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A Spatio-Temporal Bayesian Network for Adaptive Risk Management in Territorial Emergency Response Operations

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1. Introduction

In this Chapter we intend to show that Bayesian Networks may act as an excellent Decision Support System (DSS), even when very complex risk scenarios must be evaluated in real time.

The complexity of the specific application described derives not only from risk variability depending on spatial and temporal domains, but also from the high number of variables involved.

Forest Fire Management is a tough task for emergency squads, because they are called on to take decisions very quickly and control vast territorial areas. In addition, the behaviour of fire is strongly dependent on weather and soil conditions, and is hence difficult to predict in a short time through the concurrent implementation of consolidated analytical models.

For this reason the availability of a Bayesian model is the only solution capable of allowing emergency squads to exploit the backward propagation of Bayesian networks and perform real-time diagnoses. In other words, once the user sets the desired state for the output variable(s), the network is able to work out the most likely state values for the corresponding input, thereby helping to discern how to act optimally in order to control the spread of fire. The same tool may also be used for scenario analyses.

The main problems tackled in this chapter are connected with the spatio-temporal nature of the spread of forest fire and with the complexity caused by the great number of time slices involved, which are proportional to the duration of the phenomenon.

The suggested solution is to model the spatial features through the use of Object Oriented Bayesian Networks, where every elementary territorial area is mapped over one of the elementary pieces of the whole network. To that end, the evolution of phenomena over time was modelled through the approach known as Dynamic Bayesian Networks: the time step to complete any passage from one network to another is dictated by the time it takes for the fire to burn down any elementary territorial area and to move into any of the others. Due to the unknown number of needed time steps (because it is not known *a priori* how long any fire will last), the whole model was developed as a combination of dynamic networks and

VBA programmed tools. Programming was mainly needed to cope with the great number of variables involved and to find a computationally acceptable approach to spatio-temporal simulation, when there is no pre-determined limitation on the timeline.

The next paragraph will give some insight into the state-of-the-art regarding spatio-temporal Bayesian modelling, forest fire risk management and available techniques for CPT learning.

The third paragraph supplies the basic technical concepts, relative to forest fires (e.g. ranking, qualitative behaviour, variables involved in the phenomenon, analytical models presently used for their simulation etc..), which are relevant for the development of the desired Bayesian model.

The same paragraph also addresses how to build the graphical model, as well as how to estimate the quantitative strength of the connections between variables expressed as conditional probability distributions, how to translate the dynamic nature of the physical phenomenon into Bayesian formalism and how to overcome the barrier of NP-hard complexity for problems of this kind.

The fourth paragraph implements the quantitative part of the final model, including CPT estimation.

The fifth paragraph of this chapter shows how the Bayesian model developed in the previous parts can be translated into Visual Basic programme language and then interfaced with a Graphic User Interface (GUI). Finally, a validation of the whole model applied to a real case study in the forest of the Esino-Frasassi (Ancona, Italy) mountainous district will be proposed.

2. Scientific background

Bayesian Networks have been extensively celebrated for their unique capability to provide, at the same time, both intuitive and scientifically rigorous representations of complex systems. In addition, after validation, they can be used for performing both scenario analyses, through inference propogation algorithms, and diagnostic reasoning, through backward propagation based on the well known inversion rule (Pearl, 1988).

These networks also have the advantage of enabling qualitative and explicit representation, where nodes represent variables and arcs represent quantitative relationships among the same, worked out through parametric probabilistic models. We invite readers to refer to the numerous and well written reference texts available on the subject, such as (Korb & Nicholson, 2004; Jensen, 1996), for basic rules about how to develop robust models. In the rest of this paragraph we prefer to go into detail regarding spatio-temporal Bayesian networks and the Conditional Probability Table (CPT) estimation procedures used in the application presented here.

When the domains to be modelled are very complex, Object Oriented Bayesian Networks (OOBN) are usually used: they are made up of several elementary networks, sharing some of the variables, which constitute the links between the networks (Naticchia et al., 2007). Each elementary network is generally developed separately (and models one of the many physical phenomena involved) but the inference algorithms are propagated over the whole set of elementary networks.

A straightforward extension of this approach is given by Dynamic Bayesian Networks (DBN): these are based on a discretized time course and are made up of several time slices, each representing the state of the system at a particular moment in time. In this case, some of the variables have no fixed states, but change over time. Therefore connections hold not only between those variables linked by a causal relationship but also between the same variables represented in different time slices, because this takes into account their variability as time elapses.

These concepts are better explained in 2.1, which reports the algorithms used to implement CPTs in the networks developed for the Bayesian model for forest fire risk management.

Finally, paragraph 2.2 gives a brief survey of the procedures currently adopted to cope with forest fire risk management and the approaches used for operations in the event of emergencies.

2.1 Spatio-temporal Bayesian modelling

Spatial Bayesian Networks (SBN) are BNs that represent data regarding spatial domains and Spatial Dynamic Bayesian Networks (SDBN) are BNs that represent spatio-temporal data, that is spatial status changes over time. The application of BNs to model the evolution of processes that have temporal dynamics requires, in its simplest formulation (Neapolitan, 2004):

- an initial instance of the Bayesian network that contains the formulation of the problem at time t=0, that is the set of random variables $X_{i,0}$ and the related conditional probability distributions: $P(X_{i,0} | X_{i-1,0})$, $P(X_{i-1,0} | X_{i-2,0})$, etc.;
- one or more transition networks that correlate the variables of the BN instance at t=0 with the variables of the BN instance at t=1.

Fig. 1 shows a graphical representation of three time slices of a DBN.

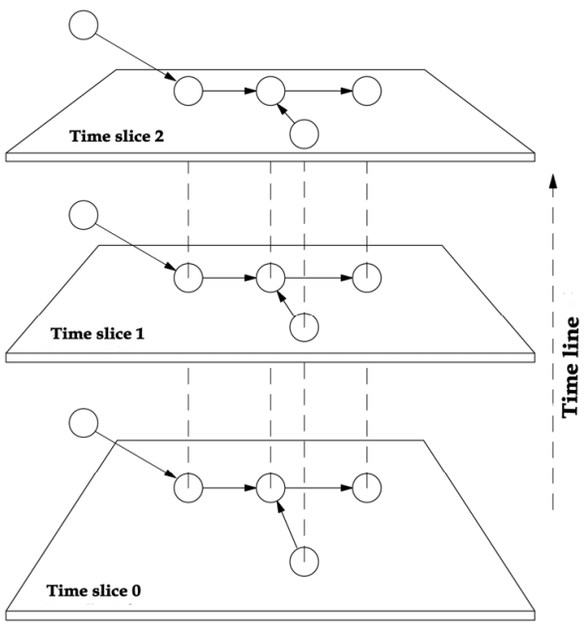


Fig. 1. Graphical representation of a Dynamic Bayesian Network: it is made up of three instances of the same BN. Yellow dashed lines represent the transition network. The evidence variables are represented by the nodes placed outside the time plane.

Two simplifying assumptions can usually be made about the physical processes at hand:

- all the information needed to predict the state of the process at time t+1 is contained in the description of the process state at time t. No information about earlier time is needed. These kinds of processes are called Markov processes of order one;
- the process is steady, that is, the transition networks remain the same for any $t_i \rightarrow t_{i+1}$.

The representation of the spatial evolution of a dynamic process by means of SBNs requires, above all, the domain space to be tessellated in such a way that each tessera represents a portion of the space with uniform behaviour. We will call this portion of space a cell. If the overall domain space is relatively uniform, different instances of the same type of BN can be used to represent different cells. In our case for example, the whole territory is covered by different types of fuel loading (e.g. grass, conifer trees etc.) which have essentially the same fire dynamics. Therefore each cell is represented by means of a different instance of the same BN. Each instance is then specialised for its fuel-loading type by means of a set of parameters that are modelled as evidence variables. Secondly, in order to grant the spatial continuity of the process evolution, the transition network must involve only neighbour cells. In our case this means, for example, that a cell cannot be ignited if neither of its neigbours is (please refere to Fig. 2).

