Flood Prediction and Risk Assessment Using Advanced Geo-Visualization and Data Mining Techniques: A Case Study in the Red-Lake Valley

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Abstract: Throughout the last century, flooding has been one of the most costly natural disasters concerning of human casualties, property damage, and environment degradations. Flooding is a complex natural phenomenon which is highly constrained by the geospatial environment where it evolves. The need for flood prediction and risk assessment is increasing, and decision makers still lack intelligent tools to study flooding. Artificial intelligence and knowledge discovery advances offer approaches for the modeling and simulation of such complex phenomena. To this extent, we propose to build a computer simulation platform to support flood prediction and risk assessment using advanced geo-visualization and data mining techniques. The outcomes and results of our simulations aim to better manage floods through prevention, protection, and emergency response perspectives.

Key-Words: -Multi-Agent Geo-Simulation, Visualization, Data Mining, Predictive Models, Frequent Pattern Mining.

1 Introduction

After the record floods of 1997, communities all along the Red River of the North took different approaches to protect themselves from future floods. Floodwaters spread over large areas of Grand Forks, ND and East Grand Forks, MN; 60,000 people were forced out of their homes and downtown Grand Forks was burning (Figure 1). Even cities such as Crookston miles away from the Red River need protection, which feeds into the Red River. Moreover, in June 2008, the levees of the Mississippi River were breached by a large flood. More than 22 breached levees flooded many areas in several days with 24 fatalities. Thousands of people were affected and lost their homes; many industries and farmers in 51 counties of 5 states (Illinois, Missouri, Wisconsin, Iowa, and Minnesota) lost their products and ability to recover. Catastrophic flooding is a major security concern in the United States. Failure of dams, levees, and flood gates of water infrastructures such as on reservoirs, lakes, rivers, and coastal water will result in losses including many lives, billions of dollars in property damage, and environmental degradation. Although most of the rivers in the US are confined within manmade levee systems, these existing infrastructures are in great need of improvement and strengthening.

The need for flood prediction and risk assessment is increasing yet decision makers still lack intelligent tools to study flooding. Indeed, flooding is a complex natural phenomenon which is highly constrained by the geospatial environment. In order to study flooding, a number of challenges need to be addressed: (1) we need to reproduce and simulate such phenomena in a virtual environment using computer simulation; (2) we need to analyze large amounts of data representing collected observations for frequent pattern discovery and flood prediction purposes; (3) we need accurate and intelligent predictive models to predict floods ahead of time based on the related attributes; and (4) we need to geo-visualize and assess risks entailing potential flooding phenomena.

(a) (b)

Figure 1: (a) The Sorlie Bridge between Grand Forks, North Dakota, and East Grand Forks, Minnesota, during the 1997 Red River of the North flood (photograph by Steven W. Norbeck, U.S. Geological Survey). (b) A forest service plane bombards downtown Grand Forks with fire retardant chemicals in a last ditch effort to knock down fires raging out of control (source: http://www.usgs.gov).

Advances in artificial intelligence evolved the geo-simulation paradigm for the modeling and simulation of complex natural phenomena. In addition, data mining which is concerned with new knowledge discovery from large databases can be applied to analyze collected observations such as: flood history, water levels, snow-fall amounts, weather conditions, and geospatial data. Moreover, virtual reality provides techniques nowadays that enable accurate geo-visualization of large scale environments. The integration of the aforementioned techniques within a simulation platform aims to support flood prediction and risk assessment.

In this research paper, we propose to build a computer simulation platform to support flood prediction and risk assessment using advanced geo-visualization and data mining techniques. We intend to collect and analyze observation data in order to identify frequent patterns and to discover important relationships between the data variables using predictive modeling that we propose to build. These models will be integrated into a Geo-Simulation platform which offers 3-D geo-visualization to help decision makers predict potential floods and assess associated risks.

The goal of this research paper is to help the local Red Lake Valley community with better flood prevention planning. We believe that the proposed platform, associated set of models, and algorithms will be of interest to community leaders to help with the elaboration of effective strategic flood prevention planning. We will first target local areas surrounding the Red River as a case study, but we anticipate that our geo-simulation platform can be adapted to other geographic areas.

