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Improved Situational Awareness in Emergency Management through Automated Data Analysis and Modeling

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Abstract

In this paper we address the problem of situational awareness in the context of emergency management. Due to the widespread application of information technology, emergency managers face a new challenge in information overload, rather than the lack of information as in the past. These new tools deliver large volumes of data to the decision makers, often in real time. However during the crisis the task of identifying the key relevant information poses a real challenge and failure to do so can have disastrous consequences. To address this problem, we propose a model for the fusion of data from diverse sources, both real-time and static, to derive numerical measures that represent the status of a jurisdiction. In our approach we combine the data available from various sources with human expertise to build customized models based on threats characteristic for particular jurisdictions. We developed a prototype based on data collected for several municipalities and implemented it as a computer model.

KEYWORDS: Situational Awareness, Expert System

INTRODUCTION

A reliable assessment of the current situation at risk is a fundamental need for an emergency manager. Understanding the situation derived from this assessment is crucial in making informed decisions in emergency operations. *Situational awareness* describes the human perception of a complex and rapidly evolving situation that enables emergency managers to draw conclusions, build understanding and make decisions. Situational awareness involves not only knowing the current status of an incident but also forecasting how it could evolve to provide advanced warning of impending threats and to facilitate the planning of response and mitigation actions. The development of information technology (IT), and in particular, massive data bases, computer networks capable of carrying large volumes of data in real-time, remote sensing techniques that are becoming very affordable and capable of taking various measurements, leads to empowering decision makers with large volumes of data. In this setting, the challenge of situational awareness has changed from a lack of sufficient information to information overload – the situation when the amount of information available exceeds human cognitive limits. While large volumes of data can be potentially beneficial, they require analysis and interpretation to transition from raw data to actionable knowledge. In the increasingly complex, dynamic and multi-disciplinary environment that emergency management has become, it is critical to find solutions that can provide the support needed to increase the effectiveness and efficiency of decision makers while enhancing the safety of responders and victims.

We propose a model for the fusion of data from diverse sources, both static and real-time. Our model derives numerical measures that are intended to represent the status of jurisdictions from the perspective of emergency management. The model provides emergency responders from multiple organizations with increased situational awareness through automated data gathering and analysis. This task is accomplished by using IT technologies for data collection, sorting and computer modeling that incorporate real-time data from a variety of sources into a computer model. This process converts a large volume of data from real-time information on the current status of a jurisdiction to provide early warning of possible hazardous conditions.

The goal of the Situational Awareness Module (SAM) is to improve situational awareness through supporting decision makers by delivering real-time actionable information in an operational context. The SAM is intended to assist emergency managers in assimilating changing information from multiple sources regardless of the emergency managers' level of expertise, experience, or familiarity with the area or hazard. It provides a method by which various agencies or decision makers can access information at the same time through the web interface. Since the model uses a series of abstract measures derived from publicly available sources, we avoid concern about confidentiality of data. This open sharing of information allows each agency to determine the relevance and impact of the information on their operations and create a common operating picture.

Situational awareness has many definitions. The term was coined in military aviation and, used as a decisive factor in air combat, it was quickly adopted in many other disciplines where human decision making processes are made under time stress and with potentially fatal consequences for error. A more formal definition comes from Endsley (1995) in which she defines situation awareness informally and intuitively as “knowing what’s going on” and, more formally, as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future” (p. 36). In this paper, we define situational awareness using a synthesis of Green’s definition (1995), “[to] detect, integrate and interpret data gathered from the environment” and Endsley’s (1995) concept. Situational awareness is a foundation for decision-making and performance (Livnat, 2005) and holds a central role in this process. Resch (2007) states that developing situational awareness is a critical skill for emergency managers and a crucial prerequisite for successful and efficient emergency management. It has been included as the first key action in the National Response Framework (NRF) (FEMA, 2006).

Situational awareness can be analyzed on different levels. Most practitioners follow Endsley’s (1988) definition borrowed from aviation. Accordingly, situational awareness is an “internal model of the world around him [the pilot] at any point in time.” This model is the result of information received through a variety of sources that incorporates the individual’s capabilities, training, and experience to arrive at a final model. Using the disaster metaphor when bad things are happening, these sources assist the emergency manager in determining who/what is at risk and what resources are available to intervene constructively.

