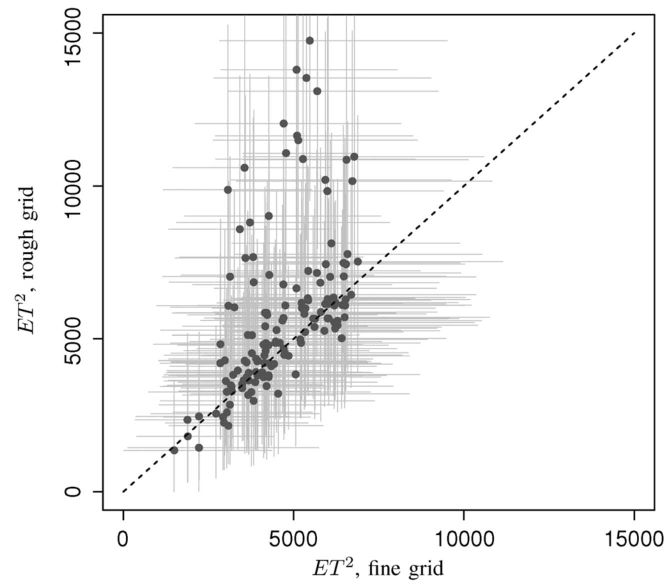

Fig. 5. Expected total yearly quadratic fire duration for the patrol regimes defined by fine and rough observation grids.

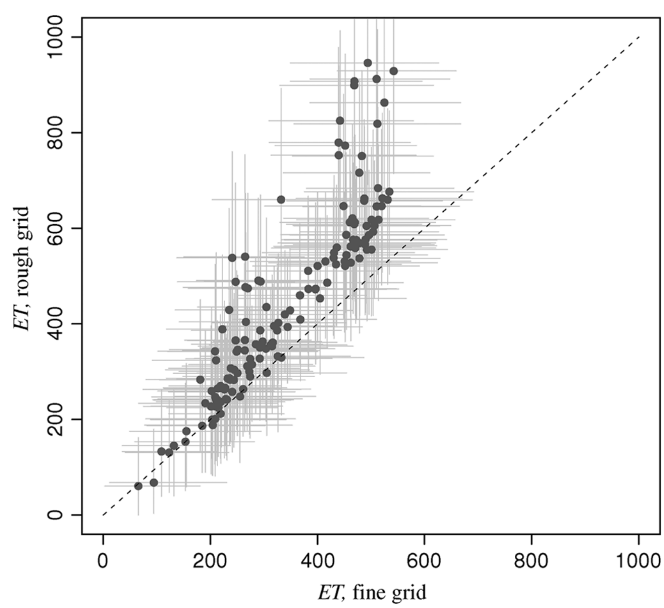

Fig. 4. Expected total yearly fire duration for the patrol regimes defined by fine and rough observation grids. The gray lines demarcate the 95% confidence intervals, the gray points are the respective means. The dotted 45-degree line indicates where the equality would be obtained.

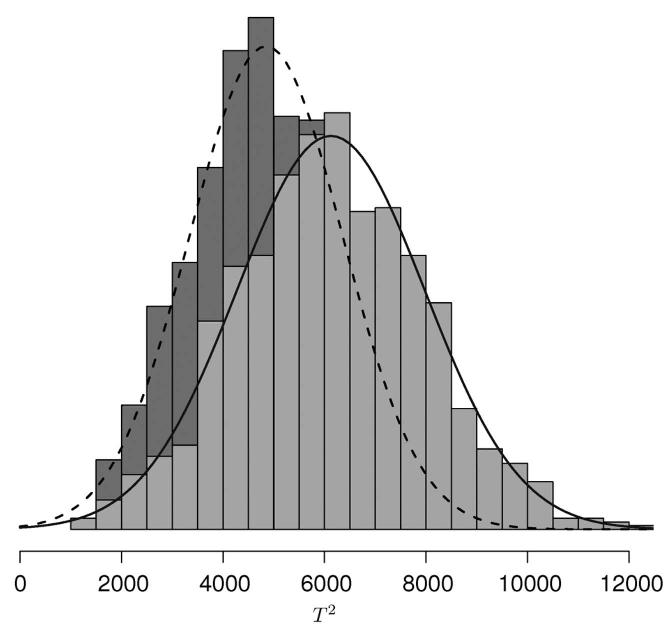

Fig. 6. Simulated distribution of the squared fire duration (T^2) for the fine (dark gray) and rough (light gray) grids. The solid and dotted curves illustrate the corresponding fitted 0-truncated normal densities.

