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A data-driven model for large wildfire behaviour prediction in Europe

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Abstract

The European Forest Fire Information System (EFFIS) has been established by the Joint Research Centre (JRC) and the Directorate General for Environment (DG ENV) of the European Commission (EC) in close collaboration with the Member States and neighbour countries. EFFIS is intended as complementary system to national and regional systems in the countries, providing harmonised information required for international collaboration on forest fire prevention and fighting and in cases of trans-boundary fire events. However, one missing component in the system is a wildfire behaviour model able to cover the whole Europe. We propose a new general conceptualisation for wildfire prediction. It relies on an array-based and semantically enhanced (Semantic Array Programming) application of the Dynamic Data Driven Application Systems (DDDAS) concept, so as to predict spread of large fires at European level. The proposed mathematical framework is designed to simulate with an ensemble strategy the wildfire dynamics under given sequences of actions for controlling the fire spread and updated data-driven information. First results on data and software uncertainties associated with the problem have been presented with a real case study in Spain.

Keywords: Dynamic Data Driven Application Systems; Forest Fires; Partial Open Loop Feedback Control; Approximate Dynamic Programming; Semantic Array Programming

1. Introduction

European landscapes and their ecosystem dynamics are affected by many disturbances [1–4]. Among them, fires play a key role [5, 6] especially in the Mediterranean region [7, 8]. Uncontrolled fires may cause significant economical and environmental damage. Every year in Europe around half a million hectares of wildland and forest areas are burnt as a consequence of approximately 65000 fires – with over 85% of the burnt area occurring in the European Mediterranean region [9].

1.1. Integrating wildfires in a wider context

Besides being potentially dangerous for human life (and health [10]), fires alter [11–13] habitat connectivity and fragmentation [14–16] affecting biodiversity of wild animals and forest plants [17, 18]. Burnt areas are exposed [19] to soil erosion [20, 21] whose in-site effects might also be complemented by off-site impacts [22–24].
(e.g. increased sediments in downstream rivers, also influencing water resources quality [25, 26] and water storage losses). The involved land cover degradation may affect the precipitation-runoff relationship [27], especially in mountainous areas. This might have a role in exacerbating moderate floods [28] if not even major ones [29]. At the same time, climate change [30] and pest outbreaks may affect the way in which vegetation reacts to fires (e.g. in case of wide die-offs and subsequent high share of dead trees) [31]. It is therefore evident that properly addressing wildfire management also involves the analysis of several coupled ecosystem services [32] in the wider context of integrated natural resources modelling and management (INRMM) [33]. Here a multi-criteria mathematical framework (eq. 5–6) is discussed for better addressing this variety of impacts which might otherwise be oversimplified within uni-dimensional approaches (e.g. cost-benefit analysis) [34, 32]. On the other hand, this proposal of mathematical modelling structure is intended to be flexible enough to be applicable in emergency situations where information is frequently lacking. Depending on the local conditions of applicability, this conceptual framework aims to contribute to wildfire management with adaptive support, ranging from data driven simulations of fire dynamics’ scenarios up to possible proactive support in selecting efficient management options.

1.2. Interactions between fire events prediction and management

Timing and strategy are most important for effectively handling the situation during a fire event. For a long time [35], computational modelling has supported the analysis of wildfires’ dynamics [36]. Time plays a critical role (section 3) even in the conceptualisation of this modelling problem (from the time interval \( U' = [t_{\text{start}}, t_{\text{end}}] \) of the fire event – where \( t_{\text{end}} \) is unknown, ranging from hours to weeks after \( t_{\text{start}} \)). While the complete mathematical framework will be presented in section 4, the relationship between fire events prediction and management is discussed here because of its multifaceted nature situated at the science-policy interface [37] which deserves specific attention. Since the simulated dynamic of an uncontrolled wildfire in many cases completely differs from a real one, predicting wildfire behaviour necessarily implies modelling the anthropogenic control (e.g. firebreaks, wetting, fire retardation and fuel reduction: here denoted as the set \( \mathcal{U}^u \) of controls \( u \)) applied to contain the fire evolution (eq. 2). The complete sequence of actions for controlling the fire spread \( u, u_{t+\Delta t}, \cdots \) along a fire event may be described as an instantiation for that specific fire and conditions of a general fire management policy \( u(t) \) which reacts to (as a function of) the actual wildfire state \( x \):

\[
u_0, u_{t+\Delta t}, \cdots \quad \text{such that } \forall \tau \in U', \ u_\tau = u(x_\tau)
\]