Endsley (1995) later expands the definition to include three levels of situational awareness from perception through comprehension, and finally projection. This delineation allows us also to look at what may be equally or perhaps more important concerns about the potential for secondary and tertiary hazards. Such hazards not only complicate the primary hazards, but can have an overall impact equal to, or greater than, the initial hazard. The ability to foresee and monitor these potential complications, as well as the trends of the initial event, allows an emergency manager to intervene effectively to reduce hazards and the overall impact of the event.

In order to address the complexity of situational awareness in the context of emergency management, we propose to divide the problem into Mileti’s (1999) three systems: earth’s physical (geophysical), human, and constructed. The SAM is intended to be a composite of three interrelated models displaying information on these systems. In this paper we focus on the first of the three systems: earth's physical (we use the term *geophysical* as it more accurately describes the phenomena being measured in SAM). We focus on the geophysical aspect, given the dominating frequency of weather and geological disasters in the area for which our prototype was developed.

Charles Philips (1999) notes that the earth's surface is active and complex, making accurate measurement difficult. It is marked by a web of interrelated components dynamically linked which result in complex changes in conditions. To monitor this type of system requires the use of multiple data sources and analysis to develop actionable information. It is evident that the gathering, analysis and synthesis of such data exceeds the capacity of a single individual (Sonnenwald, 2000) especially under disaster conditions. This justifies the development of a decision support tool to support planning and response phases for the emergency situations that are caused by geophysical phenomena. Comfort, Mosse and Znati (2009) point out the capacity for response to hazards is characterized by four decision points: 1) detection of risk; 2) recognition and interpretation of risk for the immediate context; 3) communication of risk to multiple organizations; and 4) self organization and mobilization of a collective, community response system to reduce risk and respond to danger. Our work is intended to address these decision points by enhancing Endsley's (1995) three levels of situational awareness as they relate to each of Mileti's systems. This provides a tool for "subsequent decision making and performance in the operation of complex, dynamic systems..." (Endsley, 1995)

The importance of situational awareness for these complex and dynamic conditions was supported when the National Academies' report, *Facing Hazards and Disasters* (2006) recommendation 3.3 stated that research should be conducted to identify better mechanisms for intervening into the dynamics of hazard vulnerability. This recommendation is reinforced by the key IT-based capabilities for disaster management and related promising technologies put forth by the National Research Council in the publication, *Improving Disaster Management* (2007). In that edition, they include "improved situational awareness and a common operating picture". Under the long term capabilities they included automated information fusion from diverse sources which is one of the tasks included in our proposal.

SITUATIONAL AWARENESS IN EMERGENCY MANAGEMENT

When an event is unfolding or when emergency management personnel suspect that an emergency may occur, they begin to glean information from various sources. These sources typically include contacts with other agencies, various web sites, and/or monitoring response agencies. Experienced managers seek to heighten their situational awareness for two primary reasons: (1) to determine the current state of the system and (2) to compare current conditions with "normal" conditions to identify aberrancies that might indicate problems are developing. The development of situational awareness currently is achieved through a combination of human reconnaissance and review of selected data sources, primarily accessed from the Internet and occasionally with the use of specialized proprietary software. If conditions warrant the attention of outside agencies, managerial staff, or elected officials, then briefings are developed to establish a common operating picture and often the Emergency Operations Center (EOC) is activated.

The EOC staff faces several challenges in this process. The first is the variance in staff capabilities. The transition of raw data into situational awareness requires multi-disciplinary, experienced and trained personnel that may not always be available. Another challenge relates to working with numerous agencies that serve as sources of information regarding current and forecast conditions. The EOC staff that is developing the common operational picture must not only be aware of the information sources, but also how to access the data and, if necessary, call on specialized personnel within those agencies to explain the likely impact of the information on the region. Many of these data sources are prepared for specific audiences and provide information that is not readily interpretable for emergency managers. Interpretation and synthesis requires at least a working knowledge of the associated field to allow valid transformation of the data into usable intelligence that will inform decision makers. The most common of these is the National Weather Service (NWS). They provide not only the atmospheric forecast but also hydrological information for rivers and most importantly various types of advisory information when the threat of severe weather is elevated. Other organizations are equally applicable, such as the US Geological Survey for stream level information or earthquake reports. The American Red Cross uses the National Shelter System which is a valuable source of information on shelter capacity and use. Finally, an increasing sophistication in the data requires analysis and interpretation in order to transform it into actionable knowledge. The ability to turn the situational awareness into actionable knowledge requires not only an understanding of the information, but also knowledge of emergency operations so that the response strategies based on that information can be developed effectively.

