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Forest fire propagation prediction based on overlapping DDDAS forecasts

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Abstract
Forest fire devastate every year thousand of hectares of forest around the world. Fire behavior prediction is a useful tool to aid coordination and management of human and mitigation resources when fighting against these kind of hazards. Any fire spread forecast system requires to be fitted with different kind of data with a high degree of uncertainty, such as for example, meteorological data and vegetation map among others. The dynamics of this kind of phenomena requires to develop a forecast system with the ability to adapt to changing conditions. In this work two different fire spread forecast systems based on the Dynamic Data Driven Application paradigm are applied and an alternative approach based on the combination of both predictions is presented. This new method uses the computational power provided by high performance computing systems to deliver the predictions under strict real time constraints.

Keywords: Dynamic data driven, parallel computing, data uncertainty, model, simulation

1 Introduction

Computer simulations have been widely used for studying and predicting wildfire spread [1][2][3]. The accuracy of these simulations depends on many factors, including GIS data, fuel data (burnable items), weather data, and high fidelity wildfire behavior models. Due to the dynamic and stochastic nature of wildfire, it is impossible to obtain all these data with no error. For example, the weather data used in simulation is typically obtained from local weather stations in a time-based manner. Before the next data arrives, the weather is considered unchanged in the simulation model. This is different from the reality where the real weather constantly changes (e.g., due to the interactions between wildfires and the weather). In addition, a major

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issue that should not be dismissed is the landscape features. The terrain characteristics that are involved in wildland fire spread comprise the alignment toward the sun, which influences the amount of energy received from the sun, and the steepness of the mountain slopes that directly affects wind behaviour [4][5]. Besides data errors, the wildfire behavior model also introduces errors because of its computational abstraction. Due to these errors, the predictions from the simulation model will almost certainly be different from what is in a real wildfire. Without dynamically adjusting the simulation model, the difference between the simulation and the real wildfire will continuously grow. The goal of dynamic data driven simulation is to establish a feedback connection from a real wildfire to the simulation model by utilizing the real time data collected from the wildfire. By assimilating these data from the real wildfire, the simulation system continuously adjusts itself, e.g., estimating the continuously evolving fire front and tuning the model parameters, in order to achieve more accurate predictions of wildfire spread. There exist two different ways of approaching the design of DDDAS for forest fire spread forecast. On the one hand, we can find those schemes where the aim is to couple the fire model with the atmospheric model by taking into account physics modifications in both models in a feedback scheme [6]. These works are oriented to physically model the atmosphere behaviour variation close to the fire event caused by the forest fire itself. The complexity of this approach is described in [7] because of the unstability of the atmospheric model when the state of the system is updated on the fly. For that reason, alternative dynamic data driven approaches for forest fire spread prediction arises whose aim is to drive the model forecast using control variables. That is, to enhance basic forest fire spread simulations with the knowledge obtained from a calibration/adjustment stage. This calibration stage consists of executing a large set of simulations with different configurations of the selected control variables (input parameters of the simulator). Afterwards, evaluate all obtained simulations in order to weight them according to some fitness function, which determines the similitude to the observed real fire propagation. Once the best scored simulation is selected, the configuration of the control variables associated to that winner, is applied for prediction purposes in the near future [8][3]. As in the case of numerical weather forecast, relying on a single solution, could lead to non feasible forecast results. For that reason, weather prediction typically is obtained from the analysis of more than one model output. In this paper, we propose to a Dynamic Data Driven Application System for forest fire spread prediction based on overlapping the results of two DDDAS schemes.

In the next section, the Cardona fire characteristics are described. This study case has been used to analyze the advantages of considering more than one DDDAS forecast. Section 3 deals with the description of the two Dynamic Data Driven Applications Systems applied to the Cardona fire. The analysis of taking into account the forecast results of both strategies is described in section 4 and, finally, the main conclusions are reported in section 5.