This management policy is generally subjected to procedures, legal obligations and constraints which may differ from country to country, with varying degrees of freedom in the spatio-temporal allocation of the possible controls. A wide scale approach over heterogeneous spatial domains as those in Europe needs to consider this fact explicitly. This suggests a flexible, lightweight approach and thus to avoid embedding those aspects as monolithic controls. A wide scale approach over heterogeneous spatial domains as those in Europe needs to consider this fact explicitly.

The information on the anthropogenic control may be used in two ways.

1.2.1. Simulating with external control scenarios

First, it can serve as a required input for a realistic prediction of the wildfire dynamics. In this case, the fire controls are decided elsewhere and notified to the predictive model. This may be exploited by simulating the effects of the particular data series constituted by a planned sequence of controls \( U_{t, t_{\text{end}}} = [u', u_{t+\Delta t'}, \cdots] \in \mathcal{U}^u_{t, t_{\text{end}}} \) entirely known in advance (i.e. decided or hypothesised as a scenario) at time \( t \in U' \). The information may also be updated periodically so as to simulate the fire evolution with a timely revised control strategy \( U_{t+\Delta t, t_{\text{end}}} \) which could adapt the foreseen management to changing conditions (e.g. weather). An a posteriori analysis of the fire management history is also possible by simulating the past fire dynamics once the fire event is concluded. This would require the actually implemented sequence of controls \( \mathcal{U}^u_{\text{hist}, t_{\text{end}}} \) or alternative sequences \( \mathcal{U}^u_{\text{alt}, t_{\text{end}}} \) which could have been implemented instead – to be used as control input along with the recorded sequence of non-anthropogenic conditions (i.e. occurred disturbances in eq. 2) and the static characterisation of the system (slope, aspect of the terrain, ...). Uncontrolled wildfires are easily simulated by just using a special case of \( \mathcal{U}^u_{\text{begin}, t_{\text{end}}} \) namely the absence of control actions and constraints.
1.2.2. Supporting the generation of control strategies  
Second, the feasible alternative options \( U_{t_{\text{end}}}^{u_{t}} \) for managing the fire at a given time \( t \) might be used for simulating their corresponding effects within the model and deriving possible (sub-)optimal strategies according to assessment criteria (whose choice is never a technical detail but instead a policy-making decision [37]). As in the first approach, \( \text{in itinere} \) changing conditions during the fire event may suggest iterative re-optimisation for updating the suggested control strategy and dynamically supporting the firefighting and emergency operations. In a wider temporal scale, such a modelling approach might be exploited in advance for simulating possible future fires and contributing to a better spatial allocation of fire crews and equipment. This second way of addressing control strategies may clearly be set in the context of a decision support system. Here, approximate or heuristic optimisation strategies may be essential.

Although the European countries have collected information on forest fires since 1970s, the lack of harmonised information at the European Union (EU) level has prevented a holistic INRMM approach for forest fire prevention in the Region. The European Forest Fire Information System (EFFIS) [9] has been developed jointly by the European Commission (EC) services (Directorate General Environment and the Joint Research Centre) and the relevant fires services in the countries (forest fires and civil protection services) in response to the needs of European bodies such as the Monitoring and Information Centre of Civil Protection, the European Commission Services and the European Parliament. However, one missing component in the system is a wildfire behaviour modelling architecture able to systematically cover the whole spatial extent of Europe. Our contribution aims at proposing a conceptualisation based on a semantically-enhanced application of the concept of Dynamic Data Driven Application Systems (DDDAS) [38]. Along with the mathematical modelling framework, first results on the data and software uncertainty [39] associated with the problem are presented with a case study.