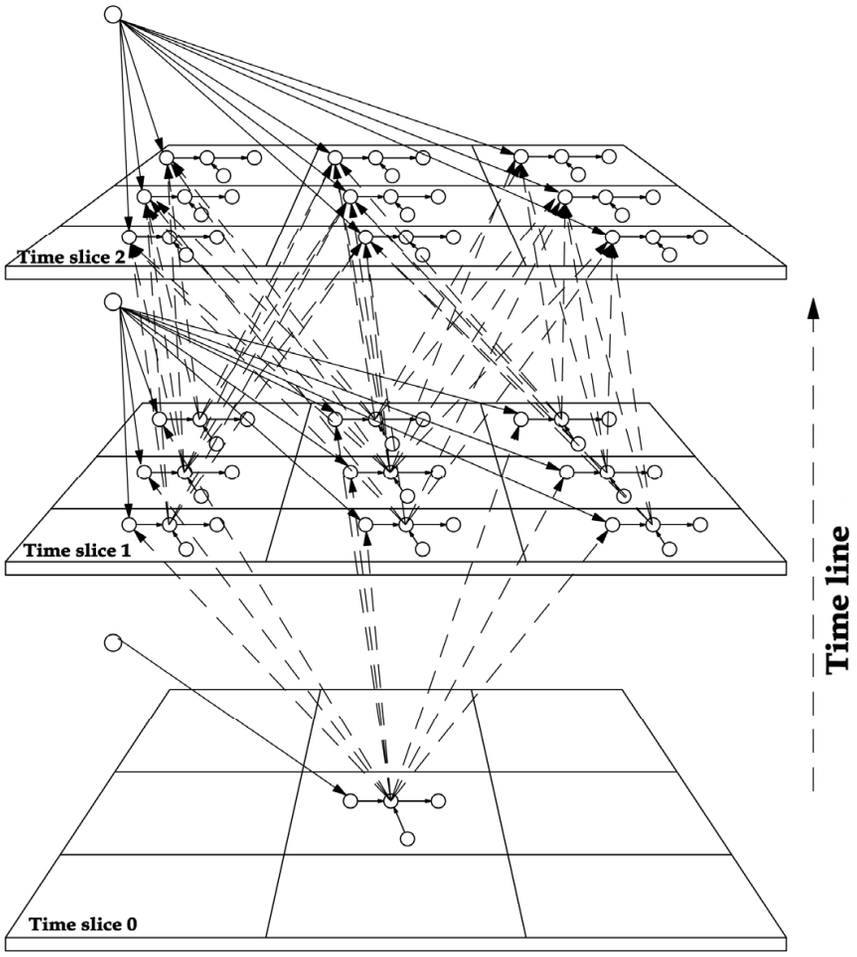


Fig. 2. Graphical representation of a Spatial Dynamic Bayesian Network, where the DBN is made up of three instances of the same BN. Dashed lines represent the transition network.

The evidence variables are represented by the nodes placed outside the time plane. Due to the space continuity assumption, transitions between different time slices occur only through neighbour cells.

Modelling spatio-temporal processes through SDBNs does not differ in principle from the standard methods of BN modelling, therefore it requires the definition of the cell structure, of the transition network structure and the implementation of the CPTs. The methodologies for direct implementation of network structures (both cells and transition) through domain knowledge modelling, using for example techniques like parent divorcing, temporal transformations, unidirected dependence relations, etc. (Kjaerulff & Madsen, 2008), are still applicable, as well as Data-Driven Modelling, like PC and NPC algorithms.

The problem arising with SDBN implementation is mostly related to complexity. Data-driven structure identification of SBDN is usually hindered by the great number of available options. Some algorithms are currently being developed to drive the optimal structure selection (Tucker & Liu, 2004).

In the case of a large SBDN, standard procedures suggest a two step approach: first learning the structure of the cell network, and then, after constraining the identified cell structure, learning the transition network. This usually helps in keeping the complexity to a manageable level.

EM algorithms provide batch CPT parameters for learning capabilities from data. If data are not available direct implementation of CPTs from domain data is the other option. In our case we found the application of a simple Montecarlo simulation tool very useful; this is implemented in many commercial BN packages, that are able, through a Montecarlo simulation, to map an analytical equation onto CPT involving random variables with numerical interval domains (Hugin Expert, 2008).

A final remark should be made to highlight the computational complexity of SDBN. Probabilistic inference in an SDBN can be performed using standard algorithms. However, since the size of an SDBN can become enormous when the simulation continues for a long time and when the domain is large, the algorithms may be quite inefficient and/or the network footprint in the computer memory may become impractical. There is a special subclass of SDBNs in which inference can be carried out more efficiently. This subclass includes BN in which the cell networks in different time steps are connected only through non-evidence variables. In that case, to update the probability of the current time step, we need only the values computed in the previous time step and the evidence at the current time step. This means that it is possible to implement an algorithm that keeps only the bare minimum network structure needed in order to represent two time steps (Neapolitan, 2004). In our case, excluding the cell "woodtype" and the "environmental" and "weather" variables from the transition network allowed us to implement an algorithm, as described in section 5, that inherited this necessary property.

2.2 Forest fire risk management

(Luke & McArthur, 1978) performed a lot of analyses regarding the spread of the fire frontline because this is affected by several parameters, such as environmental temperature, brush, topography and so on, which will be further detailed in paragraph 3.

Forest fires are usually ranked according to their types and are described according to evolution phases. (Brown & Davis, 1973) name the three basic types of fires according to the vegetation layer in which the fire is burning, that is ground, surface and crown fire:

- Ground fires: they spread in subsurface organic fuels, such as duff layers under forest stands, Arctic tundra or taiga, and the organic soils of swamps or bogs;
- Surface fires: they spread by flaming combustion through fuels on or near the surface – grass, shrubs, dead and downed limbs, forest needle and leaf litter, or debris from harvesting or land clearing;
- Crown fires: they burn through the tree crowns, they are often dependent on surface fires and are invariably ignited by surface fires.

The phenomenon generally evolves according to four burning phases:

- Initial build-up: when the fire's intensity, even if capable of keeping itself alive, is not capable of raising the temperature of the fuel, producing weak burning which is faster over earth covered with grass and low trees, than in high-tree forests;
- Transition stage: the fire frontline has increased to such an extent that it is able to dry the fuel (e.g. underwood and trees) and favour the spread, of fire also due to the flame angle and height which is affected by winds;
- Final stage: when the fire reaches its maximum intensity and strength, generating spotting phenomena, setting a balance with the external climate; in this phase external factors are less liable to influence the spread of fire which goes ahead autonomously;
- Extinction stage: the intensity of the fire decreases and its behaviour is newly determined by external factors (environmental and of the context in general), until extinction.

The measuring of intensity is of basic importance and one of the meaningful ranking approaches is known as Byram intensity (I), i.e. the product between the amount of heat generated per metre and the fire frontline propagation speed:

$$I = 0.007 \cdot H \cdot W \cdot R \tag{1}$$

where H is a parameter called heat of ignition (cal/g), W is the fuel weight per unit of surface (t/ha) and R is the propagation speed (m/min).

The greater the energy per unit of surface that is released by the fire, the greater is the damage caused to vegetation. However the frontline speed is another factor strongly affecting the difficulty involved in fighting the frontline. (Andrews & Rothermel, 1982) have worked out the "Fire Behaviour Characteristics Chart", where propagation speed is proposed as a function of the heat released per unit of frontline length and flame intensity per unit of surface (Fig. 3-a).

Of course there are a number of factors to be evaluated in order to determine the best counteraction for the spread of fire during emergency operations. Experts' decisions are generally based on a consolidated knowledge of the forest and on the symptoms indicating how the fire is behaving. One example is "blow-up", which is any quick evolution from transition to the final stage, suggesting that the fire will be very intense and generally caused by a mixture of high speed and intensity, feeding each other. Data about the humidity content of the fuel, topography and weather forecast are also of great help in

supporting decisions (Scott & Burgan, 2005). A typical phenomenon encountered in high intense fire frontlines is known as spotting: organic matter is thrown into the air and floats as a result of the convective movement caused by the fire's intensity, until the wind scatters it and causes other fires to be triggered in the forest.

(a) (b)

Fig. 3. Fire Behaviour Characteristics Chart (a) and one example of preventive action (b)

All these and many more data must be evaluated when planning defensive action against the spread of fire. The general approach is to simulate fire behaviour (speed and intensity during propagation) under several boundary conditions, in order to design remedial action. The manager of emergency squads then evaluates the available input and decides on the best action to take. The availability of accurate simulators is critical during the early phase in the spread of fire because emergency action should be taken at this stage, before the fire burns up. Some of the most widely used simulators are: FOCUS™ (Fire Operational Characteristics Using Simulation), and FIRESCOPE™ (Fire-fighting Resources of Southern California Organized for Potential Emergencies). They are based on fire spread models like the ones described in the next paragraph and they drive the choice for the preventive or active response, to be adopted when the fire is burning.

The most usual preventive action is aimed at diminishing the amount of fuel available for feeding the fire (Brown & Davis, 1973): fuel is removed in specific areas, sometimes along strips of forest, or roads may be built in order to impede ignition or break the spread of the fire in the early phases (Fig. 3-b). However the efficiency of this type of response is limited when fires are very intense, hence active means are needed. The same authors also suggest drawing forest maps, where all the parameters are graphically represented and using them as reference for fire management.

Active means are ranked according to direct or indirect action: the former requires water or chemical products to throw over the fire, while the latter tries to clean the areas along the boundaries of the fire frontlines so as to hamper spreading.

It is clear that in any case, for both preventive action and active response, it is necessary to forecast how fires will behave.

The strategy suggested in this paper, and feasible once dedicated spatio-temporal Bayesian Networks are available, is to build an expert system containing the knowledge deriving from various fire models, which can support decision processes during emergency management.

3. Translating forest fire behaviour into a Bayesian Network

The Bayesian model was developed in five steps:

1. preliminary general analysis of the problems and their implications;
2. break-down of the problems into several elementary models, which have been translated into elementary networks, to be connected later;
3. estimation of the quantitative relationships among the variables of each elementary network, starting from the availability of data and equations;
4. enhancement of the basic model into the final dynamic network made up of several time slices and its implementation into a VBA-based software tool;
5. validation of the final interconnected networks in a real scenario.