within each grid cell. The corresponding median dynamics is illustrated in Figs. 4 and 5. Not all individual cells necessarily benefit from the improved information quality. However, as the Table IV shows, on average an improved information system will result in a slightly decreased number of patrols (3.6%) and major savings in terms of burned area (21%).

An example of a positive distribution shift in an individual cell is illustrated on Fig. 6. Not only the average fires become bigger, but the probability of extreme events increases. The latter is true for the whole area, as shown in Fig. 7, where the probability of an event larger than the T^2 is plotted.

B. Sensitivity Analysis

We have considered so far two grid resolutions—"rough" and "fine". The question about the sensitivity of the model to the amount of data used to feed it is of great practical interest. In this section, we use three different methods to adjust the amount of information containing in the input data set: 1) we implicitly vary the number of weather stations and their locations by varying the grid resolution; 2) we explicitly vary the number of weather stations; and 3) we refine the "low" resolution data set in most critical sub-areas.

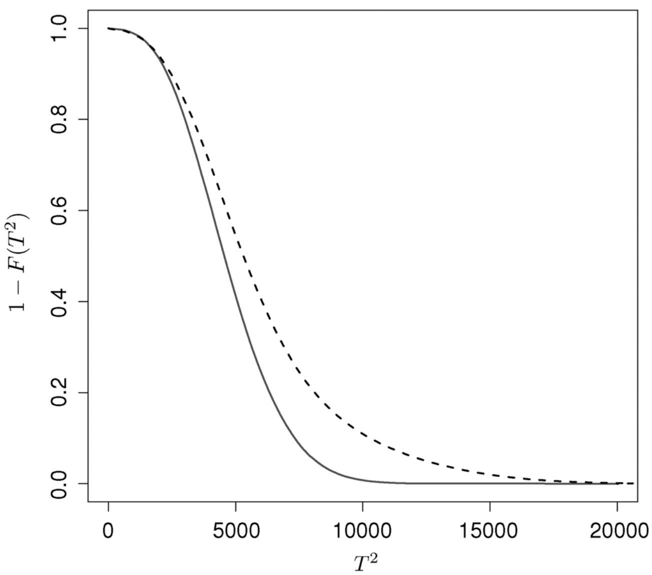

Fig. 7. Cumulative probability of extreme events for fine (solid curve) and rough (dotted curve) grid.

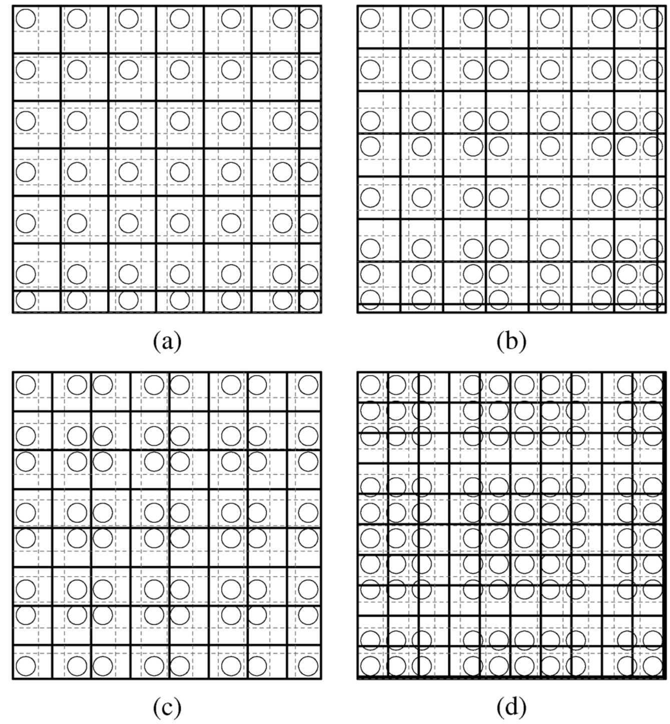

Fig. 8. Grids with decreasing cell size and increasing number of stations over the basic grid. Grid cell sizes are, respectively, (a) 185%, (b) 165%, (c) 150%, and (d) 120% of the original cell.