2. The European Forest Fire Information System

EFFIS is a comprehensive system covering the full cycle of forest fire management; from forest fire prevention and preparedness to post-fire damage analysis. The system provides information to over 30 countries in the European and Mediterranean regions and receives detailed information on forest fire events from 22 European countries, supporting their prevention and fighting in Europe [9].

Exploratory research is currently on-going to integrate fire behaviour models, with emphasis on extreme conditions, physical modelling, smoke dispersion and spotting from forest fires. Also, existing models to assess fire behaviour and adaptation for EU are under investigation. Another aspect relates the use of high resolution meteorological data from organisations such as ENCCWF [40] and Meteo France [41] which may help to localize information, also improving the fire behaviour prediction.

EFFIS is part of the European Forest Data Centre [42] which widely exploits geospatial and computational modelling tools [43] within a modelling paradigm aiming at robustness and semantic transparency [39, 37].

2.1. Detecting large forest fires from satellite images

FireNews EFFIS module is a web based application integrated within the EFFIS portal as a toolset which provides automatic geoparsing and simplifies the management of the fire news collected by the operator [44]. The satellite images used for detecting burnt areas are the Moderate-Resolution Imaging Spectroradiometer (MODIS) by NASA’s Terra and Aqua satellites. These images are updated daily and have a pixel size of 250m. To ensure higher reliability, the procedure is only partially automated, with a key role for expert judgement:

1. Hot Spots from NASA are loaded and visualised in the workspace of the desktop GIS as a layer of points.
2. Fire News events are visualised in the same workspace as a layer of points.
3. The MODIS images are analysed near the hot spots/fire-news, which may be affected by a certain shift from the actual fire. In general such a shift has a spatial error within 1 km. In order for a fire to be detected, comparing at least two MODIS images is essential (before and after the fire) – although normally images corresponding to several days are compared. The burnt area is detectable as a dark spot not present before the fire. A detection problem may arise in cloudy days, when the images are not usable.
4. Once a fire is detected, it is digitised by generating a polygon which is stored in the database. If the fire is still active the day after, the polygon is updated with the new perimeter. The record of a fire stores all the perimeters day by day, so as to enable the use of such data for future needs and research purposes.
3. Static versus dynamic parameterisation of fire models

Traditionally, forest fire models embrace three broad factors, called by some scientists the fire environment triangle, which are fuel, meteorology and topography [45]. However, assuming those conditions to be stable and permanent within a given fire lifespan would easily lead simulation results to diverge from the actual fire behaviour. To mitigate this modelling phenomenon, time has been proposed as an explicit variable inside fire models, converting the triangle into the square of fire factors [46, 47]. “Classic” (open-loop) prediction methods may read all environment variables at the time $t_{\text{start}}$ populating with them the model parameters and generating a fire propagation map in $\mathcal{U}^t$. Should any updated data be available within $\mathcal{U}^t$, they would often quickly outperform the increasingly outdated information provided by the initial data [46].

A data driven feedback approach would instead need a system capable of obtaining or estimating (e.g. by means of specific data transformation models, D-TM [48, 43, 39], see also table 1) the updated values of input parameters for the involved simulator. The system should adapt itself dynamically to the constant change of conditions associated with real-time measurements. As detailed in section 4, such characteristics recall the definition of DDDAS, which “is a paradigm whereby application/simulations and measurements become a symbiotic feedback control system. DDDAS entails the ability to dynamically incorporate additional data into an executing application, and in reverse, the ability of an application to dynamically steer the measurement process” [49].

Methods reducing the negative effect of uncertainty in input parameters, so turning the classic prediction into DDDAS, complement each predictive step with an associated calibration phase – where information on the fire system evolution is considered. Data-driven methods are based on very simple conceptual principles: knowledge and adaptability. Knowledge here focuses on two aspects. First, measuring/reconstructing the conditions where the fire develops in real-time (wind speed and direction, fuel moisture, terrain slope, ...). Second, observing the actual fire’s dynamics (the evolving fire geometry). Adaptability is here obtained by modifying the simulator behaviour (parameterisation, inputs) following data driven changes which may occur in environmental conditions.