2 Literature Review

Flood models are a major tool for mitigating the effects of flooding [1]. They provide predictions of flood extent and depth that are used in the development of spatially accurate hazard maps [2]. Predictive models allow for the assessment of risk to life and property and the prioritization of either the maintenance of existing flood defences or the construction of new ones [3]. Computer simulation and geo-visualization techniques enable the study of such scenarios. In this section, we provide the present state of work in the field of predictive modeling, flood modeling, and simulation using GIS data.

Predictive modeling (supervised learning) has been widely studied for a broad number of applications such as: medical diagnoses [4], classifying web services [5], and fraud detection [6]. The needs for flood prediction models are of the highest importance since they critically impact the lives of people and their properties. In the past few years, several flood prediction models have been proposed. A web GIS system has been developed for decision support [3]. Artificial Neural Networks (ANN) with fuzzy theory has been used to enhance flood predictions [7]. A model based on support vector machines has been created to predict flood velocity [8]. A model to predict flood occurrence patterns [9] is presented. A series of data mining techniques has been proposed in for flood prediction [10].

There have been significant advances in flood modeling over the past decade. Progress has been made in the understanding of the processes controlling runoff and flood wave propagation, simulation techniques, uncertainty handling and risk assessment, and in collecting and analyzing of data [11].

The flood phenomenon is highly constrained by the spatial environment in which it takes place [2]. Existing analytical models usually fail to capture the interaction between this phenomenon and the geospatial environment in which it evolves [12]. The movement of flood waters through the landscape can be approximated using many different methods. Describing natural physical phenomena using numerical methods requires making broad assumptions to develop governing equations [3]. While simple hydraulic modeling methods may be sufficient for approximating propagation of flood peaks through river channels, more complex hydraulic analyses may be necessary to incorporate effects of infrastructure (i.e. bridge, building, roads, etc.) or complex overland flow [2].

There are several well-known methods to assess the impact of a flood on the urban areas. Some of them consider the economic effects of flooding [1], while others focus on estimating the number of fatalities [11] [12] [13]. Some of these use empirical models which try to predict the number of casualties by some heuristic rules. For example [12] uses numerical flood simulation to estimate the flood characteristics (depth, flow speed, and so on) in the modeled area. They apply an empirical formula to estimate the fraction of fatalities (mortality function) for each spatial location. Given the initial population distribution, this can provide a useful estimate of the number of loss of life events.

Some researchers use agent-based modeling (ABM) to employ more details of population behavior into the simulation. For example [11] uses ABM to model the cycle of daytime routines being interrupted by a flood. The researchers consider the case of vehicle evacuation over a road network. The Life Safety Model [13] is another agent-based model of flood evacuation; it uses a sophisticated set of rules to predict loss-of-life events depending on an agent's health condition and actual location (building, vehicle, pedestrian).

Although, several flood prediction models have been proposed, none of these models have been adapted to take into account the characteristics of the geospatial environment. In addition, none of the aforementioned models integrate GIS data and supports agent-based geo-simulation with geo-visualization that enables "what-if analysis".

Geospatial environments are usually complex and large-scale. The creation of computer generated virtual geospatial environments is difficult and needs large quantities of geometrical data originating from the environment characteristics (terrain elevation, location of objects and agents, etc.) as well as semantic information that qualifies space (building, road, river, park, etc.) [14]. Most current agent-based simulation models consider the environment as a monolithic structure, which considerably reduces the capacity to handle large-scale, real world geographic environments as well as agent's spatial reasoning capabilities [15]. These models do not take into account the valuable semantic information associated with the geospatial

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features [2]. The complexity of building such a description should only depend on the geometrical complexity of the geospatial environment rather than on its scale [16].