The consequences of incomplete situational awareness during the developing incident may range from over-assigning resources when assessments over-estimate the threat to losing property and/or lives when critical needs are unknown or not anticipated in time for appropriate response assets to be available.

An important message often repeated by experienced practitioners is that establishing situational awareness as early as possible during an incident is crucial. Since incidents are dynamic, characterized by complexity, and often rapidly evolving it is difficult to assess initial conditions when information available to the decision makers is limited. This stage of the incident is typically the most rapidly evolving and critical in determining the course of actions. Understanding the initial conditions is fundamental to determining not only the causes of the current situation, but equally important the direction in which the incident is evolving in order to take appropriate response actions.

The SAM is intended to assist emergency managers gain situational awareness both by providing insight into the current situation and estimating changes in the situation. Once the incident turns into a crisis situation, SAM may provide summarized data and guide the user in maintaining real-time situational awareness. Finally, the system can be used as a planning tool; it can be used to investigate potential threats by simulating various threats and/or providing static measures of vulnerability of particular jurisdictions.

Many emergency management agencies are woefully understaffed both for their duties and in comparison to other public safety agencies. Outside of the large cities many emergency management agencies and many public safety agencies rely on volunteers. This dependence increases diversity in both staffing levels and the skill sets of personnel. This has been true over many years, but especially under current fiscal conditions when acquiring additional staff is unrealistic. In areas where career staff is assigned to emergency management duties, it is often a secondary role, as when a police chief is also assigned as Emergency Management Coordinator. In both scenarios, the provision of necessary services requires the use of other solutions. Given limited staffing and additional duties, agencies requiring deeper analysis may not have staff with the time or analytical sophistication to monitor secondary and tertiary hazards. These agencies in particular can benefit from the proposed module. This assistance to bounded rationality (Simon, 1982) helps to expand the available information pool and better inform decision makers.

MODEL DESIGN

In this section we describe the conceptual design of the quantitative model that serves as a tool that collects, interprets and summarizes available data to deliver concise measures of the aspects of interest for the emergency managers.

The basic goal of the SAM is to summarize a status of the jurisdiction (or some aspect of it) by means of a single number, which we will further refer to as a *score*. The score describes a status of a jurisdiction or some aspect of it and it can be mathematically derived from other scores. We use a value from the range 1 to 10 to summarize every concept in the model. In our approach we use 1 to describe situations that are of minor concern: individual medical emergencies, minor household fires, car accidents, etc. and we use 10 to denote a catastrophic event.

The range 1 to 10 was selected arbitrarily, as we found it intuitive for knowledge elicitation from domain experts during the development of the model. If some other range of values is preferred by the user, for example 0 to 1, a direct mapping can be used to translate the SAM score into the user preferred values.

The total score for a jurisdiction is derived from a set of scores that address different aspects of emergency management: such as vulnerability, potential risks, available resources, preparedness level, etc. In our model, the scores form a *concept hierarchy*, where the total score for a jurisdiction is placed at the top, and at the second level the major threats based on the risk assessment for the given jurisdiction are located. At the lower levels, the structure of the concept hierarchy is strictly determined by the particular variable from the second layer. An example of a concept hierarchy is shown in Figure 1. Each node in this hierarchy corresponds to a variable that defines a score, with values ranging from 1 to 10. The score for a variable is calculated based on scores of variables immediately below it in the hierarchy and additional data specific for that variable.