4. Modelling methodology: DDDAS for uncertain and semantically enhanced problems

Within the DDDAS approach, computational models are explicitly designed so as to preserve the ability to incorporate data-driven information not only at the stage of modelling static design, training and tuning but also dynamically, along the whole life-cycle of the models. At the same time, DDDAS models may dynamically guide/support the selection of useful new information.

The idea of adapting the way in which a dynamic system is managed by using the best available updated (e.g. real-time) information is at the basis of several dynamic/adaptive control strategies [51–53]. Some of them are also able to provide an explicit conceptual framework for incorporating varying uncertainties related (among others) to data-driven information. Environmental systems are routinely affected by disturbances whose variability may depend non-linearly on complex patterns of conditions within and outside the system’s spatial extent. A typical example is constituted by local meteorological information (future forecasting) which – depending on the required time scale – is generally influenced by regional (short-term) or global (mid-term) climatic conditions as well as by seasonal and interannual variations (long-term).

Natural resources management often relies on adaptive control [54]. For example, stochastic dynamic programming (SDP) is widespread in water resources management as a modelling tool for generating optimal seasonal allocation of water reservoirs (such as dams or lakes) [55]. Due to the increased complexity of forest resources management, a growing amount of SDP applications may be found, particularly in relation to fire risk management [56–58]. However, SDP is affected by the well known curse of dimensionality (the computational resources exponentially grow with the number of state variables) where accurate description of nontrivial systems increases the required dimensionality of the state vector $x$. Various general strategies [52–53] have been applied in natural resources applications for mitigating the intractability of complex problems, by approximating the SDP with modified algorithms [60–62].

The fire event dynamics may be conceptualised as the D-TM evolution of the state $x$ of the system (the probability for each spatial cell to be a burnt area) in the discrete time interval $\Delta t$ with respect to the disturbances $\xi_{t+\Delta t}$ (the spatial field of wind speeds and directions, humidity, rainfall, ...), the anthropogenic control $u$, and the system characteristics (slope, aspect, fuel distribution, parameterised as $\theta$):
\[ \mathbf{x}_{t+\Delta t}(t, \mathbf{x}_t) = f \left( \mathbf{\theta}_t, \mathbf{x}_t, \mathbf{u}_t, \mathbf{\xi}^{\tau} \right) \] \] 

where:

\[ t \in \mathcal{U}^{\tau} \]

\[ \mathbf{\xi}^{\tau} \sim \phi(\cdot \mid I_t) \in \mathcal{U}^{\xi}_t(\mathbf{x}_t, \mathbf{u}_t), \tau \in \mathcal{U}^{\theta}_t \]

\[ \mathbf{u}_t \in \mathcal{U}^{\mathbf{u}_t}(\mathbf{x}_t) \]

\[ \mathbf{\theta}_t = \theta(\mathbf{x}_t, \mathbf{u}_t) \]

which enables modular modelling of legal obligations by just redefining \( \mathcal{U}^{\mathbf{u}_t}(\cdot) \). The D-TM module \( f(\cdot) \) is subject to the semantic checks \( \text{sem} \) as pre-, post-conditions and invariants on inputs, outputs and the D-TM itself [63, 39]:

\[ y = \text{sem}(f(\theta, x, u, \xi), \text{sem}) \iff \square \text{sem}(y, f, \theta, x, u, \xi) \] \] (4)

The modal/deontic logic operator \( \square \text{sem} \) means: “it ought to be that \( \text{sem} \)”, where \( \text{sem} \) is a set of valid array-based semantic constraints (within the semantic array programming paradigm [48, 64], e.g. sections 5.3 and 6). The notation for time refers to the instant in which a given quantity will be known without uncertainty. The disturbance vector \( \mathbf{\xi}^{\tau} \) may be described in terms of a pdf \( \phi(\cdot \mid I_t) \) – generally a function of the state and control at time \( t \), also dependent from the available data-driven information \( I_t \). This notation expresses the uncertainty associated with the disturbances forecast. Depending on the typology of information and on the time \( t \) in which the information is available, the uncertainty of the predicted disturbances will typically be highly variable.