3 Methods

We propose to build a multi-agent geo simulation platform to support flood prediction and risk assessment using advanced geo-visualization and data mining techniques. First, we will introduce the data mining concept while emphasizing the fundamental processes including the data collection, data cleaning, data warehouse construction, and data cube creation. Next, we provide an overview of multi-agent geo-simulation techniques.

3.1 Data Mining

Data mining (DM), also known as knowledge discovery from data (KDD), is the process of extracting interesting non-trivial, previously unknown patterns or knowledge from large amounts of data. The process of finding new knowledge consists of a series of steps including: 1) data cleaning, 2) integration of multiple sources, 3) data warehouse (DW) construction, 4) data selection, 5) knowledge discovery, and 6) pattern evaluation. Below we discuss how we can adapt these general DM tasks to flood prediction and risk assessment.

3.1.1 Data Collection

This step aims to collect statistic and geographic data including:

- historical rainfall and runoff data across a catchment;
- historical river height and discharge information;
- catchment topography and land use;
- surveys of river and floodplain levels and cross sections;
- models of the hydrologic processes (rainfall, runoff, infiltration, concentration etc.);
- models of the hydraulic processes (propagation, attenuation etc.).

Table 1 shows the data sources. The collected data are time series. Relevant attributes such as rainfalls, snow amounts, and temperatures are measured over time. Our aim is to integrate all these multiple-source data sets into a single coherent and consistent data warehouse repository.

3.1.2 Data Cleaning

The collected data will be analyzed and pre-processed in order to use the most relevant data. We will evaluate and pre-process the data using the following criteria:

- Data completeness: we will use statistical measures, such as parameter mean or median to pre-process missing data. In addition, inference-based methods can be used, such as Bayesian theory or decision trees to infer missing data expected values.
- Data Integration: data collected from multiple sources will be integrated in a systematic manner to ensure the elimination of redundant data and detect and resolve value conflicts.

The GIS data will be used to build the virtual geographic environment. Maps depicting elevation, population, infrastructures, and land coverage and use will be used.

3.1.3 Data Warehouse Construction

A Data Warehouse (DW) will be created by integrating the entire collected multiple source data. The planned data warehouse will contain historical Red-lake River data represented in multiple dimensions. This DW will help community leaders in decision making for potential floods.

Next we will build the simulation engine and integrate the hydraulic models that will be used to produce inundation maps. The final step in the DW process involves integrating the virtual geographic environment and the specification of the experimental simulation scenario.

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3.1.4 Data cubes creation

Several data cubes can be created from the DW. These data cubes will allow extracting task-relevant data to be analyzed. These data cubes can be created by integrating as many parameters as needed. Below we provide a schematic of a sample data cube representation for 3 parameters: snow amounts, water level, and time. These data cubes will be used in step 5 for prediction purposes and step 6 to extract interesting patterns (Figure 2).

In this step, we will integrate the data warehouse with the simulation engine and perform the required validations and calibrations of all developed models.

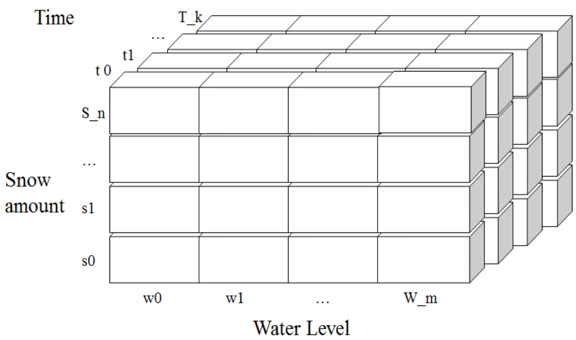

Figure 2: Schematic of data representation using data cube technology of 3 parameters: 2 variables over time.

3.1.5 Predictive Modeling

Classification is one major task in DM that has been widely used for predictive modeling. Classification consists of two main steps: first, establishing the classifier model through supervised learning. This model is trained using historical data. Second, the classification model is evaluated using accuracy measures. The accuracy is measured by splitting the data into two sets, testing and training. This model will be consulted to predict the testing data class labels. This model then can be used to predict new instances once it is accurate enough (at least 80% accuracy).