2 Study case: 2005 Cardona Fire

The forest fire used as a test case in this work, took place in Catalonia (northeast of Spain) (lat. 4154 N, long. 1 40 E) during the summer season in 2005, in particular on 8th July. The 2005 Cardona Fire burned a total surface of 1439 ha. and it lasted 5 hours. The fire started at 14:45 and it keeps burning during 5 hours, until 19:45 approximately. At that time, the fire was considered to be controlled by the firefighters because the perimeter remained stable. A relevant characteristic of Cardona Fire was the sudden change on the rate of spread that happened after, approximately, two hours from its ignition. During the initial fire evolution, the measured rate of spread in terms of meters per minute (m/min) was around 10 m/min. After this initial "meal" evolution, around 16:40, the rate of spread increased to values closer to

100 m/min. However, during the fire spread no drastic changes in the meteorological conditions were observed, taking into account wind speed and wind direction. After analyzing the data collected by the meteorological weather station closer to the fire ignition, we ontained that during the interval time when the fire spread reached its maximum rate of spread, the registered wind speed range varied from 4.8m/s to 2.2m/s and the wind direction ranged from 185 degrees east of north to 190 degrees. This fact rises the hypothesis of analyzing the influence of the topography and the influence of the fire itself in the micro-meteorological conditions. Figure 1 shows the elevation map of the affected zone. Darker zones denote low elevation, meanwhile light colored zones indicate high elevation areas. Figure 1 also includes the final burn area once the fire was extinguished and, with arrows, the principal fire runs showing the path of the maximum rate of spread.

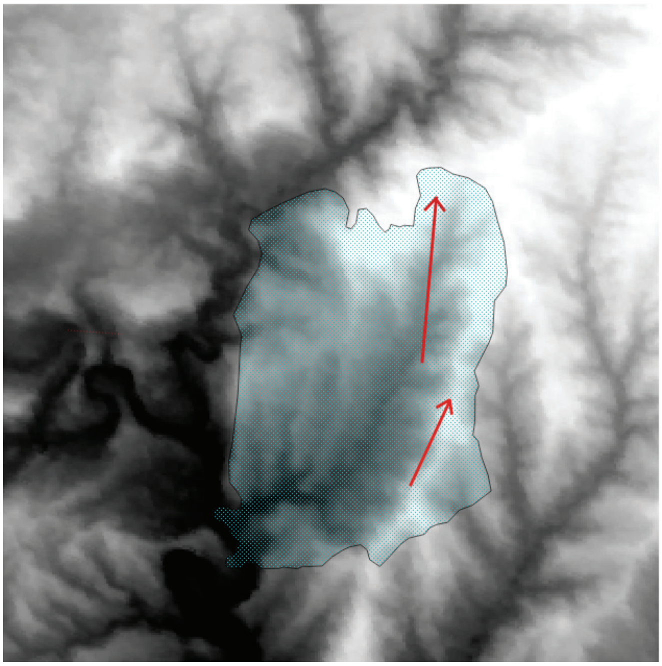
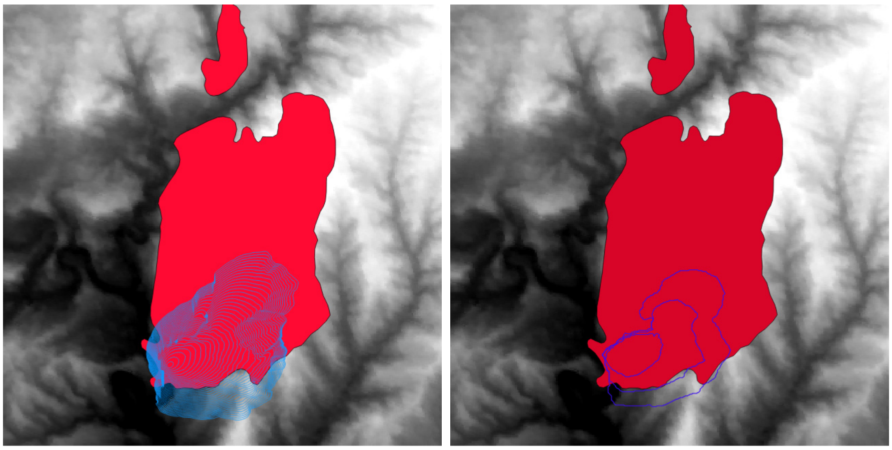


Figure 1: Digital Elevation map of the Cardona's fire area including the final burnt area and the principal fire runs