As anticipated in section 1.2, the definition of the anthropogenic controls may be provided as external input. In this case, the evolution of the system can only be simulated with eq. 2. As an alternative, control sequences could be generated from the feasible alternative options \( \mathcal{U}^{\mathbf{u}_t}_{t_{\text{end}} \rightarrow t} \). This way, the system may be used for supporting the decision-making, either in real-time or as off-line assessment. The control problem in this case implements a Partial Open Loop Feedback Control (POLFC) approach [62] for minimising the overall costs associated with the fire event, from the time \( t \in \mathcal{U}^{\tau} \) onwards:

\[ u^*(\cdot) = \arg \min_{u \in \mathcal{U}^{\mathbf{u}_t}_{t_{\text{end}} \rightarrow t}} \left[ C^{1,t} C^{2,t} \cdots C^{i,t} \cdots C^{n,t} \right] \] \] (5)

where each cost \( C^{i,t} \) is linked to an impact assessment criterion (section 1.1) and is described as a composition of step-wise costs \( c^i_t \) which are estimated with the data-driven information \( I_t \) available at time \( t \) for the future time \( \tau \in \{ t, \cdots t_{\text{end}} \} \):

\[ C^{i,t} = \mathbb{E}_{\mathbf{\xi}_{t+\Delta t}^{\tau} \cdots \mathbf{\xi}_{t_{\text{end}}}^{\tau}} \left[ \sum_{\tau=t}^{t_{\text{end}}} c^{i}_t(\mathbf{x}_\tau, \mathbf{u}_\tau, \mathbf{\xi}^{\tau}_{t+\Delta t}) + c_{t_{\text{end}}}^{i}(\mathbf{x}_{t_{\text{end}}}) \right] \] \] (6)

with \( \mathbb{E} \) a statistical operator and \( \mathbf{\xi}_t \) estimated by iterating eq. 2 from the known state \( \mathbf{x}_t \), and information \( I_t \).

5. State transition function

As a case study, the software uncertainty [37, 39] associated with the state transition function (eq. 2) has been investigated by means of an ensemble approach relying on two particular simulators. It should be underlined that the proposed method is general and applicable to other simulators. As is well known, the performance of ensemble approaches tends to increase with a larger number of models (here, fire spread simulators).

5.1. FireSim

The first selected simulator is FireSim, proposed by Colins D. Bevins, which implements the library FireLib [50]. This simulator uses a cell-based approach, the relationship between neighbours being used to evaluate whether and when the fire may reach a given cell.

FireSim is a deterministic parametric and discrete event type simulator, implemented as a cellular-automata simulator. It uses the FireLib library which composes the processing as a pipeline structure of four stages (see figure 1(a)). The model implemented in the kernel of FireLib is the one of Rothermel [65].

The structure of the FireSim simulator is shown in figure 1(a). The main loop operates using a contagion algorithm applied to the 8 neighbours of each cell. For each burnt cell, the algorithm analyses the eight neighbouring cells and determines their ignition times, as long as conditions (humidity, wind, etc.) allow the fire to reach them.
Fig. 1. (a) FireSim structure. (b) Implemented fire behaviour model with GRASS GIS.

5.2. GRASS GIS

The second selected simulator is implemented in GRASS GIS [67], a Geographic Information System (GIS) available as free and open source software (FOSS) for geospatial data management and analysis, image processing, graphics/maps production, spatial modelling and visualisation. The complete control over implemented functions and the possibility to customise them to fit the user’s requirements are among the advantages of FOSS. A simulator based on the least cost path algorithm and simulating elliptically anisotropic spread is implemented in the function r.spread [68], which takes as input the rate of spread (ROS) generated by the function r.ros [69]. This latter computes the ROS following the Rothermel model [65] and is based on the Fortran code by [70]. The direction of the maximum ROS is the vector sum of the forward ROS in wind direction and that in upslope direction. The obtained raster map layers serve as inputs for r.spread.