The aforementioned general data mining tasks can be adapted to our problem statement for potential flood prediction. The collected historical data stored in the modeled DW will be used to train several classifier models such K-Nearest Neighbors (KNN), Decision Trees (DT) and Bayesian Networks (BN). These classifiers will be evaluated and if accurate enough, they can be used for predicting potential floods. The aforementioned data cubes will be used to train these classifiers (supervised learning). The collected time series dimensions will be used as classifier attributes to predict potential floods (which will be represented as a binary class label). These models will be built based on decision tree theory, Bayes theory, and rule-based classification. All the models will be evaluated using standard classification measures: accuracy, sensitivity, and specificity. The results of a classification style data is represented in (2 X 2) confusion matrix as can be seen in the below table:

Table 2: Classification Style Confusion Matrix

TP	FN
FP	TN

Where,

• TP: are the true positives. Data with class label 1 and predicted as 1.

• FN: are the false negatives. Data with class label 1 and predicted as 0 (type I error).

• FP: are the false positives. Data with class label 0 and predicted as 1 (type II error).

• TN: are the true negatives. Data with class label 0 and predicted as 0.

The below measures are used to evaluate the classifier performance:

$$Sensitivity = \frac{TP}{TP + FN} \quad (1)$$

$$Specificity = \frac{TN}{TN + FP} \quad (2)$$

(3)

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$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$$

The aforementioned models will be integrated to the simulation engine and perform usual testing and validation tasks. This will include building and integrating the geo-visualization modules to support the geo-simulation engine.

3.1.6 Association Rule Mining (ARM)

Association Rule Mining (ARM) is another task in data mining used to discover interesting relationships and patterns between variables in a large database. ARM is well known for market-basket analysis which is a modeling theory that states that, based on historical data, if you buy a set of items, you are most likely to buy another group of items. The discovered rules can be evaluated using the support (proportion of transactions in the data which contains the item set) and confidence (percentage value that shows the rule head frequency among all groups containing the rule body).

We will use association rule mining theory to find the most interesting patterns that relate to higher probabilities for folding. We intend to analyze all parameters and establish rules, using Apriori and Frequent Pattern (FP) Growth Algorithms. The derived rules will be evaluated using standard support and confidence measures.

Data cubes will be further evaluated to derive interesting patterns that occur frequently. For example, finding the relationship between specific latitude and longitude coordinates and water fall amounts at certain times with flood probability. All the derived patterns will be represented as association rules between data parameters that induct an event with specific support and confidence.

The user-interface then will be built for simulation geo-visualization, data collection, and results display.

3.2 Multi-Agent Geo-Simulation

A fundamental idea underlying our approach is to reproduce, in a realistic manner, the real world in a virtual environment. Indeed, in this virtual environment, which imposes no physical limits, it is possible to create a system for the simulation of flooding phenomena. In order to faithfully mimic the dynamics of water resources (i.e. river) in an area of interest, we need to simulate the water resource, the weather conditions as well as the geographic environment. We propose to use software agents for the virtual representation of geographic features. An agent is a program with domain knowledge, goals and actions [17]. An agent can observe and sense its environment as well as affect it. Agents' capabilities may include (quasi-) autonomy, perception, reasoning, assessing, understanding, learning, goal processing, and goal-directed knowledge processing [18]. The reproduction of the geographic environment in which physical sensor nodes are deployed should be based on reliable data obtained from Geographic Information Systems (GIS) [2]. The concept of Multi-Agent Geo-Simulation (MAGS) evolves from such type of simulations involving software agents immersed in a virtual geographic environment.

MAGS has attracted a growing interest from researchers and practitioners to simulate various phenomena in a variety of domains including traffic simulation, crowd simulation, urban dynamics, and changes of land use and cover, to name a few [19]. Such approaches are used to study various spatial and complex phenomena (i.e. car traffic, crowd behaviors, etc.) involving a large number of simulated actors (implemented as software agents) evolving in, and interacting with, an explicit description of the geographic environment called Virtual Geographic Environment (VGE) [14].