The basic Bayesian network developed for this application was intended as a snapshot, modelling what happens at a certain time in a pre-determined spatial cell. It has already been represented in Fig. 2, where square cells subdivide all the territory covered by the forest. The output variables estimated by the model and useful for forecasting where and how the fire will spread are the frontline speed, its direction and intensity. On the basis of these variables, it is possible to make an estimation of the moment in time when the cells will be completely burnt down and the fire will propagate towards one of the adjacent cells.

The input needed by the network may be divided into two categories, the first related to climatic variables:

- air temperature;
- wind intensity and direction;
- air humidity level;

and the second related to territorial features:

- forest type;
- forest wood maturity;
- ground slope;
- site or cell orientation.

It should be noticed that some of the input data may be collected directly by sensor measurements, because they are unsteady variables; while other data may be directly supplied by a GIS system.

3.1 Fire spread modelling

Fig. 4 shows the whole structure of one elementary network resembling the system logic underlying the whole phenomena and analysed thanks to the support of Rothermel's surface fire spread models.

Starting from the work by (Rothermel, 1972), the surface spread models that he developed were simplified by (Scott & Burgan, 2005): the new set was conceived so as to simulate only surface fire behaviour at the flame front, but not the residual combustion that takes place after the flame front has passed. These sets were drawn up starting from empirical observations, fire behaviour simulations over a range of midflame wind speeds and several moisture scenarios, hence several environmental conditions were taken into consideration. Dotted lines connecting solid filled circles (adjacent to some of the variables) in Fig. 4 mark those nodes to be merged at the final release of the whole network.

Among the fuel models proposed by the cited authors, eight have been used in the application developed in this Chapter (Fig. 5). Their naming follows a well-known rule: NB means non-burnable, GR means grass, GS stands for grass-shrub, SH for shrub, TU is timber-understory, TL for timber litter and SB is the abbreviation for slash-blowdown.

The following factors are listed for each forest type: the fuel loading available, extinction humidity values, relationships between midflame wind speed, rate of spread and flame length.

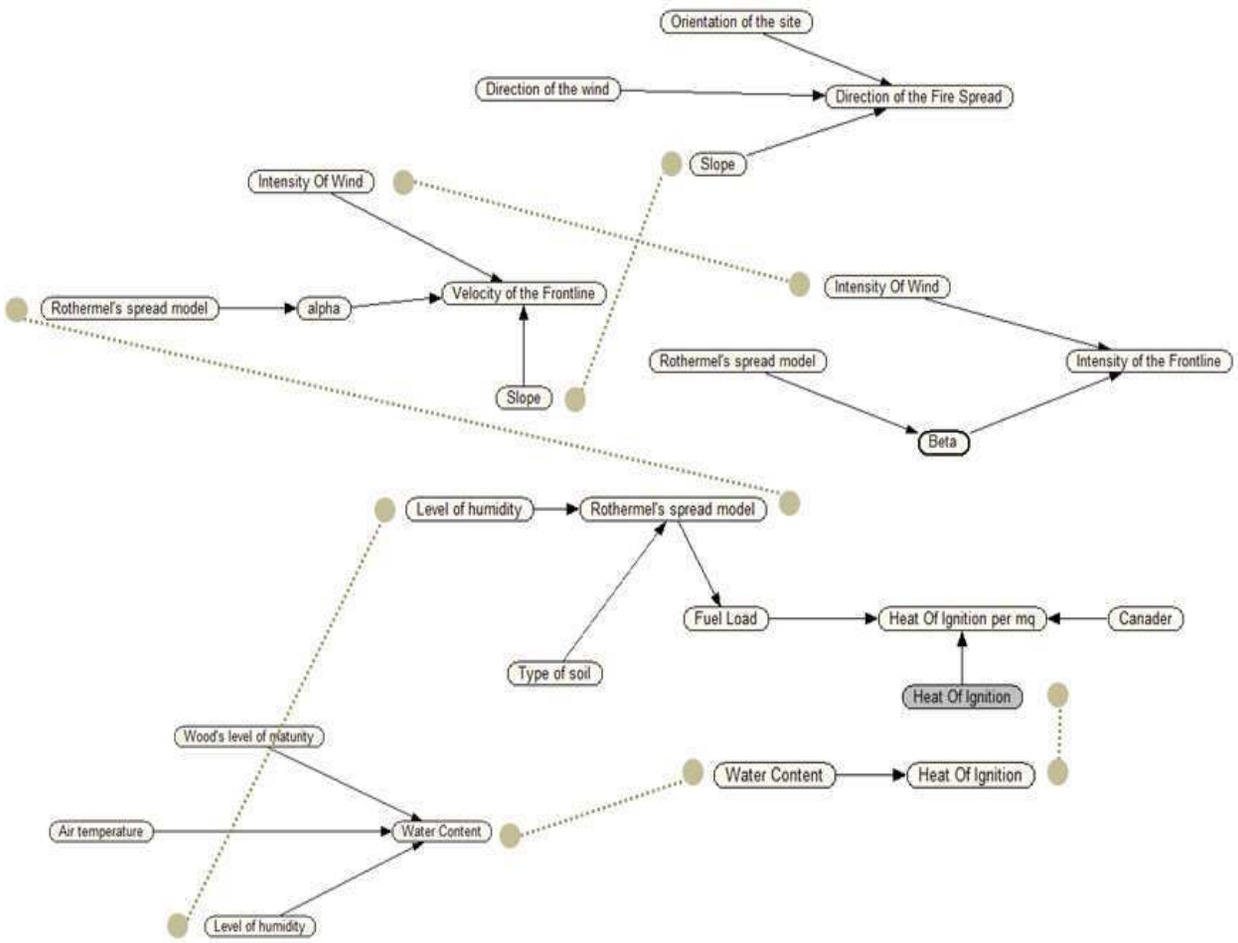
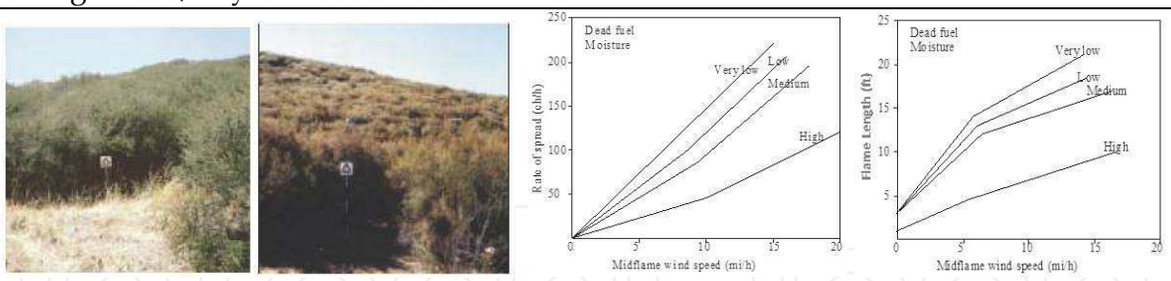


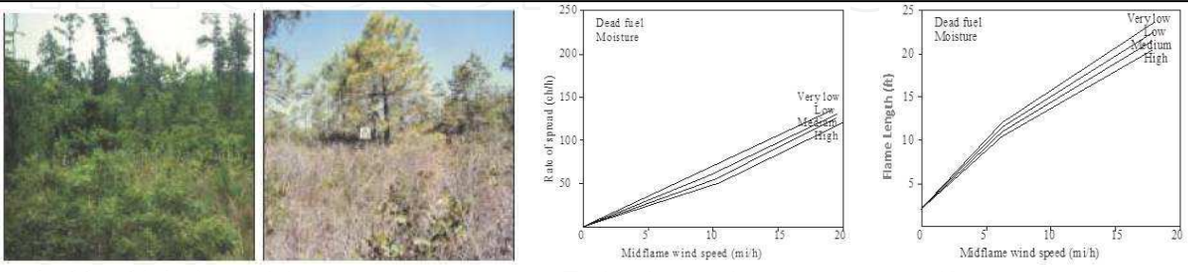
Fig. 4. Logic framework of the spatial cell of the Spatio-temporal Bayesian model

SH5: High Load, Dry Climate Shrub



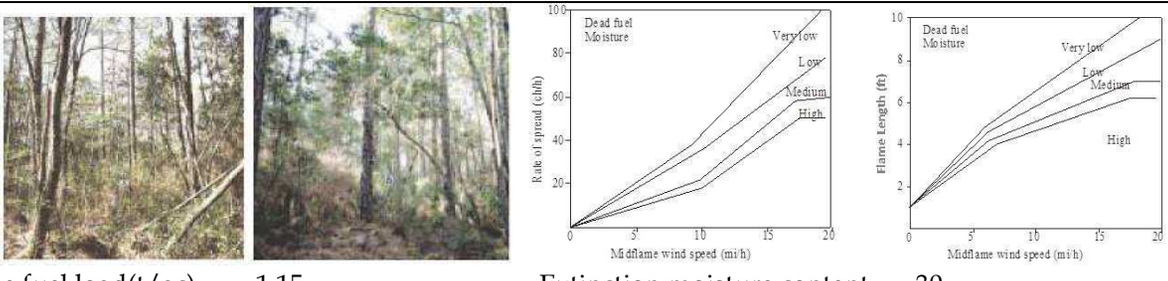
Fine fuel load(t/ac) 6.5 Extinction moisture content 15