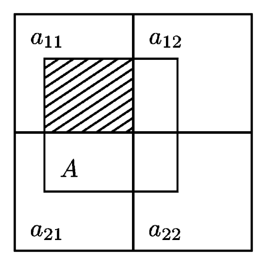

Fig. 9. Rule to select a station to represent weather data within a "big" cell. Here $(i_A, j_A) = (1, 1)$.

1) Grid Resolution: In this section, we consider a "smooth" change of a grid cell size and apply the corresponding range of grids to the forest fires fighting model. The purpose of this exercise is to explore how the outcome of the model depends on the grid resolution.

Fig. 8 illustrates several grids with decreasing cell size over the basic grid. The circles show weather stations, which are used to observe weather conditions in specific "big" cells. The rule to select a station to represent weather data within a "big" cell is based on the intersection area of "small" cells with the "big" cell. A weather station located in the upper left "small" cell having the biggest intersection area with the "big" cell is used to represent weather data for that "big" cell. Fig. 9 illustrates this rule. The mathematical formulation is following. Let A be one of the "big" squares corresponding to cells of the "rough" grid, let a_{ij} be the squares corresponding to the "fine" grid. The index (i_A, j_A) of a weather station corresponding to the square A is defined as follows:

$$
\begin{aligned}
&s_A = \max_{i,j} \rho(A \cap a_{ij}) \\
&Z_A = \{(i,j) | \rho(A \cap a_{ij}) = s_A\} \\
&Y_A = \{(i,j) | (i,j) \in Z_A, (i, j-1) \notin Z_A\}, \\
&\qquad (i_A, j_A) : (i_A, j_A) \in Y_A, \quad (i_A - 1, j_A) \notin Y_A
\end{aligned}
$$

here $\rho(U)$ is the area of the planar set $U \subset R^2$.

Fig. 10 shows the dependence of the burned and patrolled areas when applying the patrolling rules discussed in the Section II-C to grids with cell sizes ranging from 200% to 100% of original size. The figure shows, also, the number of weather stations used for observations and disposition change of those weather stations. Obviously, the dependence of burned area and patrolled area on cell size is non-monotonous. This means that however the general trend shows the system performance is improving with refinement of the grid resolution, an increased resolution may sometimes, also, lead to a downgrade. To comment this counter-intuitive phenomena we would emphasize the irregular structure, variable spatial density of weather stations, and step-wise change of their locations (see Fig. 8).

2) Variation of Number of Stations: In Section III-B1, we considered the implicit dependence of the model performance on the number of weather stations and their locations by varying the grid resolution. In this section, we apply a more explicit approach to vary the amount of input data and consider the reduction of number of weather stations just by sequentially switching off some of them. Fig. 11 shows the selected 36 stations on the 12×12 grid, which are subject to switching off.

Figs. 12 and 13 show the dependence of burned and patrolled area, respectively, on the number of non-operating stations. Each of the figures shows five curves that correspond to alternative ways to fill the data gap arising from switching off a weather station. We consider the usage of weather data from a neighboring station (next to the right, next down, next right, and down—together further referred to as *neighboring cells*) as well as using minimum, maximum, and average fire danger