As can be observed, the main fire runs were located in the valley zone and, in particular, in the south face of the mountain slope. It is well known that wind and slope are critical factors in fire rate of spread and all existing fire propagation models take into account the effect of combining these two parameters. However, few efforts have been done in modeling the influence on the fire itself in the local meteorological conditions [6][9]. That is one of the reasons why, in events like the one we are describing, current models denote problems in delivering reasonable predictions. A way to overcome this problem consists of helping models by using dynamic data driven strategies. These schemes have the capability to modify the model behaviour according to real observations obtained during the event. Eventually, these on-line observed and collected data could be used to reduce the input data uncertainty by injecting it into the model. Furthermore, this data could also be used to guide the simulation process. Under this scheme, the detection of drastic changes in environmental conditions could lead the simulation system to ask for more frequent data to produce more accurate results. This feedback approach is known as Dynamic Data Driven Application System (DDDAS) [10]. In the following section, two DDDAS approaches to enhance forest fire spread prediction shall be described and, later on, the results obtained when applying both schemes to the above described study case will be analyzed.

3 DDDAS forecast approaches

As we have previously mentioned, part of the predictions mismatches in forest fire spread predictions come out from the lack of accuracy of existing fire spread simulators to consider the effect of the fire itself into the environmental conditions where the fire take place. The microclima generated by the fire directly affects the local meteorological state and, consequently, the information that should be fitted into the system. In order to overcome the uncertainty due to this situations, we analyze two DDDAS approaches based on two different forest fire spread simulators FARSITE [1] and WildFire Analyst (WFA) [3]. Despite implementing both simulators the Rothermel's equation [11], the way to obtain the global prediction evolution differs and, therefore, the final predicted perimeter is not identical. This fact is shown in Figure 2. In this Figure, both forest fire simulators provide a forest fire spread prediction considering as initial fire point the first recorder perimeter at 14:38 and a fire simulation time of 5 hours. The data related to the meteorological conditions have been set up to the one gathered at the ignition time and have been kept constant during the simulation time.



(a) (b)

Figure 2: Basic fire spread prediction obtained by applying FARSITE (a) and WFA (b) in the case of Cardona Fire.

As we can observe, none of these two basic prediction approaches are able to match the real observed propagation. The propagation obtained when using FARSITE (Figure 2(a)) underestimates the real fire propagation, as well as the propagation generated by WFA (see Figures 2(b)). For that reason, Dynamic Data Driven strategies have been applied to overcome this limitations. The scheme used is based on extracting relevant information about the real observed

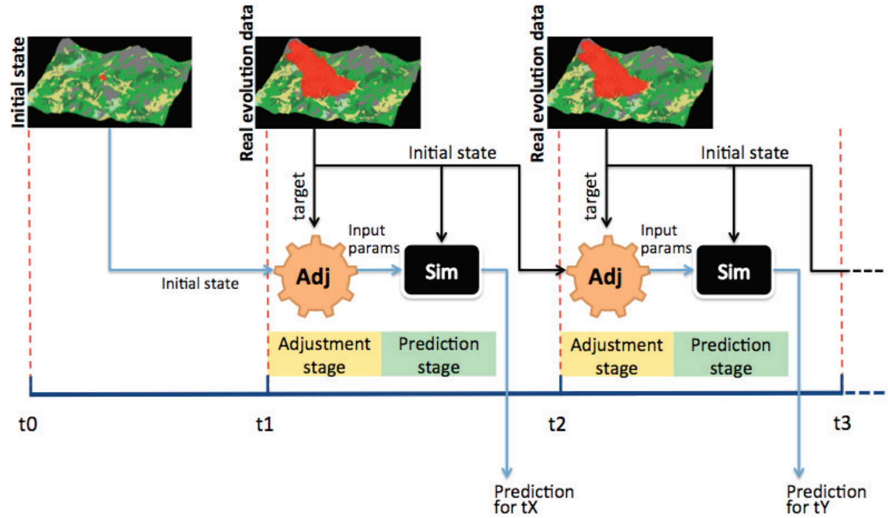


Figure 3: DDDAS approach for forest fire spread forecast.

