An Integrated Environmental Decisional Support System Framework using Earth Observation, Cellular Automata and Multi-Agent System

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Abstract: The paper is about the modeling of natural disasters, taking in account both the natural elements than the human behaviors and working on mixed scenarios of forests, build-up area, rivers and roads.

We propose a three steps methodology that spans from the earth observation to categorization towards environment forecast modeling and action planning. As case study, we focused on fire spreading. Geographical Information Systems (GIS) and remote sensing tools are used to implement this scenario, while a multi-layer cellular automata is used to model the environment evolution. Finally, a multi-agent system is used to model human behaviors.

We evaluated the performance of the proposed method using a case study in a real Italian Region, Sicily. The goal is to employ our integrated approach as standard base in developing a real Decisional Support System to support environmental protection and people life preservation.

Keywords: Fire spreading; Environmental Decisional Support System; Cellular Automata; Multi-Agent Systems; Modeling

1. INTRODUCTION

The defense of the environment and people living in requires a solid understanding of the environment dynamics based on timely information. We can gather that information from ground sensors and remote sensing, in particular satellite images, and use them to feed a previsional systems obtaining understanding of in the risks for people and nature.

Our study is focused on a generic decisional support system (DSS) framework that use Earth observation to forecast environment possible changes computed under experimental conditions, giving the decision maker a stronger ground to plan recovery and preventive actions.

With this goal, our framework is based on

- Satellite image classifications,
- Geographical Information System (GIS) technology;
- Evolving Cellular Automata (CA) and
- Multi-Agent System (MAS)

respectively for:

- identify the ground conditions (e.g. the vegetation state);
- unifying that conditions with already known knowledge (as the altitudes, the presence of rivers or houses etc.) and unifying raster and vector data;
- receiving input from decision makers and modeling the evolution;
- analyzing the human behaviors resulting from the change in the analyzed region.

The first test bed of the framework is fire spreading in a heterogeneous landscape with woods and town. Although the main goal of our study was to verify an integrated methodology, the chosen subject it is *per se* interesting. We consider utmost important to test our methodology with real data gathered from a real sized context, in order to experiment with a large scale use of the framework.

2. SATELLITE IMAGE CLASSIFICATION: VEGETATION ANALYSIS

Study area

We studied area of 1.5 x 0.8 Km of the Italian Sicily Region. The zone include woodland, urban areas, roads and rivers.

Figure 1. The Sicily target zone

For this zone we used Ikonos images (4-bands and panchromatic), GIS layers for road etc.

The main variable that influence the fire spreading is the vegetation health.

Vegetation indices are widely used in remote sensing of woods and grassland (Rouse et al. 1974; Chena et al., 2004; Hea et al., 2005) and more generally of the vegetation surface; this is possible because the healthy vegetation has a high spectral response in near-infrared bands.

The Normalized Differing Vegetation Index (NDVI) is one of the most used index to measure vegetation strength (also defined *stress*). The NDVI is calculated by using the ratio of the reflectance in red band and near infrared band (Langley et al., 2001)

$$NDVI = \frac{\rho(\lambda_{NIR}) - \rho(\lambda_{RED})}{\rho(\lambda_{NIR}) + \rho(\lambda_{RED})} \qquad (1)$$

Using the Ikonos images, NDVI works by dividing the difference and the sum of two band intensities (band 3 and band 4) on pixel-by-pixel basis. The resulting index value of pixel typically ranges from around 0.1 to 0.7 for vegetation. The higher value means the denser vegetation. Rocks, bare soil, roads, rivers, and man-made objects produce the index value around 0. The NDVI calculated for the Sicily zone is shown in **Figure 2**.