Because of the nature of hazards related to the geophysical aspect, we used two different concept hierarchies for the same jurisdiction: one for summer and one for winter conditions. Therefore, we defined two different concept hierarchies for temperatures above and below the freezing point – these two models were named the *warm concept hierarchy* and the *cold concept hierarchy*. We use the following criteria to determine which concept hierarchy to use: the average of the mean virtual temperature derived from thickness of the North American Mesoscale (NAM) model maintained by the National Weather Service's National Centers for Environmental Prediction's Environmental Modeling Center, and the current temperature for the area taken from the National Weather Service. If the average falls below 0 Celsius degrees, the cold concept hierarchy is used, otherwise the warm concept hierarchy is used.

The census tract is used as the atomic spatial unit in our model. Using a census tract was primarily dictated by practical considerations: availability of structured and consistent data nationwide, jurisdiction area sufficiently small to reflect heterogeneity from the hazards viewpoint and at the same time large enough to calculate meaningful scores for the status assessment. For each census tract in the study area, a risk assessment was performed and based on its outcome a concept hierarchy was created. In practice however, most of the tracts in the area have the same or very similar patterns of natural hazards risks. This reduces the task of defining concept hierarchies to identifying the areas with similar concept hierarchies rather than posing a tedious process of defining unique concept hierarchies for each individual tract.

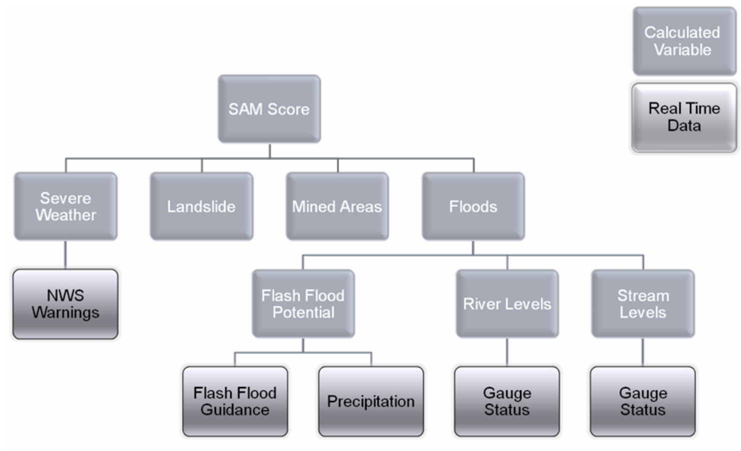

Figure 1 Example of a concept hierarchy

Once the concept hierarchy is defined, the next step is identifying relevant data and formulae to calculate scores for each variable. Both the data and formulae are specific to each variable and can vary significantly throughout the hierarchy. The only common element for all variables is the range of acceptable values (1 to 10) and its interpretation (1 means normal and 10 indicates a catastrophic event). The scores are defined using data that can be static (do not change over time, such as: tract area, population, etc) or dynamic. The dynamic data include any kind of data that can change in real time – for example weather information, river and stream stages, etc. In our approach, the domain experts are asked identify dynamic data sources. The SAM Web grabber (described later) was implemented to access automatically the identified data sources and in real-time to fetch the data to our system. A good example is weather data (or more precisely selected aspects of it) that is pulled from the National Weather Service websites. To ensure real-time situational awareness all scores are updated every minute. All historical data are archived for training and system improvement purposes.

Once a final score for each tract is determined, the next step is to derive scores for larger jurisdictions. In our approach we define the score for an upper level jurisdiction solely based on the scores of the lower level jurisdictions. For example: assuming three levels of jurisdictions: tracts, municipalities, and county, the score for a municipality is derived based on the total scores for its tracts and the score for the county is derived only from its municipalities' scores. This approach enables easy scaling of the model into large jurisdictional hierarchies. The premise for this is simple: risk assessment is done at the low municipal level by the emergency managers who are familiar with the area, historical events, hazard patterns and actual threats and response capabilities. At the same time, it allows users the flexibility to scale the information to their jurisdictional level and have the option to drill down to the tract level to view specific problem areas.