Further pre-processing D-TMs were created for providing r.spread and r.ros with the needed inputs (fig. 1(b)):

- The SRTM [71] digital elevation model (DEM), from which the aspect and the slope are computed.
- The initial perimeter, retrieved from EFFIS database.
- The fuel model map (see section 6)
- Moisture: 1, 10 and 100 hour fuel models are required by the model. When only one of them is provided, the others can be estimated by the model [69]. The Rothermel’s model has been developed for local scale (i.e. with accurate information on the vegetation and moisture). Applying the model at the European scale implies a certain degree of oversimplification. We assume live moisture is 0 because we refer to the dry season, and the 1 hour fuel model is obtained from the DMC index. DMC (Duff Moisture Code) is an index that describes the relationship between temperature, relative humidity and rain.
- Wind field: the model takes as input the midflame wind speed and the direction in the GRASS convention (degrees from East counterclockwise). We have wind data from ENCWF Ensemble Prediction System [40], measured every 12 hours and projected every 3 hours on a grid of 25 x 25 km (grib file). The direction of the wind is expressed in degrees clockwise from North (direction the wind is blowing from). This is converted by a script to the GRASS convention. The speed refers to 10-meters WMO Standard, which is converted to 20-ft wind dividing by 1.15 according to [72]. The mid-flame wind speed is estimated with the Wind Adjustment Factor (WAF) [70]. See table 1.

Table 1. Wind Adjustment Factors (WAF) values assigned according to the fuel models present in the study area.

<table>
<thead>
<tr>
<th>Fuel Model</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>WAF</td>
<td>0.36</td>
<td>0.36</td>
<td>0.44</td>
<td>0.55</td>
<td>0.42</td>
<td>0.44</td>
<td>0.44</td>
<td>0.28</td>
</tr>
</tbody>
</table>

The simulation is carried out varying the wind field every 3 hours. For each stage, the burnt area resulting from the simulation is taken as input for the next step. For testing purpose, we simulated the fire spread on case studies stored in the EFFIS database, in which the burnt perimeter was available in an interval of 24 hours. After a 24h simulation, we compared the actual burnt perimeter with the result of the simulation.

5.3. Semantic constraints

The two implementations (instances) of the state transition function (eq. 2) work as semantically-enhanced modules within the overall mathematical modelling structure. Despite the differences in the local structure and interface of the two instances, they have been wrapped around so as to present the same module semantics sem (eq. 2–4: a few more obvious constraints are exemplified in the next section as active links ::constraint::).
6. Data and software uncertainty analysis: a case study in Valencia, Spain

The two instances of the state transition function (eq. 2) are deterministic. Within each run, the state \(x_{t,c}\) of a given cell \(c\) at time \(t\) is converted to be a \texttt{binary} flag recording whether \(c\) is burnt. The instances originally assign a proxy value \(\kappa_{t,c}\) to each cell; being either the time \(\tau \leq t\) in which the fire reached it or otherwise an IEEE 754 \texttt{not-a-number} value \([73, 74]\): in this case, the conversion is the GNU Octave/MATLAB codelet \(x_{t,c} = \sim\text{isnan} (\kappa_{t,c})\). Ensembling multiple runs of the instances allows an uncertainty analysis to be performed for different scenarios (ensemble inputs might be more general: valid runs are expected to provide \texttt{probability} values \(\in [0, 1]\)). The weighted-quantile analysis of the ensemble requires all output \texttt{matrix} layers to have the \texttt{same size} for generating a \texttt{sortable} 3-dimensional array \texttt{3-array} – this is why the conversion from \(\kappa_{t,c}\) to \(x_{t,c}\) is needed. Here two scenarios are compared (fig. 2) for a case study. The first scenario assumes the initial wind information to be static along the whole simulation runs (persistent wind forecast, fig. 2 (c)), while the second simulates a perfect dynamic wind forecast (fig. 2 (d)) by exploiting the observed wind information \(\xi_{t+\Delta t}\) (unknown at time \(t\)) instead of the one which could have been predicted with the help of real forecast systems.