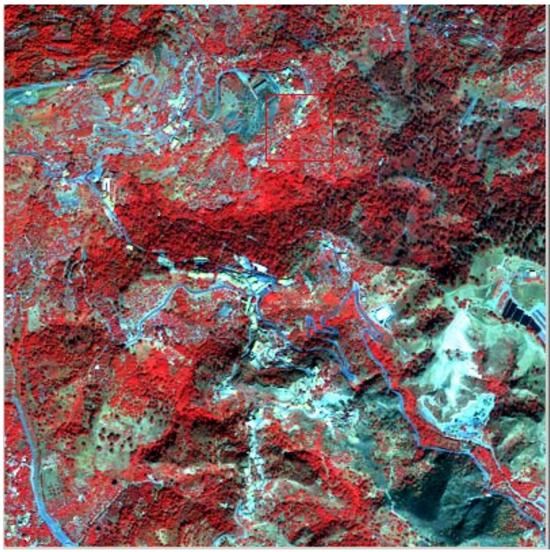

Figure 2. NDVI image classification

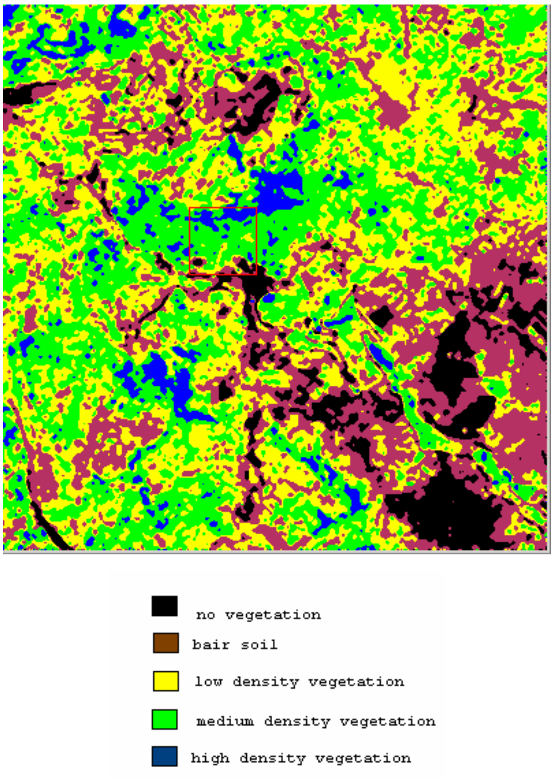

Figure 3. NDVI image classification with applied median filter

The NDVI classification is divided into 5 classes (0-4) to estimate of vegetation in study area; these results are obtained from the infrared image and then applying the median filter to smooth each class of image, as shown in **Figure 3**. In this way we elaborate the vegetation coverage map. The map is used as input by the modeler to compute the possibility of ignite and the speed of an ongoing fire.

We used the satellite images to also analyze the panchromatic band of Ikonos. These one-band images have 1-meter resolution, giving us the possibility to recognize house, other buildings, roads. The results of this processing is used to update GIS, e.g., road map. All these information are used by the modeler.

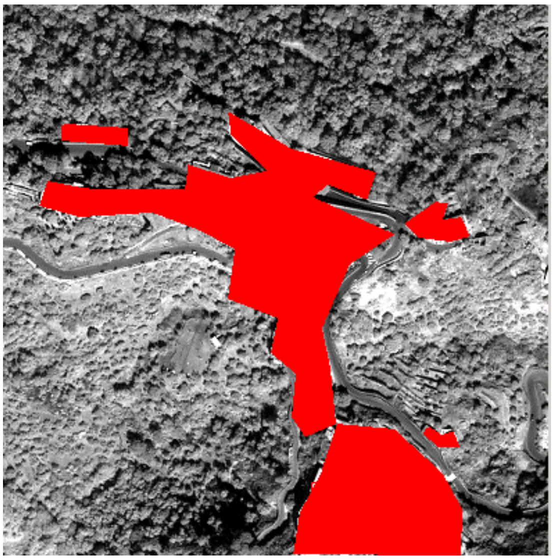

Figure 4. Panchromatic band image with building coverage area classification (in red).

From the above raster analyses, we obtain several classification using the KNN and other algorithms, e.g., computing the vegetation coverage classification, its stress, the building and road presence and area.

3. GEOGRAPHICAL INFORMATION SYSTEM (GIS)

All the classification information from the Earth observation are georeferenced and collected within a GIS. In this way we can better manage and correlate not only the different classified image data, but also other vector information gathered from other sources.

For spatial alignment, all the data are transformed to the same Universal Transverse Mercator (UTM) geographical projection.

At the end of the process, we have all the information in a geo data base with each category, raster or vector, organized in layers.

Some data, for instance the building and road presence, are obtained either from the vector layer or from the image analyses. In this way we can complement them having all the already known knowledge and the up to date one from the Earth observation (e.g., tracking new buildings).

Another advantage of the GIS is the possibility to use geographical operator to get valuable parameters for modeling, for example the distance of a point from a river or a road. This kind of queries are important for the Cellular Automata and for the agents.

4. CELLULAR AUTOMATA (CA)

Once analyzed the images, classified them and unified with vector data into a GIS, we are ready to exploit them to forecast environmental phenomena.

In the test case we choose, the fire spreading, this means to forecast the direction and the speed of the fire and hence the area involved.