SH8: High Load, Humid Climate Shrub



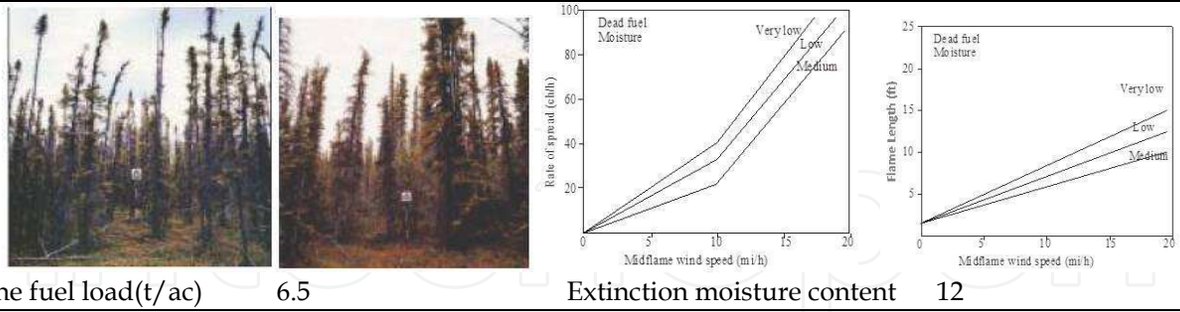
Fine fuel load(t/ac) 6.4 Extinction moisture content 40

TU2: Moderate Load, Humid Climate Timber-Shrub



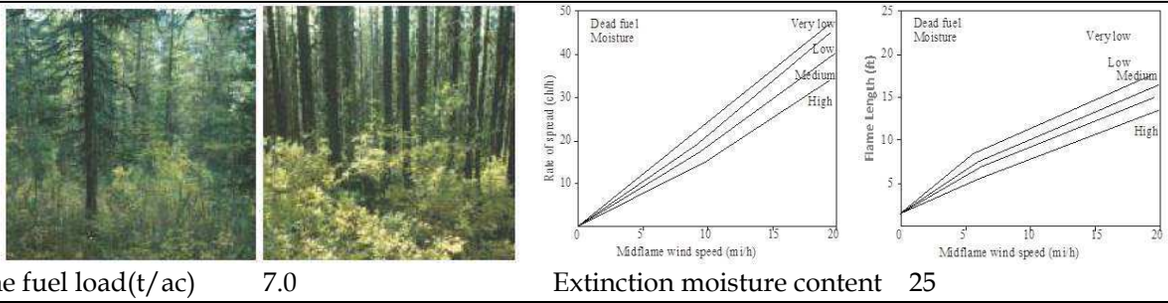
Fine fuel load(t/ac) 1.15 Extinction moisture content 30

TU4: Dwarf Conifer With Understory



Fine fuel load(t/ac) 6.5 Extinction moisture content 12

TU5: Very High Load, Dry Climate Timber-Shrub



Fine fuel load(t/ac) 7.0 Extinction moisture content 25

TL6: Moderate Load Broadleaf Litter

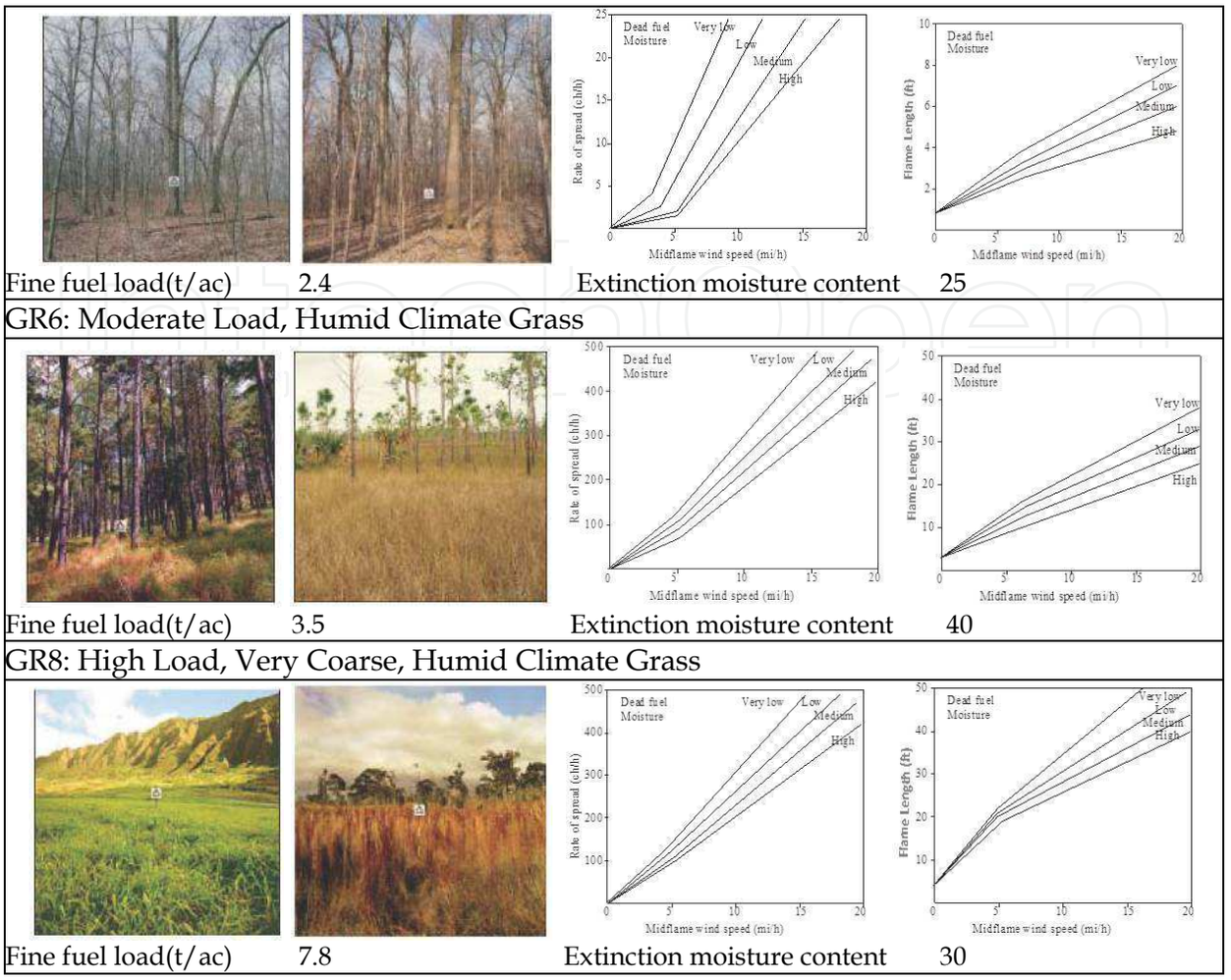


Fig. 5. Rothermel's models

Besides the aforedescribed models, other important analytical relations are those regarding the heat of ignition: this is the amount of heat which has to be released by the burning process so that the fire is not extinguished. It is strongly affected by the water content (hampering the process) and other parameters. However water content has been demonstrated to be the most important variable (it is tens or hundreds of times more important than other variables such as the initial temperature of the fuel), hence it is usually approximated as (Frandsen, 1972; Wilson, 1980):

$$Q_{ig} = 119.74 + 5.34 \cdot M_f \tag{2}$$

Where M_f is the percentage of water contained in the fuel loading, and is listed according to the type of ground. Such a variable directly affects the heat of ignition per unit of surface (measured in kJ/mq), which is the product:

$$Q_{ig,us} = Q_{ig} \cdot \text{fuel\_loading} \tag{3}$$

Fuel loading is dependent on Rothermel's surface fire spread models applicable to the type of ground, which are repeated for convenience: SH5, SH8, TU2, TU4, TU5, TL6, GR6, GR8. Hence the network will select all the right values, once the users have chosen the forest type under analysis.

Flame intensity is suggested by the same authors as the following expression:

$$I_f = 273 \cdot (2 + \text{Wind\_intensity} \cdot \text{Beta})^{2.17} \quad (4)$$

where I_f is the flame length, which the models always report as dependent on wind intensity, "beta" is the slope of the linear model best approximating the average behaviour (see right diagrams in Fig. 5).

Frontline flame speed is given by:

$$S_f = \text{Alfa} \cdot \text{Wind\_intensity} + 12 \cdot (\text{Slope}/100)^2 \quad (5)$$

where "alfa" is the slope of the linear relationship best approximating fire behaviour (see left diagrams in Fig. 5).