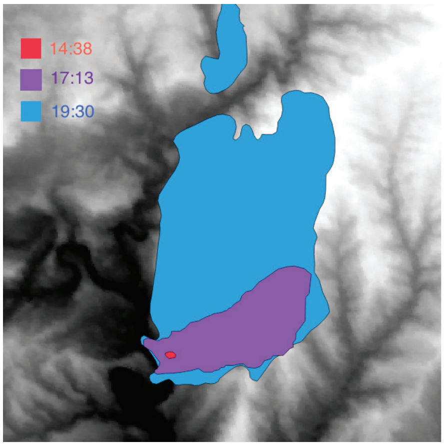


Figure 4: Real fire evolution of the Cardona Fire at three different time instants

fire spread to dynamically adjust certain parameters of the simulation process. Afterwards, those calibrated/adjusted values will be dynamically fitted into the simulation system to drive the forecast of the near future evolution. The way of dynamically extracting knowledge from the observed fire evolution to be used in the dynamic data driven strategy could be performed in different ways, but the general scheme is shown in Figure 3. As it can be observed, in order to launch an adjustment stage, it is necessary to have access to two consecutive real fire perimeters or, at least, to certain georeferenced points from the real fire spread perimeter. Each time the system could be fed with a new observed fire behaviour, the calibration/adjust process could be initiated again. The goal is to have the system working in a continuous fashion, to provide fire evolution forecasts on continuous preset times horizons. So, the input data set used for the prediction is calibrated in the corresponding adjustment stage. This methodology is simulator independent and it is flexible enough to change the simulator in a plug & play way.

In the next section, two DDDAS approaches to forecast forest fire spread evolution shall be described: DDDAS-GA and DDDAS-ROS. Both schemes use information obtained during the fire propagation interval time that goes from 14:38 to 17:13 to adjust/calibrate certain input data. Then, this data is used to dynamically drive the fire evolution forecast until 19:40. Figure 4 shows the initial, intermediate and final perimeters involved in the DDDAS forecast.

3.1 DDDAS applying Genetic Algorithm

DDDAS-GA is a dynamic data-driven prediction scheme that uses as a calibration strategy a Genetic Algorithm (GA) [12]. The forest fire spread simulator used in this approach is FARSITE [1], however, the system has been designed to be simulator independent so, the underlying simulator could be changed. The GA starts from an initial random population of individuals, each one representing a scenario to be simulated. A scenario/individual is composed of a number of different genes that represent input variables such as dead fuel moisture, live fuel moisture, wind speed and direction, among others. Each individual is simulated and all prediction results are compared to the recent pas observed propagation. Since fire spread is expressed using a cell map description where it is shown whether a cell has been burnt or not at a certain time (time of arrival), this comparison is performed by evaluating *the symmetric difference between predicted and real burned areas* (equation (1)).

$$Difference = \frac{UnionCells - IntersectionCells}{RealCells - InitCells} \tag{1}$$

In equation 1, *UnionCells* is the number of cells describing the surface burned considering predicted fire and the real fire. *IntersectionCells* is the number of cells burned in the real map and also in the predicted map, and *RealCells* are the cells burned in the real map. *InitCells* is the number of cells burned at the starting time. This difference takes into account the wrong burned cells and the mistaken for burned cells. According to this fitness function the whole population is ranked and the genetic operators *selection*, *elitism*, *mutation* and *crossover* are performed over the population, producing an evolved population which will have, at least, the best individual of the last generation (elitism). The new population is then evaluated in the same way. This iterative process allows us to find a good input parameter set, but it involves high computational cost due to the large amount of simulations required. Therefore, it is essential to speed up the execution keeping the accuracy of the prediction. For this reason, a parallel implementation of this two-stage methodology has been developed using the Master/Worker paradigm, and a MPI implementation has been developed [13]. At the first stage, the master node generates an initial random population which is distributed among the workers. Then, the workers simulate each individual and evaluate the fitness function. The errors generated by the workers are sent back to the master, which sorts the corresponding individuals by their error before applying the genetic operators and producing a new population. This iterative process is repeated a fixed number of times. The last iteration (generation) contains a population from which the best individual is taken as the best solution, and then it is used in the prediction stage.