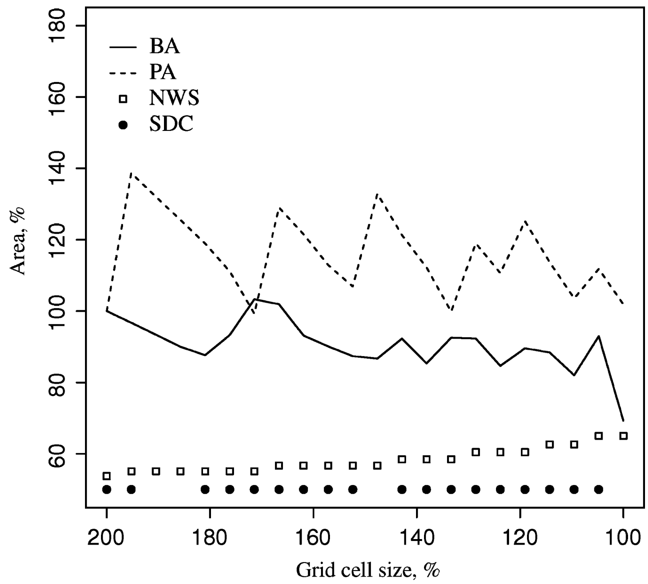

Fig. 10. Dependence of the burned (BA) and patrolled (PA) areas for cell size ranging from 200% to 100% of the original size. The total number of weather stations (NWS) is rescaled and the points when the disposition of weather stations changes (SDC) are shown.

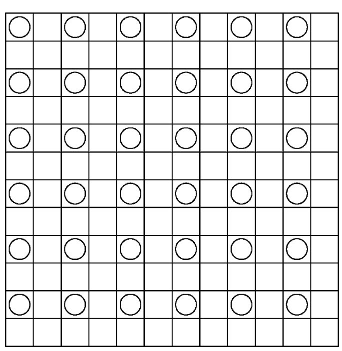

Fig. 11. Selected 36 stations on the 12×12 grid, which are subject to switching off.

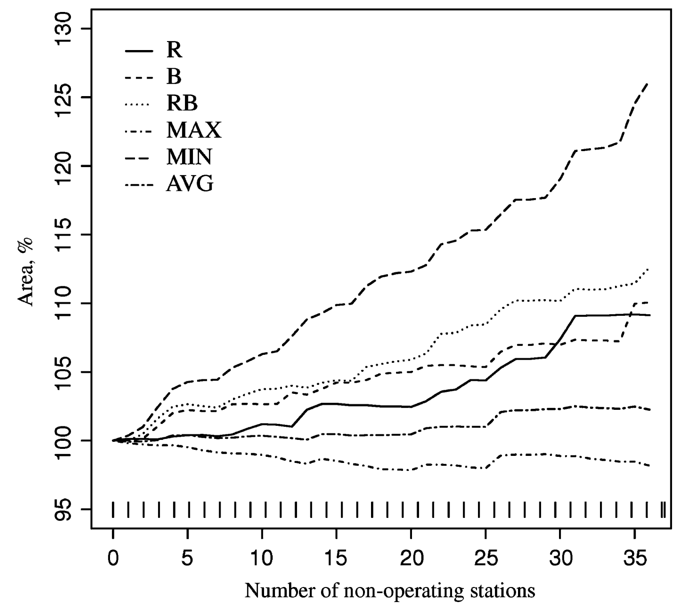

Fig. 12. Dependence of the burned area on the number of non-operating stations for selection of the neighboring substituting cell next to right (R), bottom (B), right-bottom (RB) to the non-operating cell, and based on maximum (MAX), minimum (MIN), and average (AVG) of Nesterov index.