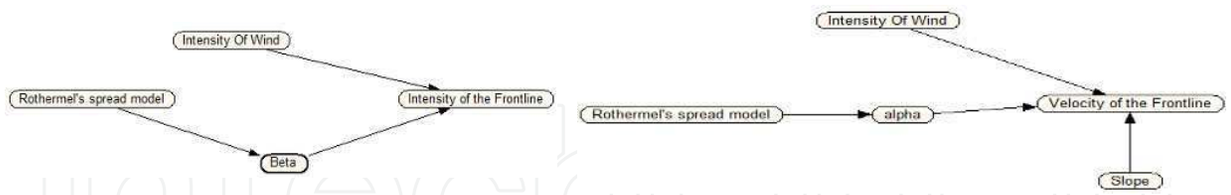
Given the chance to perform active fighting against fire propagation, in this model the use of Canadairs has been considered and modelled with the data available in literature. It is supposed that water sprayed over fires increases the heat of ignition by the amount needed to completely evaporate the water, computed using the following expression:

$$Q_{ig} = 116 \cdot 1.055 \cdot M_r \quad (6)$$

where M_r is the amount of water falling on the ground. In order to give some practical tips, the Canadair model CL125 sprays a water strip as large as 20 x 85 = 1700 m² and ensures 3.20 l/m² on the ground.

3.2 Methodology for the development of the qualitative Bayesian model

The qualitative interpretation of the equations presented in the previous paragraph allowed us to build all the fragments of the network. More information about this will be given in 4.1.



(a) (b)

Fig. 6. Bayesian network fragments relative to intensity and speed of the fire surface modelling

The fragments in Fig. 6 derive from equations 4 and 5.

Fig. 7-a pictures the fragment of the Bayesian network which estimates the fire surface spread direction. Empirical studies showed that this is related to wind direction, exposure and ground slope. Of course, when the slope and wind speed push the fire in opposite directions, spread is hampered.

The heat of ignition was derived directly from eq. (2), where its dependence on water content is clearly expressed (Fig. 7-b).

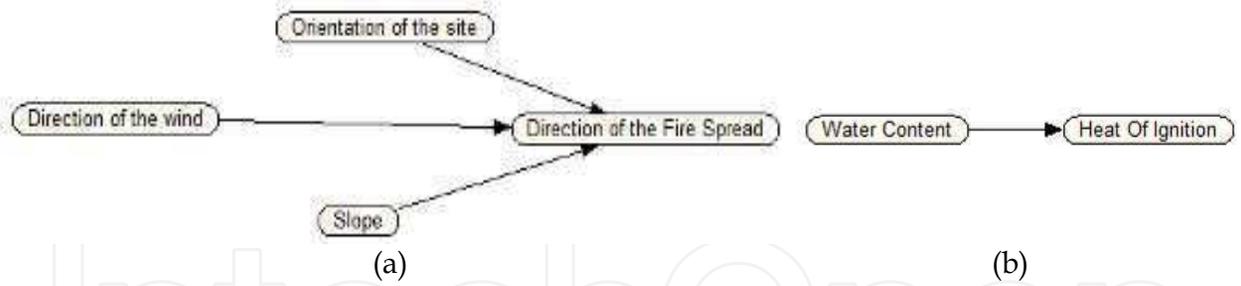


Fig. 7. Fragments relative to fire surface spread direction and heat of ignition

This last variable has repercussions on the heat of ignition per unit of surface, which is also dependent on fuel loading, as in eq. (3). By also adding Rothermel's fire surface spread models mentioned in 3.1 to this fragment, it is possible to obtain the fragment in Fig. 8:

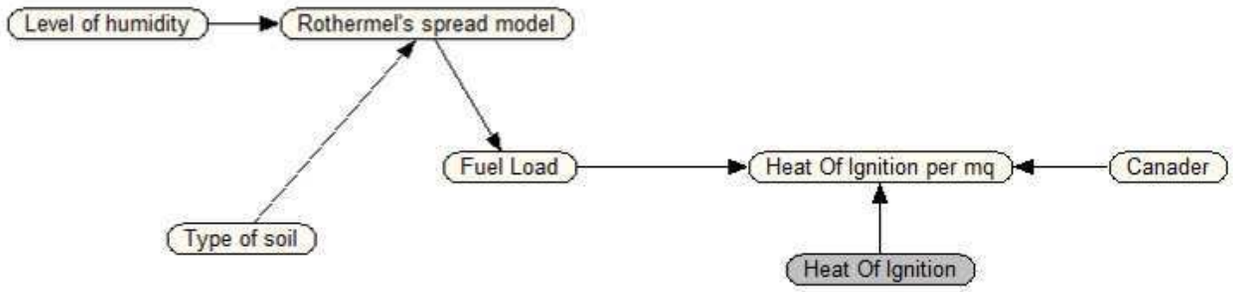


Fig. 8. Fragments relative to heat of ignition per unit of surface

This part of the model is also able to consider the possibility of active intervention through Canadairs, which would be useful to increase the heat of ignition and make the spread of fire less likely.

As a final integration to the proposed Bayesian networks, water content was considered dependent on other weather variables, which may be measured in real-time by sensors to speed up the process in emergency situations (Fig. 9).

At this stage, all the variables shared among different fragments were merged into the same variable to provide the whole final network properly instantiated (Fig. 4).

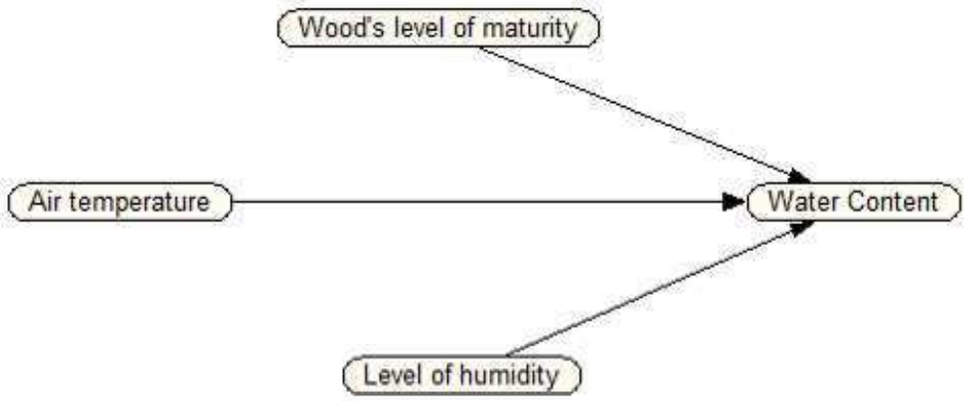


Fig. 9. Water content as a function of environmental variables

4. Model development

In this chapter we will first present the implementation of the quantitative relationships among the variables of a single cell of the whole Bayesian model. Spatial and temporal dynamics will then be introduced to produce the final model.

4.1 Implementation of quantitative relationships

The qualitative structure of the Bayesian model relative to a single spatial cell and described in paragraph 3 was integrated with the quantitative network through the use of several kinds of information. They may be roughly subdivided into two main groups:

- elementary cell networks whose CPTs have been derived directly from the observations of the available models and their translation into probability laws;
- analytical relationships explicitly available for all the networks, which have been translated into CPTs through the approach described in paragraph 2.1 (Hugin Expert, 2008).

In both cases a discretization process was carried out in an iterative way: starting from variables with a low number of states, their discretization was continuously refined until the data they provided were comparable to the numerical results obtained by running the Farsite™ software code, appropriately chosen for validation. All the elementary networks were developed in an Agena Risk™ environment.

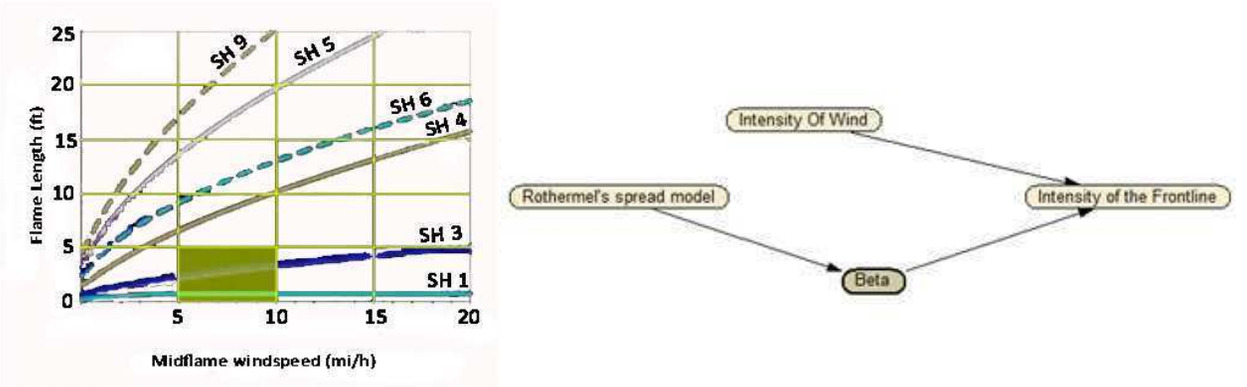
In order to explain better, two examples are reported here. Figure 10 shows the fragment of cell Bayesian networks, regarding heat of ignition, dependent on water content according to equation (2) and resembling the qualitative fragment shown in figure 7-b.