Definition of Cellular Automaton

A Cellular Automaton is a simple device able to model complex systems. Usually a CA is defined by a finite grid of cells, where each cell models a discrete portion of space, and evolving discretely in time. The state of each cell at time t+1 is determined by the state of its adjacent cells

More formally, a basic CA is 4-tuple defined as:

$$CA=(E^d,X,Q,\sigma) \quad (2)$$

Where:

- E^d is the set of cells identified by the points with integer coordinates in a d-dimensional Euclidean space (i.e., partitioned with a square, cubic, hypercubic tessellation) where the phenomenon evolves;
- $X=\{\xi_1, \xi_2,\ldots, \xi_m\}$ is the neighborhood index, a finite set of d-dimensional vectors, which defines the set $V(X, i)$ of the cell i as follows: $V(X, i) = \{i+\xi_1, i+\xi_2,\ldots, i+\xi_m\}$
- Q is the finite set of states for the cells;
- $\sigma : Q^m \rightarrow Q$ is the deterministic transition function of a cell;

$C = \{c \mid c: E^d \rightarrow Q\}$ is the set of possible state assignments to **CA** and will be called the set of configurations; $c(i)$ is the state of the cell i. The effect of the transition function σ is to change the configuration C_t into the new configuration C_{t+1} according to:

$$C_{t+1}(n) = \sigma(\{C_t(i) : i \in V(X,n)\}) \quad (3)$$

where we denote by *X(n)* the set of neighbors of the cell *n*.

The definition is well founded for regular CA with homogeneous transition function and neighbors and time scale. It is possible to extend the definition to include the heterogeneous variations.

There are several ways to compute the set of neighbors of a cell; in a regular grid, the most used are:

- the Von Neumann's, which is constituted by a central cell and the four first neighbor cells in the direction north, south, east and west;
- the Moore's, including all the adjacent cells;
- hexagonal neighbors, where the tessellation is similar to Moore's but in hexagonal space.

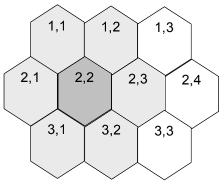

Figure 5. Hexagonal cellular space; the grey cells evidence the neighbors of the central cell (2,1)

Our framework can be used with all this types of neighbors, with any radius. However, we find more convenient to use the hexagonal one, because the more usual rectangular tessellation implies a greater distance from the center to the diagonal cells, raising the percentage of errors. Instead, using hexagons, all the adjacent cells are at same distance.

So, the transition function we are using has the form:

$$S^{t+1}_{r,c} = f(S^t_{r,c}, S^t_{r-1,c-1}, S^t_{r-1,c}, S^t_{r,c-1}, S^t_{r,c+1}, S^t_{r+1,c-1}, S^t_{r+1,c}) \quad (4)$$

where S^t_i is the cell state *i* in time *t*, *f()* is the transition function that applies the rules that governs the state change of a cell, and *r,c* are the rows and columns in the grid.

CA in the framework

The CA are not new in the ecological modeling. It is possible to find a short review of such usage in Balzter et al. (1998) or, in different forms, in Wiering and Dorigo (1998) and Parker et al. (2001).

However, the most of the studies are focused on experimenting with transition functions while the use in a real context is not the main goal. So, usually the CA used to model that environment is not based on a GIS and/or Earth observation, reducing the input the CA can process and the reuse of the observations.

We want to reverse this approach, simplifying the task of connecting real data with the CA. The initial state of the automaton is determined by the data from the GIS layers: e.g. roads, rivers, population density, vegetation stress etc.

To give maximum freedom to the scientists that use the framework, we worked with a layered CA: we use several layer, each one an autonomous cellular automaton, that concurs to the final evolution. Our approach is similar to the Cellular Automata Network described in Calidonna et. al., 2001.

In a model with n-layers, the transition function can be defined as the composition of specific transition functions:

$$\sigma = \sigma_1 \circ \sigma_2 \circ \ldots \circ \sigma_n \quad (5)$$

A transition function can read the value of another one; it is possible to establish dependencies between layers (e.g. update the water layer before the burning wood) and to use different radius and neighbors for each layer.

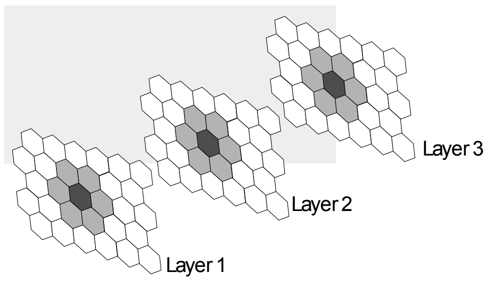

Figure 6. Layered Cellular Automata

The CA can use some global wide variables. It is possible to generalize these variables as a layer with the same value for all cells. For fire spreading, such variables include the wind direction, the humidity etc.

For visualization purpose, we establish an order in which to overlay the layers. An example output is shown in **Figure 7**: in black the burned zone, in blue the urban area, in brown the bare soil, in green and yellow the vegetation at different stress level.