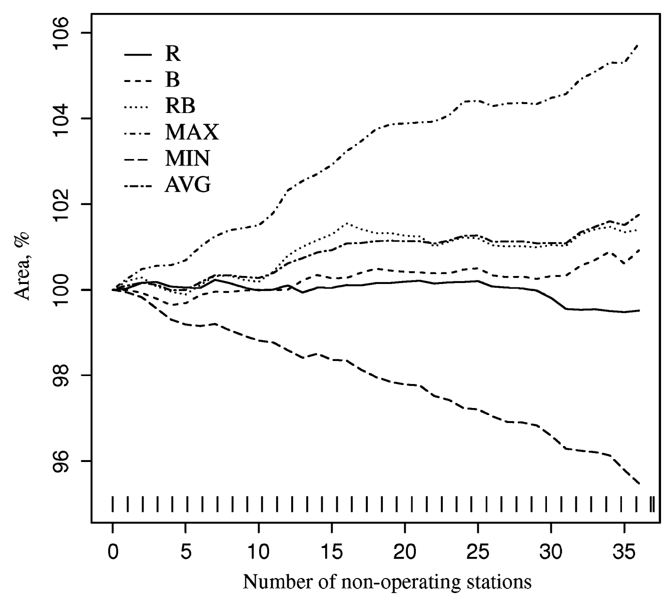

Fig. 13. Dependence of the patrolled area on the number of non-operating stations for selection of the neighboring substituting cell next to right (R), bottom (B), right-bottom (RB) to the non-operating cell, and based on maximum (MAX), minimum (MIN), and average (AVG) of Nesterov index.

index calculated for neighboring cells. Using the minimum of Nesterov index leads to the increase in burned area and decrease in patrolled area, while using the maximum of Nesterov index leads to decrease in burned area and increase in patrolled area.

3) Optimization of Stations' Locations: In addition to consideration of different grid resolutions of weather data and the value of individual weather stations for overall performance of the entire system discussed in Section III-B1 and III-B2 we proceed with the consideration of optimal locations of the stations. 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 burned area (or patrolled area) is maximal. The burned and patrolled areas are 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).

Fig. 14 illustrates the dependence of burned and patrolled areas on the number of weather stations located in cells with maximum burned area estimation. Fig. 15 illustrates the same for cells with maximum patrolled area estimation. 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

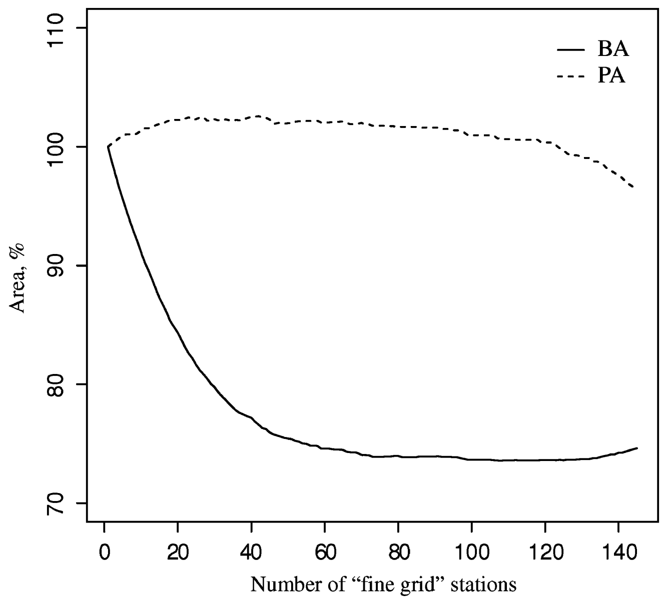

Fig. 14. Dependence of the burned (BA) and patrolled (PA) areas on the number of added weather stations. Minimization of burned area.

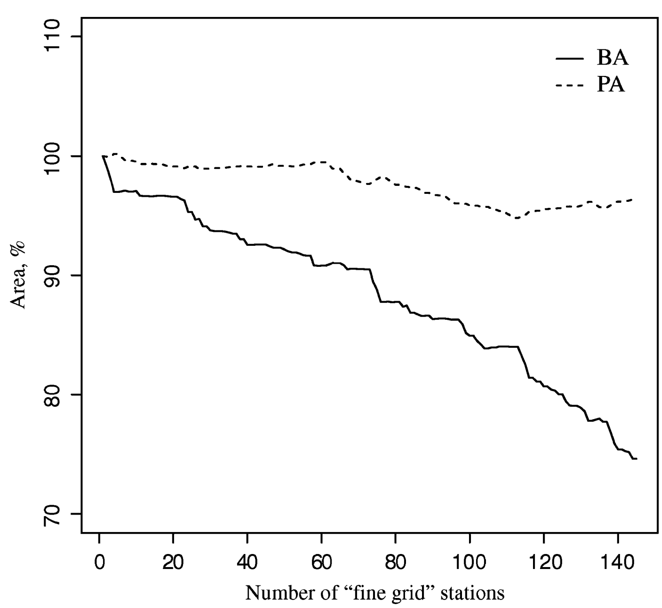

Fig. 15. Dependence of the burned (BA) and patrolled (PA) areas on the number of added weather stations. Minimization of patrolled area.