Fig. 10. Quantitative relationships among the variables

Once the discretization of the two variables has been accomplished and the analytical relationship has been inserted in the CPTs, the software computes the quantitative relationships as shown in the picture. Fig. 10-b and 10-c also show the discretization chosen for the variables and the analytical relationship inserted between the two in order to estimate the CPTs.

On the contrary, Fig. 11 represents a typical case in which conditional probabilities have been inserted directly from the reading of Rothermel's models. A direct reading of these data, as depicted in Fig. 11-a, is capable of estimating dependent variables starting from the reading of the independent ones. In this case once the type of soil is known (as in Fig. 8) the most fitting Rothermel's model can be selected and then the flame length or intensity or fuel

load can be worked out. These data have been translated into CPTs of the network fragment in Fig. 11-b by selecting the state of the dependent variable following from the known state of the independent ones. Validation was carried out as in the previous case.



(a) (b)

Fig. 11. CPT evaluation using Rothermel's models

4.2 The control of spatial and temporal dynamics

The interpretation of a complex dynamic process, like fire propagation through woodlands, requires careful modelling of the spatio-temporal dynamics. In section 2.1 we have seen that the implementation of SDBN entails the discretization of both the spatial and the temporal variables. According to Niquist's theorem, the value of the discretization rates must be greater than twice the maximum frequency of variability of the phenomena in the spatial and in the temporal dimensions respectively. In the complex transition model shown in Fig. 2, this means that the time difference ΔT between two time slices must be less than half the propagation time of the fire inside a cell. This in turn depends, among other things, on the dimension of the cell itself, as we have seen in the previous section. Therefore in our case the spatial and the time sampling rates are strictly connected. External influencing factors, like the meteorological variables, must also be taken into account. Within each time slice the phenomena occurring are considered instantaneous. Therefore the external influencing factors are considered as constants in a single time slice, and changes can occur only between two different time slices. Hence the maximum frequency of variation in the external influencing phenomena must also be considered when defining the time discretization. As a general rule the time discretization must be the minimum between the fire propagation and the external meteorological dynamics.

The propagation time of fire inside a cell is worth further comment. As we have seen, the simulation of fire propogation must consider the time delay that occurs between the fire triggering in one cell and its propagation to the adjacent cells. This depends on many factors. For the sake of simplicity we assume that fire triggering heat is instantaneous. In this case the flame front reaches the next cells after a time delay that depends only on the cell dimensions and the speed of fire propagation. The speed of fire propagation depends, in turn, on the forest types which combine the speeds of both the low level grazing flames in the underwood and the high foliage flames. Therefore the use of forest type models avoided the implementation of layered networks, one for each fire type (please ref. to section 2.2), considerably simplifying the model. In conclusion, modelling the fire propagation temporal

dynamics required the development of a specific subnetwork of the cell network that implements fire propagation tracking. This subnetwork is represented in Fig. 12 (the black node being inferred from the cell's network at each time slice as in Fig. 4).

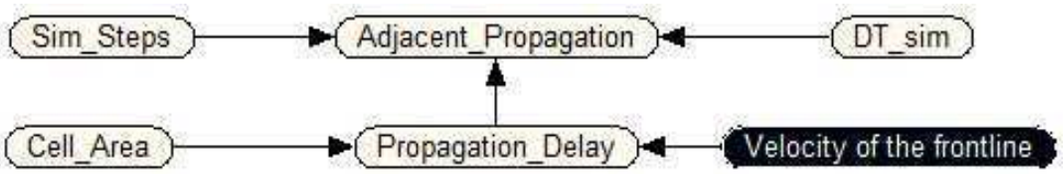


Fig. 12. Cell subnetwork implementing fire propagation control.

The subnetwork includes the following variables:

- *DT_sim:* is the simulation frequency, which is an evidence variable observed at the beginning of the simulation in seconds;
- *Sim_Steps*: is the number of simulation cycles, that is the number of time steps that have occurred from the beginning of the simulation step. The product of DT_sim and *Sim_Steps* gives the simulation time elapsed so far;
- *Propagation_Delay*: is the average time delay that occurs between the ignition of fire in the cells and its propagation to the adjacent cells;
- Adjacent_Propagation: is a Boolean variable that triggers when DT_sim ×Sim_Steps ≥ Propagation_Delay.

The propagation algorithm uses a stack of active cells, where it pushes in each simulation step the cells where the fire ignition process has started. We call these cells active. For each simulation cycle and for each active cell the *Sim-Steps* variable is observed (i.e. the simulation step is updated) and the *Adjacent_Propagation* variable is evaluated. If it is true then the adjacent cells are evaluated. For each adjacent cell, if the intensity of the flame front of the active cell is greater than the heat of ignition of the adjacent cell, and the adjacent cell has not been completely burnt down, then it is activated and pushed into the stack.

The implementation of this algorithm in the SDBN framework depicted in the previous section is straightforward, since the algorithm follows the transition rules mentioned in section 2.1. Consequently the simulation can be conducted step-by-step, instantiating the time transition frame in Fig. 12 at each step to the active cell under analysis by properly observing the evidence variables and by propagating the net. The same algorithm can be easily reversed by reversing the transition network links of the time frame in Fig. 12. In this way the fire propagation analysis can proceed backwards, in a diagnostic way. As will be shown in the next section this allows us to analyse the causes of the occurrence of fire in critical cells (e.g. small villages, roads, etc.) and to easily evaluate the effectiveness of action to contrast fire propagation, such as the use of Canadairs or fire-breaks in specific cells.

The complementarity of the SDBN-based simulation algorithm with standard simulation ones resides principally in the possibility to reverse the calculation. Backward fire propagation entails very well focused scenario analysis, since it goes from the effect to the causes. In fact, in order to obtain the same information that can easily be achieved with backward analysis many blind "generate and test" simulations are required with a forward algorithm. Backward analysis, even if affected by approximations, can give initial insight and guide the forward simulation by limiting the scope of the search space.

5. Model implementation

The complexity of the temporal model discussed in the previous sections, as well as its spatial extension to wide forest regions, usually leads to BN implementations containing thousands of nodes, resulting in unmanageable and impractical networks, that easily exceed the power of today's computers.

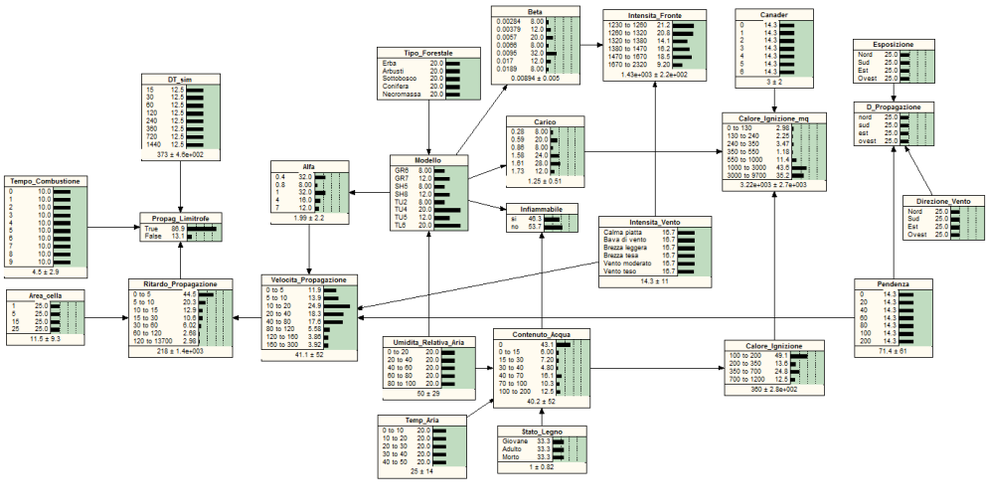


Fig. 13. Implementation of the single cell model with the Netica software

To solve such a complex issue we have used the property discussed in section 2, that allows for a stepwise implementation of the simulation algorithm. Fig. 13 shows the implementation of the single cell network in the Netica™ Software Programme, corresponding to the network discussed in chapter 4. The spatio-temporal transition network is shown in Fig. 14. This network contains 100 nodes and is able to represent large territories and support simulations for whatever time interval is necessary.