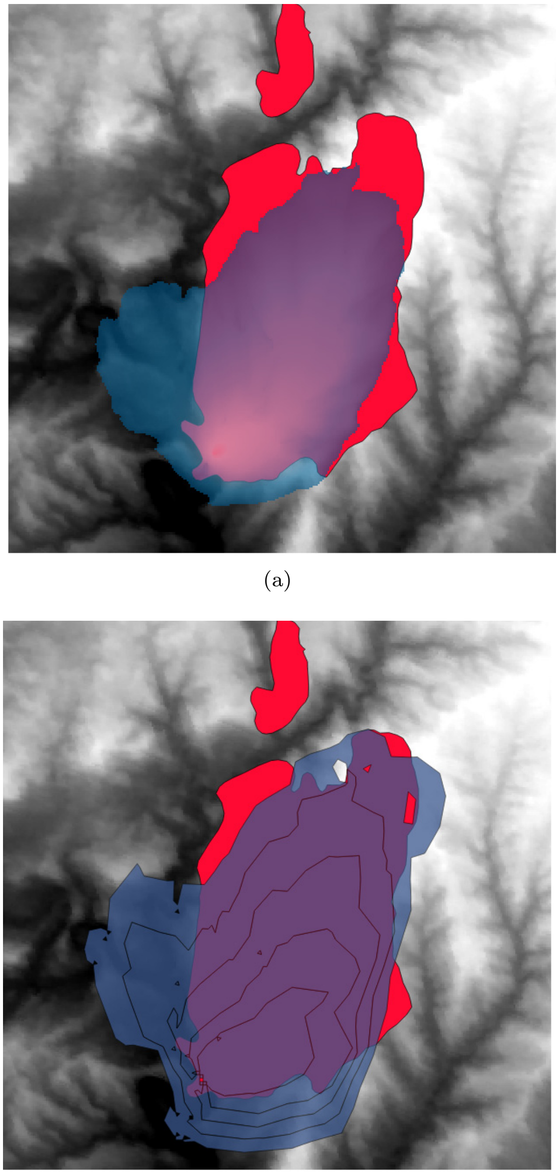
3.2 DDDAS applying Maximum-ROS-path adjustment

Wildfire Analyst (WFA) is a component of the Tecnosylva Incident Management software suite designed to directly support multi-agency wildfire incident management [3]. It provides real time analysis of wildfire spread and behavior and evacuation and impact analysis during an incident. Wildfire Analyst includes a data assimilation technique which tunes simulations to actual observed fire behavior. The method is based on seeking the best ROS(Rate of Spread) adjustment factors [14][1] minimizing the error between the simulated fire and the real data. These factors are fuel model specific and are multiplied by the rate of spread of the fire to achieve the specified adjustment.

The strengths of the method is that it is not recursive and therefore may be solved almost instantaneously, that it provides very clear and easy to interpret adjustments for fire managers at an operational level, and that it requires very few input data. Unlike other methods however, the adjustment does not try to analyze the final cause of the observed errors (weather inputs, fuel properties, etc) and simply focuses on providing estimations of future fire behavior no matter the source of error. Adjustments may be used on their own as a calibration technique, but could also be used as a search space guiding method in more general recursive optimization problems or data assimilation schemes aiming to provide the actual causes of the observed error. The algorithm is presently implemented as an operational adjustment module since it lacks the automated data feeding mechanism required for an operational data driven application. The module does not only provide the best ROS factors fitting a fire, but it also allows the user to manually fix them and instantly see the expected behavior without the need of redoing a simulation. The user may also select a tunning strengh in the adjustment in order to balance the need of minimizing the simulation errors, and the need of using adjustments that do not differ too much from (1) (are not too severe). Mathematically, the method is based on the assumption that simulated fire paths reaching the known fire location do not change significantly before and after the adjustment process. This assumption is usually fulfilled as long as adjustments are not too severe, but a small recursive algorithm may be used otherwise.