Emergency management is a challenging problem to manage by means of mathematical modeling and simulation because of the sheer complexity of emergency situations. A particular problem is the uniqueness of each emergency situation and the fact that larger-scale emergency situations are rare events. There is no comprehensive data available to use statistical or other methods that require large amounts of data to define valid models. In this situation, the best practice is to rely on human domain experts who have an understanding of the problem and the causal structure of the domain. This practice justifies our approach: to define models based on the understanding of the interdependencies in the domain elicited from the local emergency managers. Therefore our model is intended to be defined by domain experts who work closely with knowledge engineers to identify the key aspects of emergency management specific for the area of interest.

One possible criticism of our approach is that we summarize the status of a jurisdiction into a single numeric value. In fact, we acknowledge that more than one score per jurisdiction is needed. The ability to drill-down addresses the problem of justifying the scores. However the problem of differentiating between the current status and the estimated evolving situation remains. The difference is subtle, but very important in practice. The current status of a jurisdiction is important, but provides only limited utility – it does not carry information on how the situation may evolve. In particular, it may not carry warnings on an impending escalation of the problem. It is based on actual data, not predictions, so it removes uncertainty from the score. A score that would include predictions about the future would bring the additional benefit of an early warning mechanism but at the expense of the possibility of error. We postulate that two types of the scores should be calculated:

- **Current status score** – this score is based exclusively on data (both dynamic and static) that measure observable facts. The purpose of this score is to present a reliable and objective measure of the current state of affairs with no element of uncertainties related to predictions. Observed river gage status, current weather conditions (but not forecast) are examples of measures included in the current status.
- **Future status scores** – these scores are based both on actual data and estimated data. For example, scores that include elements of weather forecasts belong to this category. These scores are intended to indicate the estimated course of actions. Since they are derived from estimates (some may be more reliable than others), their interpretation should be made explicit to the users – they should be treated as indicators of possible problems rather than reliable forecasts. A severe weather outlook would be a good example of data that would be included in a future status score, with no guarantee that the event will actually happen.

One of the key design features of the model is to grant the user the ability to drill-down to understand and evaluate the validity of the score. We believe that providing not only the score itself but also enabling the user to understand how it was derived (not the general formulas, but particular values for the current scenario) builds the trust of the user in the system. The same functionality provides means to review the performance of the model and, in the situations when the model provides results that are in disagreement with the users and their experience, it allows production of causal explanations for the output.

MODEL DESCRIPTION

We implemented a prototype of the model based on principles described earlier for 42 municipalities for Allegheny County, PA (Pittsburgh metropolitan area). The model covers 61 census tracts. In terms of natural hazards (the primary concern of the geophysical model), the area is characterized by high risk of river flooding – three major rivers (Allegheny, Ohio and Monongahela) run through Allegheny County. These rivers are fed by a number of smaller size streams, some of which have a history of dangerous flash floods that caused several fatalities. There has been significant residential and industrial development along both the rivers and the streams. The landscape is characterized by a hilly terrain that causes landslides to be second only to flooding as the primary natural hazard. The co-location of both structures and transportation networks along the flood plains and along hilly terrain poses a significant threat to life, property and economic stability.

For each tract a number of static variables have been identified by the local emergency managers. Because the primary concern is flooding events, the static variables include total stream lengths and river fronts for a tract, flood prone areas, and the number of upstream watersheds. Other examples of static variables included in the model are total area, population, landslide area, etc.

The current implementation of our model uses the following dynamic data sources:

- The North American Mesoscale Model (NAM) – a numerical weather prediction model run by National Centers for Environmental Prediction. Selected output of this model is used for determining use of cold or warm concept hierarchy.
- National Weather Service (NWS) – a website with a specific weather forecast and nowcast. The service includes information specific for determination of the cold or warm concept hierarchy, temperature, wind speed, dewpoint, and relative humidity. Additionally, if any extreme weather advisories are issued for the area of interest, they are accounted for by the model.

- Precipitation for Allegheny County (IFLOWS) – the actual current and historical precipitation measured at rain gages throughout the county.
- Flash flood Guidance – the output of a specialized hydrological model implemented by National Weather Service to predict estimated amount of rainfall required to trigger flash floods.
- Advanced Hydrologic Prediction Service – the river gages' stages and forecasts delivered by National Weather Service.
- National Water Information System – current and historical stream gage readings delivered by U.S. Geological Survey.
- Snow Precipitation Forecast – the forecast for precipitation and snow accumulations derived from GFS MOS by National Weather Service.