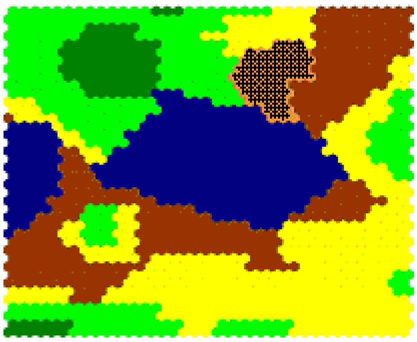

Figure 7. A view of partial test zone in CA

The output of CA engine are saved in HTML format, so it is possible to review all the time steps from a simple browser in the Web.

Transition function for fire spreading

What make the difference in the effectiveness of a modeling by a CA are the number of variables, the starting data and the transition function.

Because our goal was not related to the creation of new, more realistic, transition function, we test the framework with literature algorithms, in particular Yongzhong et al. (2004) and Karafyllidis and Thanailakis (1997). Our results are in line with that of the papers.

Yongzhong et al. start from Rothermel's fire behavior prediction model for calculating the fire-spreading rate,

$$R_0 = \frac{I_r \cdot \xi}{\rho_b \cdot \varepsilon \cdot Q_{ig}} \qquad (6)$$

where I_r is the reaction intensity, which measures the energy release rate; ξ is the propagating heat flux ratio, which expresses the proportion of the reaction intensity that heats the neighboring fuel particles to ignition; ρ_b is the fuel bulk density; ε is the effective heating number, which measures the proportion of a fuel particle that is heated to ignition at the time combustion commences (dimensionless); and Q_{ig} is the heat of pre-ignition, which measures the quantity of heat required to ignite 1 kg of fuel. Then they extend Rothermel's function and adapt it to a CA with hexagonal grid. All the details can be found in their interesting paper that includes laboratory experiments.

5. MULTI AGENT SYSTEM (MAS)

Modeling human behaviors

The last phase of our proposed approach and framework is the modeling of human behaviors depending on the environment simulated by the CA in different time steps.

The multi agent systems (MAS) are growing in interest in the environmental modeling arena, as testified by Parker et al. (2001). This interest is shared by computer scientist and geographers (a good example of latter is An et. alii, 2005).

An agent is a software system, situated in an environment, able to perceive it through sensors and capable of flexible autonomous action in that environment, through effectors, in order to respond to its objectives. A multi agent system is a group of agents that interact each other, often with the need of coordination and negotiation and hence of communication.

So, with a MAS, we can model the behaviour of single categories of persons (simple citizens, fire fighters, helicopter pilots and so on) and their interaction. The agent behaviours are modelled with plan libraries using the Belife-Desire-Intention (BDI) model, or learn to cooperate, as more usual in the a-life area.

The interaction between MAS and CA are more common in the a-life. Indeed, yet in 1996 Epstein and Axtell have described the "Sugarscape", an approach and a software, aimed to model social science from the bottom up. The problem with this approach is that it is difficult to model the "real" people behavior with a bottom-up approach.

MAS in the framework

In the test, we are using agents to simulate the escape from small town when a wildfire is going to harm it. The idea is to model the wildfire with the CA and then, if there is a potential danger for the people, to find the moment for a partial or total evacuation.

In our framework, we are using BDI agents that extracts plan using as reference a probabilistic finite-state machine. We search an improvement of the agent behaviour modifying the probabilities of the arcs in the machine, so the resulting machine is the "better one" given the problem and the surrounding environment. Therefore, the resulting architecture is BDI at run time but alife in the learning approach.

To synchronize the agents and the environment, we manage the environment as an agent (*EnvA*) including the CA, while the other agents request to the ask to *EnvA* the effects of the desiderated action; e.g., an agent *A* that want to move towards a point *P* ask to *EnvA* to compute which point it really reach, and the final point is computed on the base of the characteristic of *A*, the environment state as described by the CA and the world rules described in *EnvA*.

As agent platform we are using Jade (Bellifemine, Poggi, Rimassa 1999), a FIPA compliant Java distributed environment.

6. CONCLUSIONS

Our goal was to demonstrate the feasibility and the usefulness of an Environmental Decisional Support System (EDSS) based on a process starting from remote sensing, with a modeler and a multi-agent system able to model human behavior.

The framework implementing such process is now completed. We are now working with historical data to verify the soundness of our models with the recorded situations.

We have used it to experiment with different fire transition functions and different Earth areas. We used it to provide insight in people security trying different fire start origins and meteorological parameters. We can conclude that the approach is valid and the framework can be used as a real EDSS.

Because we want our system to be usable on real scenarios, we used consistently real world images, model dimensions and so on. This has caused a lot of troubles (the system is hard to test, the simulations carry on more time, the GIS products are not so easy to interface with a CA and so on), but we are rewarded with a flexible tool usable in real monitoring contexts.

Now we are working in extending the MAS component and to discover and try more realistic fire spreading functions.

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