4 Overlapping DDDAS forecasts

In the previous section, we have described two Dynamic Data Driven Applications Systems applied to forecast wildfire spread. Both schemes relies on the analysis of the observed real fire evolution to adjust/calibrate unknown environmental data needed to perform fire spread simulations. Figures 5(a) and 5(b) show the obtained prediction spread for the Cardona Fire when applying DDDAS-GA and DDDAS-ROS respectively. As it was expected, the predicted results obtained for both approaches denoted slight differences compared to the real final fire spread.Both DDDAS predictions clearly match the main fire run direction despite of generating a non exact shape match. In the case of DDDAS-GA, the forecast fire evolution underestimates the real fire spread, meanwhile, in the case of DDDAS-ROS, the prediction overestimates the final burnt area. Therefore, an alternative proposal to consider the goodness of both systems could be to generate an overlapped DDDAS forecast in order to take into account both prediction results. Figure 6 shows the prediction fire spread areas of both schemes and the final real burnt area. The first conclusion that arises from analyzing this figure is that using data to drive the simulation system, has a direct impact in the direction of the fire spread. In particular, the overlapped DDDAS forecast is able to find the maximum rate of spread path, which clearly depends on the underlying topography and fuel characteristics. Using the overlapped DDDAS forecast as a prediction approach, the area that is predicted to be burnt in all cases, was destroyed by the fire, except the left flank where the overlapped DDDAS forecast overestimates the area affected by the fire. However, the advantage of using the overlapped scheme is that these false alarms are reduced because of the compensating effect of using two DDDAS approaches. The same phenomena could be observed in the back propagation.



(a)

(b)

Figure 5: Forest fire spread prediction applying both the DDDAS-GA scheme (a) the DDDAS-ROS approach (b) (blue shapes) compared to the real fire burnt area (red shape).

5 Conclusions

Forest fire is a natural hazard that every year devastates hundreds of thousands of hectacres of forest area around the world. Computer simulation has become a very useful tool to enhance propagation information provided to decision support systems when taking decisions about how to mitigate an ongoing fire. However, existing forest fire simulators have not the capacity of

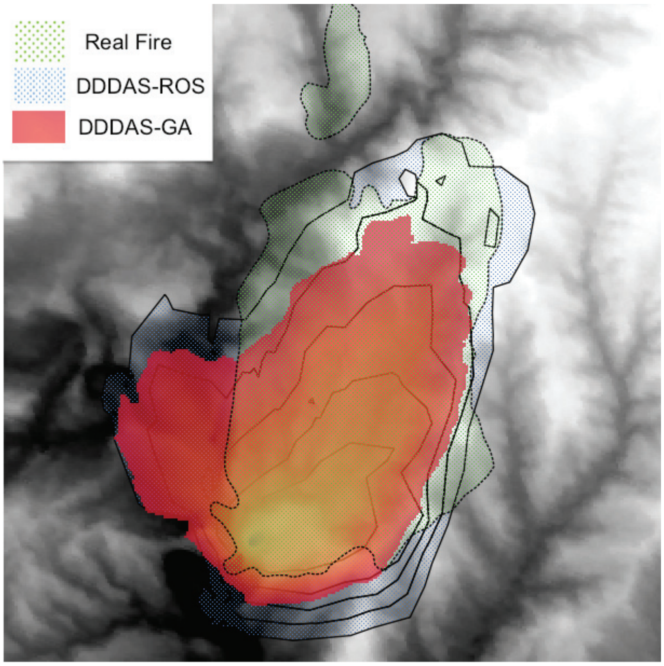


Figure 6: Map overlap including the final fire predictions applying both DDDAS schemes and the real fire spread

modify model behaviour according to the variation on environmental conditions due to the fire itself. In order to deal with this necessity, dynamic data driven approaches have been developed with the ability of updating the model behaviour according to the observed real fire spread. In this paper, two different DDDAS approaches are described: one based on Genetic Algorithms and, another one, based on the maximum ROS path. Both approaches have denoted a high ability in adapting to drastic chances in fire rate of spread due to the micro-clima generated by the fire under certain topographic characteristics. This fact has been proven using as a a test case the Cardona Fire, which took place in 2005 in the northeast of Spain. Since both approaches stem from complementary advantages, an overlapping DDDAS forecast is proposed to provide a high fidelity forest fire spread prediction.

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