system. So Fig. 14 shows that 30 precise stations covering only 20% of the territory could provide an improvement of about 20% of initial burned area, that is nearly 75% of the improvement possible (by placing the weather stations everywhere). The optimal combination should take into account the tradeoff between the costs for improved information and possible losses caused by fire.

IV. Discussion and Conclusion

In this paper, we first presented a sketchy model of forest fire fighting to quantitatively assess burned areas and patrolling efforts. The simulation-based version of the model delivers more accurate results as to average values and provides useful information on distributions of important characteristics of fires. This approach allows us, also, to investigate correlations between key parameters, e.g., average Nesterov index and expected burned area. The stochastic approach promotes the inclusion of parameters such as wind speed and variable fire spread rate. However, in this case the simulations are rather computationally expensive, and this should be taken into account when building efficient models using large number of parameters.

In Section III-B, we analyzed the impact of data quality on the forest fires management model. However, for the purposes of generality, we did not specify the way the weather parameters are measured nor the sensitivity of these measurements to other factors. Some papers related to the analysis of remote observation systems performance, depending on measurement method and current measuring conditions, include [13]–[16] and have carried out this type of analysis.

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., [6]) or more sophisticated systems (e.g., Canadian FFWI, see [1]). The comparison of the sensitivity of different fire danger rating systems to the quality of weather data with the application to the model presented in this paper could be an interesting direction for further research.

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 and additional efforts to get the data, which are usually not freely available. Although the presented analysis is quite basic, we believe that the conclusions will still remain in force and that other indices would produce the results in the same direction, although not necessarily to the same extent.

In this paper, 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. Further research in this direction could contribute to the elaboration of procedures and data standards within national and global forest fire risk management systems, including fire danger rating and fire detection.

Our results show that an increase in quality of weather information generally leads to improved performance of fire fighting. However, in some cases, where an underlying data set has an irregular structure, the increased resolution may downgrade the performance of the system. This phenomenon may be considered as an important design issue for the forest fire risk management system.

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 (SoS) 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. Further research should be performed in order to evaluate the properties of a wider and more comprehensive SoS covering more socio-economic benefit areas of Global Earth Observations.