Table 2. The two scenarios obtained by reclassifying Corine Land Cover according to Anderson et al [75]

<table>
<thead>
<tr>
<th>Vegetation type</th>
<th>Frequency [%]</th>
<th>Scenario 1b</th>
<th>Scenario 2b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sclerophyllous vegetation</td>
<td>28.95</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Transitional woodland-shrub</td>
<td>11.61</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Coniferous forest</td>
<td>9.91</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>Land principally occupied by agriculture with</td>
<td>5.04</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>significant areas of natural vegetation</td>
<td>1.55</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Non-irrigated arable land</td>
<td>0.47</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Natural grasslands</td>
<td>0.04</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Sparsely vegetated areas</td>
<td>0.01</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>Broad-leaved forest</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 2. Dos Aguas - Valencia Wildfire with ensemble forest wildfire prediction outputs
The study area is located in Dos Aguas, in the south western region nearby Valencia, the third largest city of Spain. The event is a major forest fire which occurred in 2012, from the 30th of June and the 4th of July. This was the worst fire in a decade affecting the region, since Valencia started a very efficient fire management programme following the wide fire impacts which affected the Spanish territory in 1994. The fire in Dos Aguas destroyed 32,424 hectares of forest, affecting sclerophyllous vegetation (73%) and agriculture (15%). Moreover, two thousand people were evacuated from their home places and large smoke plumes affected the city of Valencia, as widely reported by the press.

For each wind-forecast scenario (persistent and perfect), a simple unweighted ensemble of 8 runs is shown in fig. 2. The 8 runs correspond to the combinations of two simulators (software uncertainty, with differences in the predicted fire surface sometime exceeding 10%) running with two possible fuel maps (static parameters’ uncertainty) and two different wind sources (dynamic data uncertainty). The fuel maps implement possible re-classifications of the Corine Land Cover [66]. The selected wind sources are the two closest to the fire [40].

The initial and final fire perimeters refer to the digitised polygons associated with the 2nd and 3rd of July 2012, delimiting a simulation of 24 hours. The Corine Land Cover classes present in the study area have been reclassified according to [75]. Since the uncertainty with which some of the Corine categories may be remapped in fuel models, two possible fuel maps (f1b and f2b, table 2) have been generated. The control strategy $U_{\text{hist}, t_{\text{end}}}^{\text{alt1}, t_{\text{end}}}$ implemented within the runs does not consider the (unknown) sequence $U_{\text{hist}, t_{\text{end}}}^{\text{alt2}, t_{\text{end}}}$ which was actually applied during the fire event. Instead, a simple protection strategy has been implemented, in which an intense fire protection effort has been limited to urbanised and high-value (e.g. fruit/olive trees, vineyards) agriculture areas. Following this simplistic assumption, those areas have been considered as barriers.

7. Conclusions
Holistic approaches in forest fire prevention at the European scale are increasingly needed. We propose a new general conceptualisation for wildfire prediction [47]. It relies on an array-based and semantically enhanced (semantic array programming) [48, 64] application of the dynamic data driven application systems [38, 49]. Along with the mathematical modelling framework, first results on data and software uncertainties [37, 39] associated with the problem have been presented with a real case study in Spain.

The proposed mathematical framework is designed to simulate with an ensemble strategy the wildfire dynamics under given sequences of actions for controlling the fire spread. Those sequences might be externally provided or generated by means of a partial open loop feedback control [62] strategy for supporting the involved decision-making process. In both cases, the modelling architecture explicitly benefits from dynamic data-driven information for adaptively improving its robustness. In particular, data and software uncertainty is proactively exploited in an array oriented framework based on the multiplicity of static parameterisations, dynamic data and software components. The resulting array of data-transformation models is analysed with an ensemble approach.

The proposal and scientific investigation are in a preliminary stage. Nonetheless, the first analysis for assessing the data and software uncertainty highlighted the complementary differences in two implementations based on the classic Rothermel model [65]. This would suggest the need to further assess the relevance of software uncertainty with models of the same family (e.g. [76]) or others. The diversity of quasi-static system descriptions (fuel mapping) and dynamic data forecast (weather) may deserve future investigation as well.

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