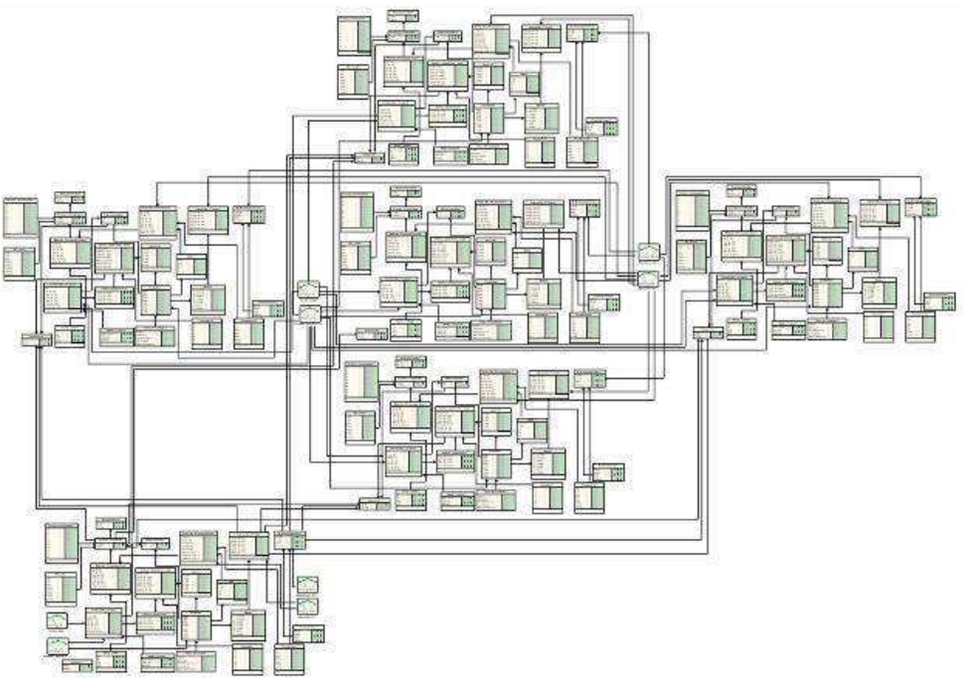


Fig. 14. Spatio-temporal transition network

5.1 The software interface

The simulator interface implemented in the prototype software is shown in Fig. 15. It consists of:

- a map of the territory which is divided into cells that can be selected with a click of the mouse;
- a cell window that allows for the input of the parameters of each cell (e.g. forest type, average slope, etc.);
- a simulator window that allows for the input of the simulation parameters (e.g. time step, time extension, type of simulation, wind direction and intensity, etc.).

It is worth noting the flag in this window that allows the selection between forward and backward simulation, as explained in the previous section. The step button makes the simulator proceed stepwise. In this way it is possible to change the meteorological conditions for each time slice. In this prototypal release of the software the grid that subdivides the map of the territory into cells is made up of a set of cells with a fixed square shape. This of course introduces some approximations in the forest type mapping, that, however, can be limited by using cells with smaller dimensions, resulting in a finer tessellation. This limitation will be overcome in future software releases.

5.2 Application to a real case study

The software prototype has been applied to analyse forest fire risk in the Esino-Frasassi forest district in the Marche region, in Italy, near Ancona. The forest area analysed extends for 3740 ha. It contains 6 main forest types. The area was subdivided into 154 cells of 25 ha each. For each cell the orographic and forestal parameters were inserted.

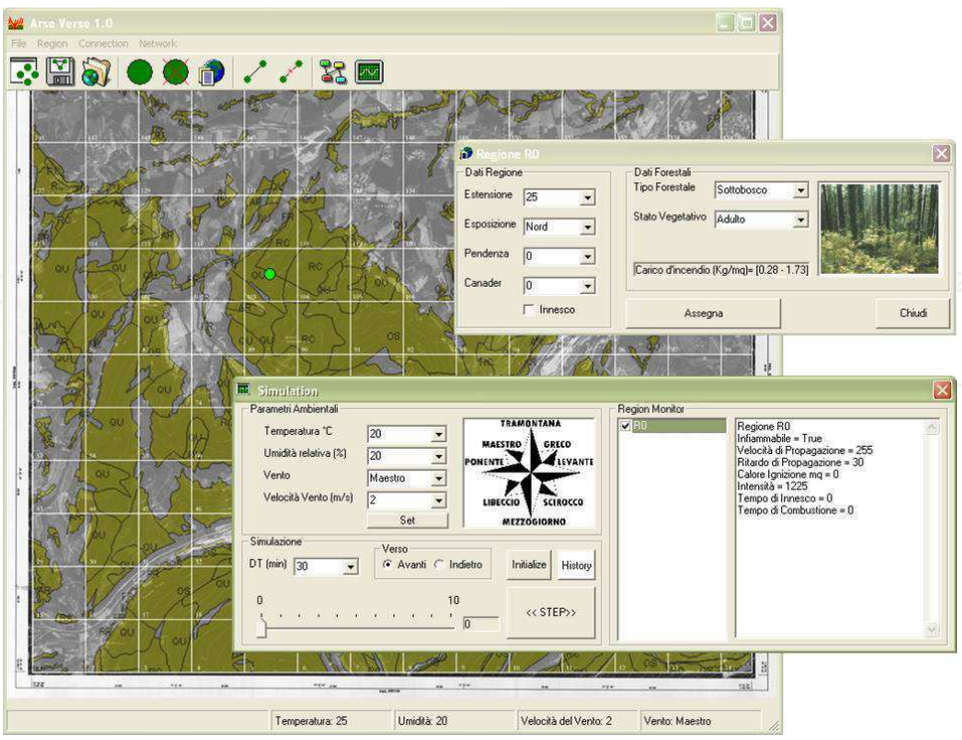


Fig. 15. The simple interface of the software prototype

Two kinds of simulations were carried out: forward standard simulations to evaluate both the risk of fire occurring when the fire breaks out in zones with a higher likelihood of ignition (roadsides, etc.) and the effectiveness of Canadair action; backward simulations to analyse the risk of disaster due to fire propagation involving areas with relatively high population density.

As an example Fig. 16 shows the dynamics of fire propagation in a forward simulation, with the fire breaking out in a west mountainside cell. The initial conditions in the triggering zone are: air temp 35°C, relative humidity equal to 40%, wind direction towards the south and wind speed 7m/s.

The direction and the extension of fire propagation depend on the forest type, on the meteorological conditions (quite severe in this case) and on the orography of the territory.

The software allows the effectiveness of the use of Canadairs and fire-breaks to be evaluated and, consequently, the optimization of their use. The use of Canadairs will increase the amount of heat necessary to light the fire in the cell, slowing down or even stopping the propagation of the fire. The use of Canadairs can be simulated by simply observing the usage rate in the Canadair node. Fig. 17 illustrates some steps in the same simulation shown in figure 16, but with the use of a Canadair.

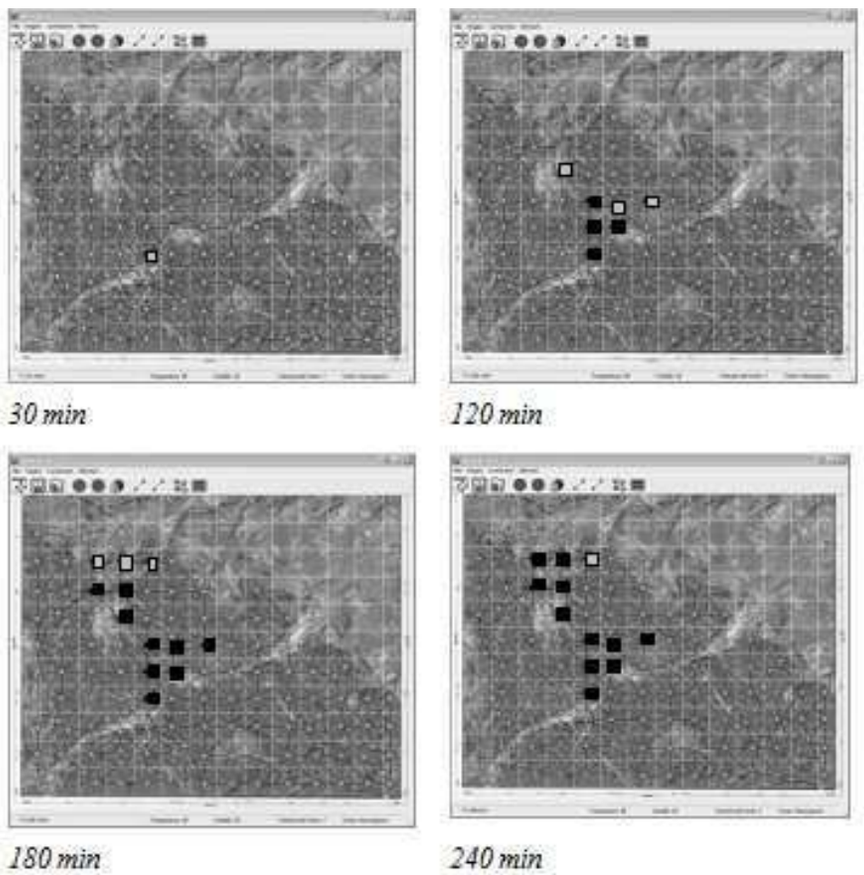


Fig. 16. Forward simulation of fire propagation. Gray = fire lighting phase, Black = final phase, the zone is almost burned down. The simulation time step is 30 minutes.

The example discussed so far has shown simulations that can be carried out, we should say even more accurately, with standard fire area simulation software. Having compared the

results of the software prototype with the FARSITE™ simulator using the same Rothermel's models, *it* shows essentially the same dynamics, providing less accurate results in terms of space and time accuracy, due essentially to the discretization of the domains of the BN variables. Nevertheless the errors that have been introduced by the discretizations do not hinder the support to the scenario analyses that the system is aimed at.