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REFERENCES

[1] C. E. Van Wagner, "Development and structure of the Canadian Forest Fire Weather Index System," Canadian Forestry Service, Ottawa, ON, Canada, Forestry Tech. Rep. 35, 1987.
[2] K. Satoh, S. Weiguo, and K. T. Yang, "A study of forest fire danger prediction system in Japan," *DEXA*, vol. 00, pp. 598–602, 2004.
[3] *Monitoring and Forecasting of Forest Fires. General Requirements* (in Russian), GOST R 22.1.09-99, The State Standard of Russian Federation, 1999.
[4] V. Nesterov, *Forest Fires and Methods of Fire Risk Determination* (in Russian). Moscow: Goslesbumizdat, 1949.
[5] S. Malevsky-Malevich, E. Molkentin, E. Nadyozhina, and O. Shklyarevich, "An assessment of potential change in wildfire activity in the Russian boreal forest zone induced by climate warming during the twenty-first century," *Climatic Change*, vol. 86, no. 3, pp. 463–474, 2008.
[6] G. Buchholz and D. Weidemann, "The use of simple fire danger rating systems as a tool for early warning in forestry," *Int. Forest Fire News*, no. 23, pp. 32–36, 2000.
[7] J. A. Goff and S. Gratch, "Low-pressure-properties of water from −160 to 212 F," *Trans. Amer. Soc. Heat. Ventilating Eng.*, vol. 52, pp. 95–122, 1946.
[8] A. Barenbrug, *Psychrometry and Psychrometric Charts*, 3rd ed. Cape Town: Chamber of Mines of South Africa, 1974.
[9] Federal Forestry Agency of the Ministry of Agriculture of the Russian Federation, Moscow, Russia, "Instructions for detection and fighting of forest fires (Part I). Order No. 100," (in Russian) Jun. 1999.
[10] 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.
[11] H. P. Telitsyn, *Lesnye Pozhary, Ich Preduprezhdenie I Bor'ba S Nimi V Khabarovskom Krae* (in Russian). Khabarovsk: DALNIILKH, 1988.
[12] P. Fiorucci, F. Gaetani, R. Minciardi, R. Sacil, and E. Trasforini, "Dynamic resource allocation for forest fire risk management," *DEXA*, vol. 00, pp. 603–607, 2004.
[13] M. Yebra, E. Chuvieco, and D. Riaño, "Estimation of live fuel moisture content from MODIS images for fire risk assessment," *Agricultural Forest Meteorology*, vol. 148, no. 4, pp. 523–536, 2008.
[14] P. Di Girolamo, A. Behrendt, C. Kiemle, V. Wulfmeyer, H. Bauer, D. Summa, A. Dörnbrack, and G. Ehret, "Simulation of satellite water vapour lidar measurements: Performance assessment under real atmospheric conditions," *Remote Sensing Environment*, vol. 112, no. 4, pp. 1552–1568, 2008.
[15] S. Saatchi, K. Halligan, D. G. Despain, and R. L. Crabtree, "Estimation of forest fuel load from radar remote sensing," *IEEE Trans. Geosci. Remote Sensing*, vol. 45, no. 6, pp. 1726–1740, Jun. 2007.
[16] R. Lasaponara and A. Lanorte, "Remotely sensed characterization of forest fuel types by using satellite ASTER data," *Int. J. Appl. Earth Observation Geoinform.*, vol. 9, no. 3, pp. 225–234, 2007.

Nikolay Khabarov studied applied mathematics and received the M.Sc. degree and the Ph.D. degree in mathematics with a specialization in optimal control theory from Moscow State University, Moscow, Russia, in 1998 and 2004, respectively.

In January 2007, he was a Research Scholar with the Forestry Program, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria, where he is currently involved in the GEO-BENE Project (www.geo-bene.eu). He conducts research in the fields of control theory, optimization, and mathematical modeling.

Elena Moltchanova received the M.Sc. degree in statistics from the University of Helsinki, Helsinki, Finland, in 2000, and the Ph.D. degree in statistics from the University of Jyväskylä, Jyväskylä, Finland, in 2005.

In 1999–2004, she worked in the area of diabetes and heart disease with the Department of Epidemiology of Non-Contagious Diseases, National Public Health Institute (NPHI), Helsinki, Finland. In 2001, she joined the Young Scientists Summer Program, International Institute for Applied System Analysis (IIASA), Laxenburg, Austria. She returned to IIASA in summer 2002. In 2004–2006, she worked as a Research Scholar at IIASA for Forestry Program. Since 2006, she has been working at NPHI on statistical modeling of health-related phenomena. She conducts research in decision theory, epidemiology, and Bayesian spatio-temporal modeling.

Dr. Moltchanova was a recipient of the Mikhalevich Award.

Michael Obersteiner studied forestry and economics and received the M.Sc. degree in forestry and the Ph.D. degree in forestry from the University of Natural Resources and Applied Life Sciences (BOKU), Vienna, Austria, in 1994 and 1996, respectively, the M.Sc. degree in economics from the Institute for Advanced Studies, Vienna, Austria, in 1996.

Since 1993, he has been working as a Research Scholar for Forestry Program, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria. He currently coordinates the EU funded GEO-BENE Project (www.geo-bene.eu). He conducts research in multiple fields, including economic analysis, integrated land use modeling, and assessment of management of biophysical systems.