MAGS is a useful approach to integrate the spatial dimension in models involving different kinds of interactions (economic, political, social, etc.) [20]. From this perspective, the Geographic Information System (GIS) plays an

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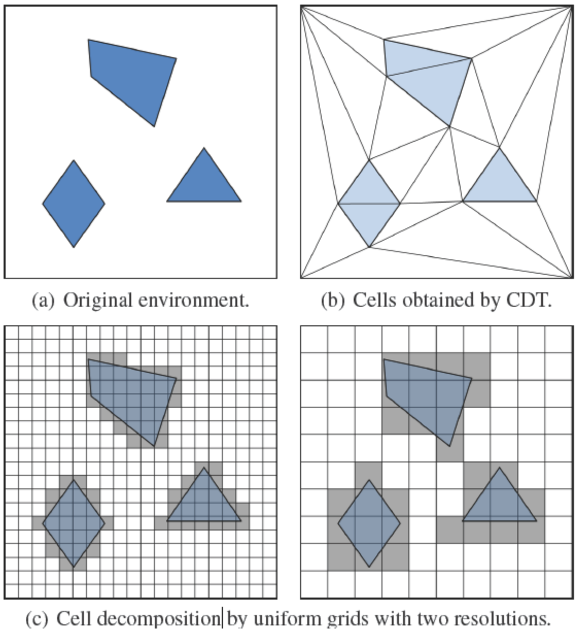
important role in the development of geo-simulation models. MAGS can be thought of as a coupling of two technologies: the Multi-Agent Systems (MAS) and the GIS [19]. Based on the MAS technology, the simulated entities are represented by software agents that can be behave and make decisions autonomously. They can interact with other agents and with a virtual representation of the actual geographic environment. They may be reactive, proactive, stationary or mobile, social or cognitive [21]. These agents evolve and interact with their VGE.

An accurate VGE requires the use of reliable GIS data. GIS data are usually available in either raster or vector formats [22]. The raster format subdivides the space into regular square cells, each associated with an attribute related to the space. In contrast, the vector format describes geographic information using unconstrained geometric shapes, and generally associates one qualitative object with each shape. Such data are usually exploited by a VGE in two ways [2]: the approximate geometric subdivision and the exact geometric subdivision methods. The approximate geometric subdivision method is the direct mapping of the raster format, but it can also be applied to the vector format (Figure 3(c)). This discrete representation can be used to merge multiple semantic data, the locations where these data are stored being predefined by the grid cells. The main drawback of the grid method is related to a loss in spatial precision, making it difficult to accurately position any information which is not aligned with the subdivision. Another drawback arises when trying to precisely represent large environments using a grid: the number of cells tends to increase dramatically, which makes the environment description very costly. The grid-based method is mainly used for overlay and animation purposes because of the fast data access it provides [23].

The second method, called exact geometric subdivision, consists in subdividing the environment in convex cells using the vector format as an input. The convex cells can be generated by several algorithms, among which the most popular is the Constrained Delaunay Triangulation (CDT) [24]. The CDT produces triangles while keeping the original geometry segments which are named constraints (Figure 3(b)). The first advantage of the exact subdivision method is to preserve the geometry of the input data, allowing accurately manipulating and visualizing the environment at different scales. Another advantage of this approach is that the number of produced cells only depends on the complexity of the input shapes, but not on the environment's size and scale as is the case with the grid method. The main drawback of this approach is the difficulty to merge multiple semantic data for overlapping shapes. Moreover, this method is generally used to represent planar environments because the CDT can only handle 2D geometries. This method tends to be used for micro-scale simulations centered on individuals where motion accuracy is essential [24].



(a) Original environment. (b) Cells obtained by CDT.

(c) Cell decomposition by uniform grids with two resolutions.

Figure 3: The two common cell decomposition techniques used to represent environments.

4 Conclusions and Future Work

In this paper, we presented an approach to predict potential flooding using historical time series data. Our goal is to combine well established data mining paradigms with novel geo-visualization technique along with intelligent computer simulation involving software agents.