If one of these sources becomes unavailable or information presented is older than a threshold determined for that particular source, the variable is flagged as unavailable and in practice ignored for the calculation of scores. This strategy ensures robustness of the model – the scores are guaranteed to be based on up-to-date data and failure of a score to calculate does not affect the model to fail – it is just reduced in complexity and ability to provide more adequate situational awareness.

As noted earlier, it is beneficial to define more than one score per tract. In our current implementation we defined two scores: *current status* and *predicted status*. The current status is based exclusively on current data and the predicted status is an extended version of the current status that includes all other variables that relate to predictions (e.g. weather forecast).

We use the dynamic variables in conjunction with static variables to determine the score for the jurisdiction. The static variables are used as a form of weighting factors to determine the relative risk of particular hazard for the area. For example, the landslide score is defined based on guidelines by the USGS (Chleborad et al., 2006) that defines precipitation level above which there is a considerable risk of landslides. This landslide score involves the amount of precipitation (measured in inches) within the last 3 days (P_3) and preceding 15 days (P_{15}). Following the USGS guidelines, it is defined as:

$$P_3 = 3.5 - 0.67\, P_{15}.$$

The measures are derived using 24 hour precipitation amount taken from IFLOWS website. The landslide score (L) is 10 points when $P_3 > 3.5 - 0.67\, P_{15}$, and 1 otherwise. Landslide Area (L_A): if landslide area is 1 then $L_A = 1$, if landslide area is less than 10% of total jurisdiction area $L_A = 0.5$, if landslide area is greater than 10% of the total jurisdiction area then $L_A = 1$. The revised landslide score (L^*) is defined as:

$$L^* = L_A \cdot L$$

Table 1 Selected National Weather Service Advisories and the corresponding scores

Blizzard Warning	10	River Flood Warning	10
Blowing Snow Advisory	8	Severe Thunderstorm Warning	10
Dense Fog Advisory	8	Severe Thunderstorm Watch	6
Flood Warning	10	Urban and Small Streams Warning	10
Flood Watch	6	Wind Advisory	8
Freezing Rain Advisory	8	Wind Chill Advisory	8
Heat Advisory	8	Wind Chill Warning	10
High Wind Outlook	4	Winter Storm Warning	10
High Wind Warning	10	Winter Storm Watch	6
High Wind Watch	6	Winter Weather Advisory	8

The landslide score is one of the scores that go into calculations of the total score for a tract. Another example of a score based solely on the external data source is the weather score (*W*). It's based on the weather advisories accessed from the National Weather Service website. Table 1 shows the list of NWS advisories that are included in our model and the corresponding scores. In practice it is possible that more than one of the advisories are issued for the area, in that case the highest score is taken into account. Since the advisories are in fact weather forecasts, they are only included in the predictive score calculation.

Because of the page limitations, we do not discuss the other elements of the equation for the warm model. The other variables in the warm model include: flash flood and precipitation score (*F*), stream score (S^*), river score (R^*), and the temperature score (*T*). They vary in the nature and complexity of their definitions. The total current status score (Q_A) and the total future (predicted) status score (Q_P) for a tract are calculated from these variables using the following equations:

$$Q_A = \min\left[\max(S^*, R^*, T) + \frac{S^* + R^* + T - \max(S^*, R^*, T)}{2}, 10\right]$$

$$Q_P = \min\left[\max(F, S^*, R^*, W, L^*, T) + \frac{F + S^* + R^* + W + L^* + T - \max(F, S^*, R^*, W, L^*, T)}{5}, 10\right]$$

In these equations, functions *min* and *max* return the minimal and maximal value from their multiple arguments correspondingly. Definition of the function is dictated by the following postulates: (1) the cumulative score should be no less than the value of the greatest of its individual scores, and (2) it should be increasing if one of its individual scores increases. The general formula for a total score (*Q*) defined for *n* scores S_i is defined as:

$$Q = \min\left[\max(S_1, ..., S_n) + \frac{S_1 + ... + S_n - \max(S_1, ..., S_n)}{n-1}, 10\right]$$

Finally, the calculation of the scores for a municipality is based on tracts' scores that belong to this municipality and currently it is taken as a simple arithmetical average. The selection of the arithmetic average is dictated by the fact that the desired property of the aggregated score for multiple jurisdictions is (1) if a single tract's score is high, but the others belonging for the same municipality are low, the cumulative score should be relatively low, and (2) the cumulative score should never be higher than the maximal score.