The complementary role of BN-based fire area simulators, compared with standard simulation software packages, lies in their ability to proceed backwards. Proceeding backwards means that, once a key area is selected, it is possible to identify, as happens in a diagnostic process, all the possible paths that the fire can follow to reach the area, and to evaluate the effectiveness of risk mitigating action. Given the great number of possible paths once all the surrounding propagation cells are combined with all the possible meteorological conditions, the statistical analysis resulting from the adoption of the BN-based simulator seems to be the only feasible approach. Once the risk map for the area has been drawn (i.e. all the critical fire paths identified and the related risk mitigating policies defined), standard simulators can be applied to have more accurate evaluations of each critical path. Fig. 18 shows a backward simulation concerning the evaluation of fire risk for a cell which contains a small village. The initial conditions in the district are: air temp 35°C, relative humidity equal to 40%, wind direction towards the north and wind speed 2m/s.

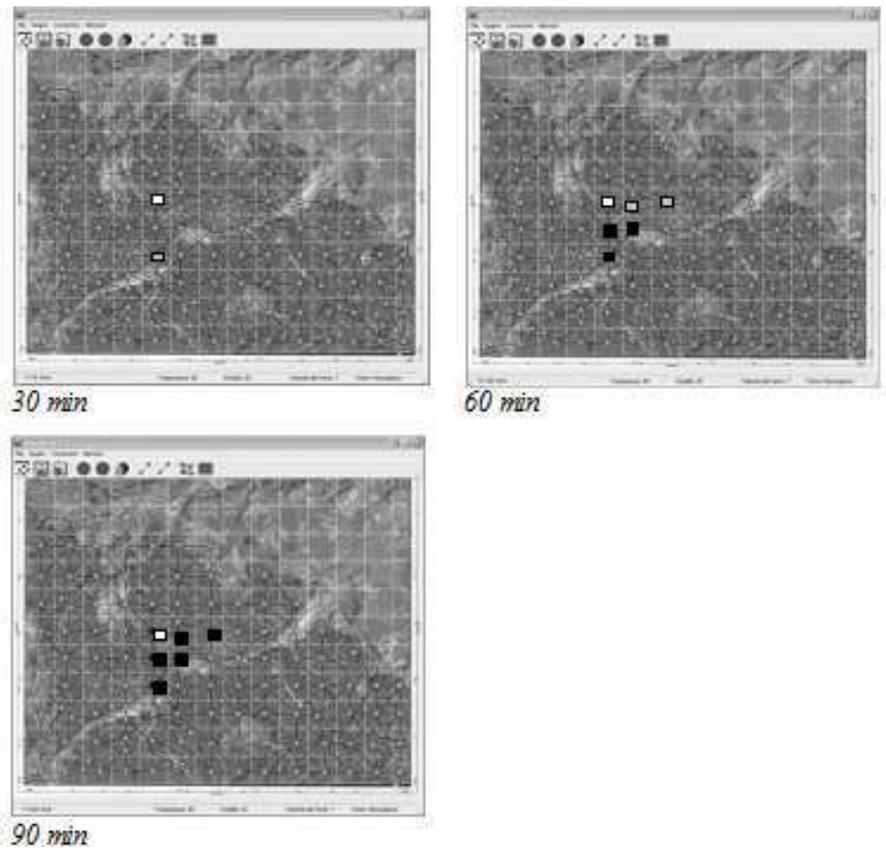


Fig. 17. Forward simulation of fire propagation with the use of a Canadair (white node). Gray = fire lighting phase, Black = final phase, the zone is almost burned down. The simulation time step is 30 minutes.

We can see that in these weather conditions the fire can reach the village essentially from one direction. Nevertheless this cell can be burned by all the adjacent cells, triggering a

number of possible paths. Of course once the critical paths have been identified the simulation can be reversed and the use of Canadairs evaluated, as already illustrated.

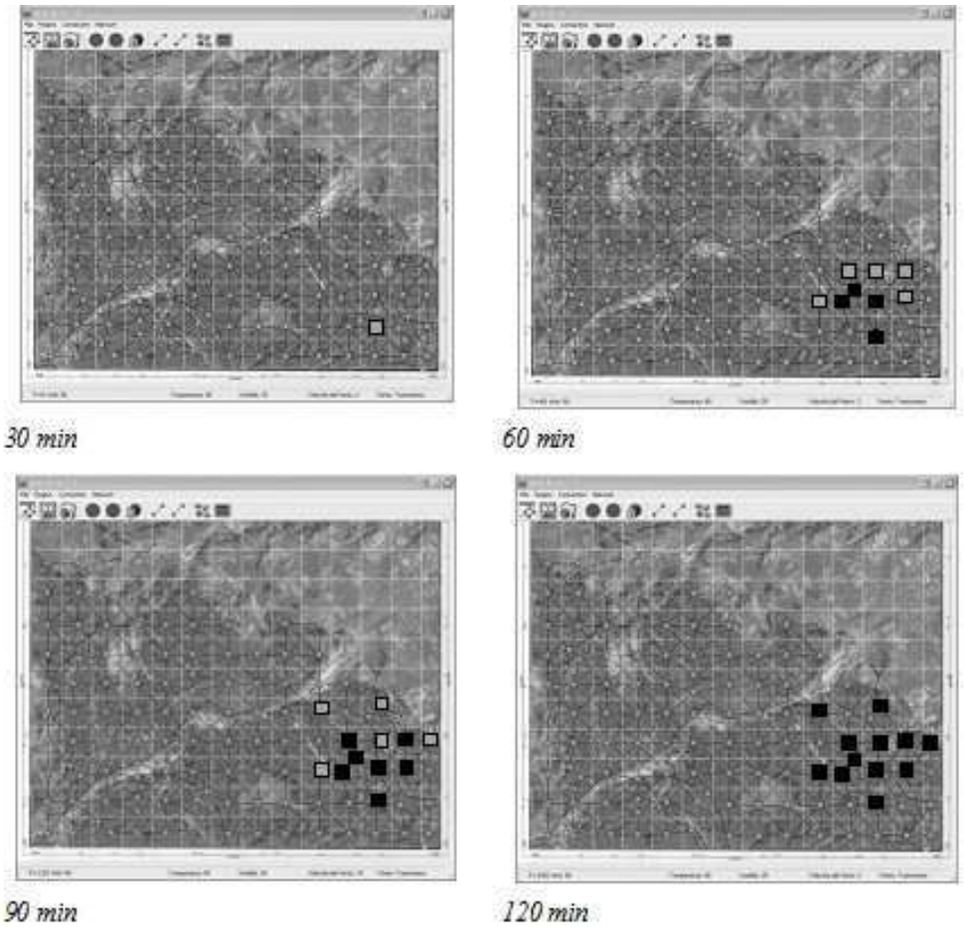


Fig. 18. Backward simulation of fire propagation and analysis of the risk concerning a cell which contains a small village. The location of the village is shown in the 30min simulation map.

6. Conclusions

The analysis provided in this paper was mainly devoted to showing the feasibility of an intelligent Decision Support System, capable of performing reliable analyses even in real-time during emergency situation management.

The particular case shown in this chapter concerns the development of a spatio-temporal Bayesian model, able to model both the spatial dynamics and the temporal evolution of forest fires. The former was tackled through the discretization of the forest into spatial cells, each corresponding to one elementary network. This discretization was used to create a spatial Bayesian network in the form of an Object-Oriented Network linking all the cells together. Time dependence was considered through the tool of Dynamic Bayesian Networks, which are able to quantify transition models between any one time slice and the next.

In order to make the models available for use by non-experts, everything was implemented into a VBA-based prototypal software tool, where a stepwise implementation of the simulation algorithm has been assumed. This means that any cell can influence only its adjacent ones, hence a limited number of cell networks must be considered at each simulation step.

The successful validation of the whole model has shown not only the reliability of the quantitative relationships implemented therein, but also the validity of assumptions regarding the stepwise spread of fire and spatial discretization. Bayesian Networks have also been proved capable of propagating complex evidence and managing a high number of variables.

7. Acknowledgment

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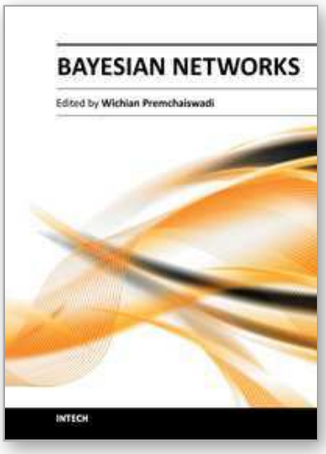

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Bayesian Belief Networks are a powerful tool for combining different knowledge sources with various degrees of uncertainty in a mathematically sound and computationally efficient way. A Bayesian network is a graphical model that encodes probabilistic relationships among variables of interest. When used in conjunction with statistical techniques, the graphical model has several advantages for data modeling. First, because the model encodes dependencies among all variables, it readily handles situations where some data entries are missing. Second, a Bayesian network can be used to learn causal relationships, and hence can be used to gain an understanding about a problem domain and to predict the consequences of intervention. Third, because the model has both causal and probabilistic semantics, it is an ideal representation for combining prior knowledge (which often comes in a causal form) and data. Fourth, Bayesian statistical methods in conjunction with Bayesian networks offer an efficient and principled approach to avoid the over fitting of data.

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