First, we propose to build a data warehouse for the Red-Lake River Valley by integrating historical multiple sources time series data. Task relevant data can be extracted from the DW in the form of data cubes. Interesting knowledge and patterns can be found from these data cubes. Such knowledge includes future flood predictions by using the aforementioned predictive models and interesting patterns and associations between several data variables. All predictions and discovered patterns will be evaluated using standard DM measure.

Second, we are currently implementing the multi-agent geo-simulation platform. Indeed, since a geographic environment may be complex and large-scale, the creation of a plausible virtual geospatial environment is difficult and needs large quantities of geometrical data originating from the environment characteristics (terrain elevation, location of objects and agents, etc.) as well as semantic information that qualifies space (building, road, park, etc.). The virtual geospatial environment's description should rely on an efficient structure which supports easy and optimized access and query techniques. The complexity of building such a description should only depend on the geometrical complexity of the geographic environment rather than on its scale.

A number of challenges arise when creating such an informed VGE, among which we mention: 1) automatically creating a precise geometric representation of a 3D VGE; 2) automatically integrating several types of semantic information in the geometric representation; and 3) making use of this representation in spatial reasoning algorithms for flooding study and simulation.

To enable an autonomous agent to interact with its environment, we might think of storing the entire interaction process within the agent's knowledge model. Thus, the agent would be able to observe the world that surrounds it and to gather raw information from its sensors. After that, it would process this raw data through a complex reasoning module in order to try to derive high-level information and to determine the interaction possibilities offered by the objects it is observing. This approach is extremely complex, very difficult to implement, and is rarely applicable to complex interaction processes. The more complex the object is, the harder it is to derive abstract information and the more complex the reasoning algorithm needs to be. This process can become extremely costly in terms of calculation time and resources when the complexity of the environment and the objects contained in it increases.

Future work will mainly focus on the integration of data mining results in order to feed the software agents' reasoning algorithms in order to reach plausible and realistic simulation of flood phenomena never achieved before.

The current case study aims to study, analyse and predict flooding phenomena and assess risk in the red river valley. However, our goal is to develop a generic intelligent flooding simulation platform which supports planners and decision makers.

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Table 1: Overview of sources of data collection

Source	Period	Records	Attributes	Data Type	Station Information
Midwestern Regional Climate Center	2002-2013	95 690	1) Date, 2) Local Std Time, 3) Air Temp (F), 4) Dew Point Temp (F), 5) Wet Bulb Temp (F), 6) Rel Hum (%), 7) -Stn Pres (in), 8) SeaLevPres (in), 9) Wind Speed (kt), 10) Wind Dir (deg), 11) PrecipTotal	Hourly Data	Station name: CRKSTN MUNI KRKWOD FLD APT. Station location: CROOKSTON, MN
Western Regional Climate Center	1948-2013	780	1) Monthly sow falls (inches)	Monthly Data	Station name: CROOKSTON NW EXP.STN Station location: CROOKSTON, MN
US Army Corps of Engineers	1965-2014	161 520	1) Time 2) Date, 3) Flood stage	Hourly Data	Station name: - Station location: CROOKSTON, MN
U.S Geological Survey database(USGS)	2007-2014	132 409	Agency info: 1) site_no, 2) date and time, 3) Time Zone, 4) Gage height, feet, 5) Data-value qualification codes, 6) River discharge(cubic feet/s), 7) Data-value qualification codes	Hourly Data	Station name: USGS 05079000 Station location: Red Lake River at CROOKSTON, MN
National Climatic Data Center	1948-2013	783	1) Station, 2) Station Name3) Elevation, 4) Latitude, 5) Longitude, 6) Date, 7) Maximum snow depth reported during month (inches), 8) Number days with snow depth > 1 inch, 9) Total precipitation amount for the month, 10) Total snow fall amount for the month, 11) Monthly mean maximum temperature, 12) Monthly mean minimum temperature, 13) Monthly mean temperature	Annual data	Station name: CROOKSTON 1.0 NE Station location: CROOKSTON, MN
Weather Warehouse	1985-2014	Not available	1) Temperature, 2) dew point, 3) relative humidity, 4) visibility, 5) cloud cover, 6) wind speed, 7) wind direction, 8) precipitation(rainfall and/or snow)	Hourly Data	Station name: Crookston Municipal Kirkwood F Station location: CROOKSTON, MN

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References:

[1] B. Gouldby, P. Sayers, J. Mulet-Marti, M. A. A. and D. Benwell, "A methodology for regional-scale flood risk assessment," 2008.