IMPLEMENTATION

The computational model described in this paper is implemented within the IISIS system (Comfort et. al., 2009). The acronym IISIS stands for Interactive Intelligent Spatial Information System and is a working prototype of a web-based decision support system. The IISIS is a computational decision support system that integrates different tools under the same World Wide Web framework to assist emergency managers in the emergency preparedness and response processes.

Because the IISIS is intended as a common framework that accommodates a set of tools that serve different purposes (managing incidents and resources, patient tracking system, geographic information system, document library, etc) its components are called *modules* and they can be interdependent or relatively independent of each other. The model described here was implemented as one of the IISIS modules and it functions under Situational Awareness Module (SAM).

The implementation of the SAM within the IISIS currently consists of three individual software components that perform three major tasks:

- SAM Web Grabber – responsible for accessing, interpreting and storing dynamic information from external data sources (such as web pages and other on-line data services). It consists of a set of conceptually independent software agents that each one is responsible for accessing a particular web page or other on-line data source. Each data source is accessed periodically and data retrieved from the source is interpreted and stored in the IISIS database allowing for collecting historical data within the system, rather than relying on the external data sources to provide archived data.
- SAM Score Agent – the software that is responsible for calculating SAM scores based on the relevant data stored in the IISIS database. The software periodically accesses the database and calculates SAM scores based on updated data delivered by the SAM Web Grabber.
- SAM API – the software responsible for communication with the SAM module using Java API. It is implemented as a thin wrapper around the IISIS database.

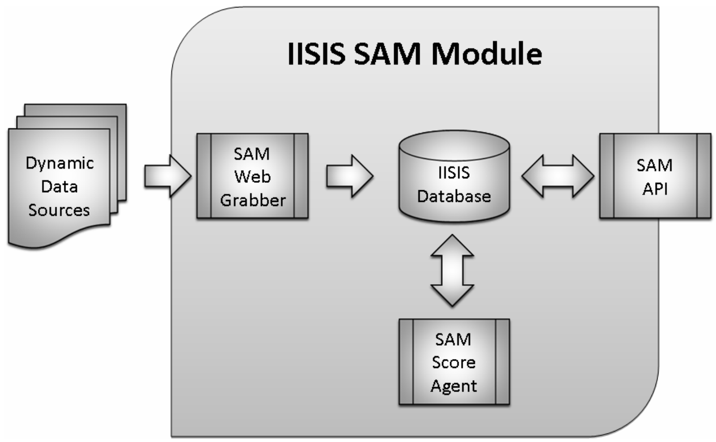

Figure 2 Design of the SAM module within the IISIS prototype

These three tasks are performed by independent software components that communicate through the IISIS database which serves as the common data repository for the IISIS prototype. The conceptual diagram is presented in Figure 2. This design enables easy data sharing framework between different IISIS modules and the SAM module utilizes a rich repository of data already collected and stored in the IISIS database for the municipalities of interest.

The user interface for the SAM is consistent with the design for the IISIS prototype – to provide intuitive visual representation of the data. A representative screen shot for detailed tract information is shown in Figure 3. One important feature of the SAM implementation is presenting the scores not in the numeric form but as a tri-color schema (green-yellow-red). The thresholds defined for the schema are: green for the score values below 0.5, yellow 0.5 to less than 3, and red 3 and above. They were determined by practitioners familiar with the study area who validated the model. These values reflect the intention of the model to provide situational awareness – for example the yellow threshold is set to a very low value – only 0.5 in the scale of 10. But this value is dictated by the intention of highlighting any potential problem at a very early stage and the expectation of the system to indicate the yellow status during any non-trivial event. The threshold for red, which may seem to be set at surprisingly low level (3 in the scale of 10) is in fact emphasizing the fact that there exists potential (however extremely unlikely in practice) interactions of hazard events that can co-occur to create a truly doomsday scenario.