[2] M. F. Goodchild, "{GIS} and disasters: Planning for catastrophe," *Computers, Environment and Urban Systems,* vol. 30, no. 3, pp. 227-229, 2006.

[3] D. Mioc, G. Liang, F. Anton and B. G. Nickerson, "Decision Support for Flood Event Prediction and Monitoring," 2007.

[4] A. Margoosian and J. Abouei, "Ensemble-based classifiers for cancer classification using human tumor microarray data," 2013.

[5] L. Y. jie and C. Jian, "Web Service Classification Based on Automatic Semantic Annotation and Ensemble Learning," 2012.

[6] M. I. Alowais and L.-K. Soon, "Credit Card Fraud Detection: Personalized or Aggregated Model," 2012.

[7] G. Corani and G. Guariso, "Coupling Fuzzy Modeling and Neural Networks for River Flood Prediction," 2005.

[8] C. Li, Y. Liu, J. Yang and Z. Gao, "Prediction of Flooding Velocity in Packed Towers Using Least Squares Support Vector Machine," 2012.

[9] N. Z. Ku, N. Katuk and M. Shbier, "Flood Pattern Detection Using Sliding Window Technique," 2009.

[10] C. Damle and A. Yalcin, "Flood prediction using Time Series Data Mining," *Journal of Hydrology,* vol. 333, p. 305– 316, 2006.

[11] R. Dawson, R. Peppe and M. Wang, "An agent based model for risk-based flood incident management," *Natural Hazards,* vol. 59, p. 167–189, 2011.

[12] M. D. Mauro and K. d. Bruijn, "Application and validation of mortality functions to assess the consequences of flooding to people," *Journal of Flood Risk Management,* vol. 5, no. 2, pp. 92-110, 2012.

[13] M. D. Mauro and D. Lumbroso, "Hydrodynamic and loss of life modelling for the 1953 Canvey Island flood," 2008.

[14] M. Mekni, Informed Virtual Geospatial Environments, LAP LAMBERT Academic Publishing, 2013.

[15] H. Lin and M. Batty, Virtual Geographic Environments, ESRI ed., 2011.

[16] I. Benenson and P. Torrens, Geosimulation: Automata-Based Modeling of Urban Phenomena, {J}ohn {W}iley and {S}ons Inc., 2004.

[17] M. Wooldridge, Introduction to Multiagent Systems, {J}ohn {W}iley and {S}ons Inc., 2001.

[18] G. Weiss, Multi-Agent Systems: A Modern Approach to Distributed Artificial Intelligence, MA: MIT Press., 1999.

[19] M. Mekni and B. Moulin, "A Multi-agent Geosimulation Approach for Sensor Web Management," 2008.

[20] S. W. Frye and D. J. Mandl, "Autonomous Mission Operations Systems," *Sensor Webs,* pp. 13-16, 2006.

[21] M. Mekni, "Using GIS Data to Build Informed Virtual Geographic Environments (\{IVGE})," *Journal of Geographic Information System (JGIS),* vol. 5, no. 6, pp. 548-558, 2013.

[22] S. Paris, M. Mekni and B. Moulin, "Informed Virtual Geographic Environments: an Accurate Topological Approach," 2009.

[23] J. Gong and L. Hui, "Virtual Geographical Environments: Concept, Design, and Applications," 1999.

[24] M. Kallmann, H. Bieri and D. Thalmann, "Fully Dynamic Constrained Delaunay Triangulations," *Geometric Modelling for Scientific Visualization,* 2003.