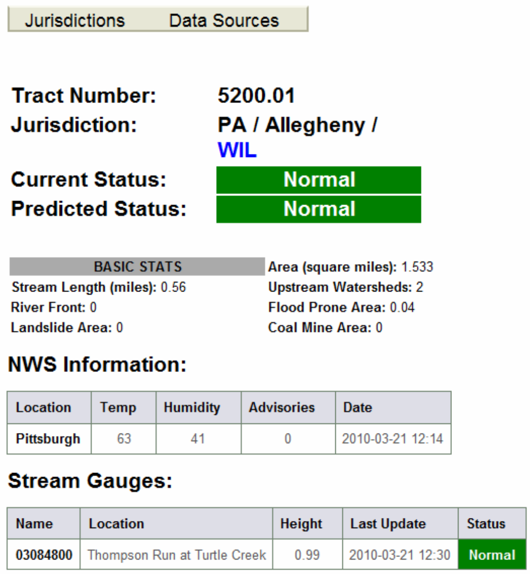

Figure 3 A screenshot from the IISIS prototype

FUTURE WORK

The work presented in this paper relates to the model of the geophysical environment, the first of the three Mileti's environments. The combining of the three modules would provide a more comprehensive and complete situational awareness tool. The development of the additional modules should include submodels that capture the patterns of the interaction of geophysical aspects, critical infrastructure and social systems and their interdependencies. These submodels will be designed to capture one of the key problems related to the complex nature of the emergency management – the situation when the effects of the cascading failures have more disruptive and serious consequences on a community than the initial hazard.

The last module we plan to develop would be the module responsible for monitoring the status of response assets. As Johnson (2005) posited, risk is the probability of harm, not the hazard itself. It can be defined as the dynamic interaction of the exposure to hazard, reduced by the capacity of the community to respond to that hazard. By monitoring all three hazard environments and the response assets dynamically we can provide decision support to ideally prevent a disaster or minimize unavoidable impact.

The knowledge elicitation aspect of our methodology requires improvement. A more structured and formalized approach to eliciting the potential threats for the area, their significance and identifying relevant and available data sources is needed. While the model was built with input from a group of experienced practitioners, we realize that not all users prefer the same warning metrics and that organizational and jurisdictional culture may dictate the modification of these parameters to better serve that agency or jurisdiction.

CONCLUSIONS

The problem we addressed is the support of situational awareness through the automation of data gathering and analysis. Emergency managers have over time struggled with the ability to gather reliable intelligence from the field in order to determine conditions upon which to base their response decisions. With the development and increased access to information technology, we have witnessed not only an increase in the amount of data available, but also an emergence of the corresponding need for data storing and interpretation of heterogeneous data from divergent data sources. The transition of that diverse data into actionable information increases the multidisciplinary skills needed from emergency managers. The volume and complexity of the information also requires means of reduction and interpretation of the information in order to be managed by humans and its relevance gauged for inclusion in decision making.

This was addressed through the creation of an initial module that captures the geophysical environment of Mileti's three environments. The module gathers information from a variety of remote sensing devices and data streams and subsequently running them through analytical processes that transform the data into actionable information. We implemented a prototype of a software system for a municipal area to prove the feasibility of the proposed approach.

From the software development perspective, the system consists of two major and distinct components – the user interface and the component that is responsible for the extraction of relevant data from the external data. While the user interface part can be implemented using technologies borrowed from dashboard systems, the extraction of data from external sources requires a customized approach. The challenge is building the bridge between the external data sources that in many instances are outside of the control of the system developers. In practice it means that the system should be constantly maintained and it is possible that the format and availability of the external data sources may change without prior warning.

While it is the first module of the three environments in the complete suite, the feedback from practitioners, both emergency management and meteorologists, has been positive. It has also revealed some challenges such as the need for customized development in order to fit the models to a particular jurisdiction. The implementation of the SAM requires customization through the collection of static data and identification of relevant dynamic data sources. These requirements make off-the-shelf implementation difficult. The developers view the implementation similar to FEMA's HAZUS program in that baseline abilities are provided with relative ease, but as the data, static and dynamic, improve the value of the output also improves.

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