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A Bayesian Network approach for risk assessment to a spatially distributed power infrastructure in a GIS environment

Keywords

Risk assessment, Geographical Information System (GIS), Bayesian Networks, Power Grids

Abstract

One of the most important applications of spatial data regards the ability to inform decision makers on spatially distributed and disaggregated hazards and risks, thus enhancing strategic decision making on how to manage and limit risks for a given area or region and prioritize investments. However, a full risk based adaptation assessment inside a Geographical Information System (GIS) can be cumbersome, since some complex tasks cannot be carried out directly. One example of these tasks involves Bayesian probabilistic analysis and decision making, which is a fundamental component of risk analysis, yet requires dedicated tools/software which usually do not belong to a standard GIS portfolio. For this reason, exploring the various capabilities of a GIS platform in connection with a Bayesian Network (BN) software is essential. The objective is to have an effective tool for knowledge representation and reasoning under the influence of uncertainty that can be displayed in a spatial manner. A case study using this tool was performed to assess the risk levels faced by the electrical distribution system of Long Island because of storm events as the Sandy Storm.

1. Introduction

Recently, Geographical Information Systems (GIS) has become an integral part of modeling risk, as it allows calculating a hazard extent using its intensity parameters and a digital elevation model. An important reason to use GIS in a risk assessment is that many regions and locations are exposed to several types of hazards, each with its own (spatial) characteristics. Nowadays GIS is an integrated, well-established and effective tool in disaster risk management. Risk assessments can be carried out at different degrees of resolution, ranging from the global scale to the regional and community level, each level with its own objectives and spatial data requirements [11]. Moreover, GIS is a popular tool for storing, analyzing and visualizing geographic data, and as such a natural fit for a probabilistic representation of uncertainties, arising from stochastic natural processes and events, imprecise environmental information, and imprecise expert judgments.

However, in some cases a full risk assessment and analysis in a pure GIS environment can be cumbersome, since some intertwined complex tasks cannot be carried out directly. One notable example of these tasks regards Bayesian probabilistic analysis and decision making, which is a fundamental component of risk analysis, yet requires dedicated tools/software which usually do not belong to a standard GIS portfolio. For this and other reasons, DNV GL Strategic Research and Innovation has worked in and is still exploring the various capabilities offered by an integration of a GIS platform with a Bayesian Network (BN) software. The objective is to have an effective tool for knowledge representation and reasoning under the influence of uncertainty that can be displayed in a spatial manner (*Figure 1*).

Another reason for linking these two technologies is that BNs and influence diagrams have been widely used for supporting decision making under uncertainty. Because BNs can present interdependencies among random variables, this has great potential for natural hazard assessment. BNs provide a complete suite of algorithms for the probabilistic and decisional aspects of a problem at hand; furthermore, they are easy to visualize and inspect and enhance modeling transparency. In addition, the integration of the probabilistic approach into a GIS allows quantifying and visualizing uncertainties in a spatially explicit manner. Such maps allow expressing confidence in the model results and visualizing its geographical variation while identifying the variables causing large uncertainties in the results. By explicitly addressing these uncertainties, the BN approach allows quantifying their effects and facilitates identifying where future model improvements and data collection efforts should be concentrated.

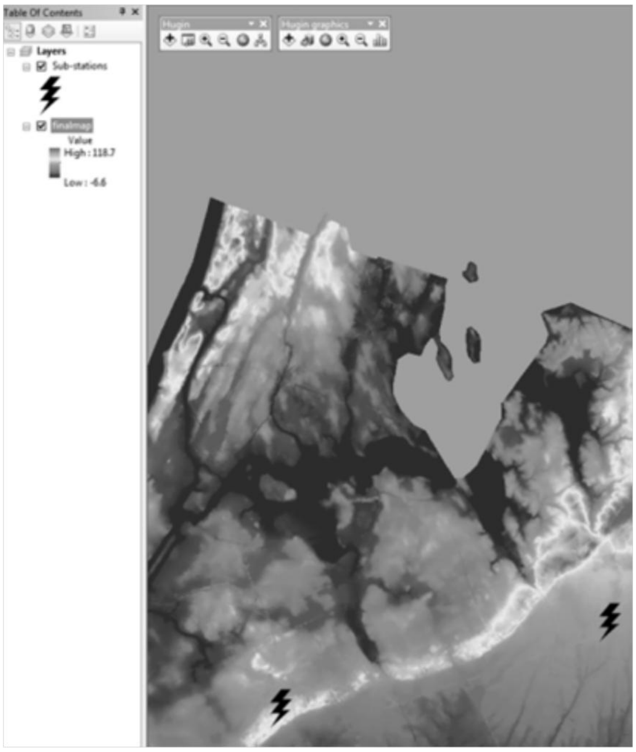

Figure 1. Toolboxes created in a GIS environment

As one critical infrastructure, the power grid is increasingly demanding efficient GIS data and system driven by the following factors:

- Our society is more and more dependent on access to reliable and affordable electric power supply due to improved living quality and increased information connectivity. This dependency became even more apparent during extreme weather conditions where the mobility was strongly limited and certain critical infrastructures (including power grid) were significantly weakened [7].
- In addition to that, the shift to non-fossil based power generation implies increased penetration of renewable power resources into the power grid [3]. Unlike the conventional generations (Thermal, Hydra, and Nuclear), these new power sources tend to be highly variable and dependent a lot on the local weather conditions. Furthermore, they are often distributed over large geographic spans.
- In certain regions of the world, the power grid assets are aging and new transmission and distribution infrastructures are difficult to build due to the lack of public acceptance. The system operators need to manage the grids with such aging assets in an efficient way, which makes the access to geographic related information (weather, geophysics, etc.) of paramount importance.

2. Methodology

The methods employed in the present analysis rests upon the classic computational architectures of BNs and GIS. In the present paper no detailed description of these two architectures is given and the interested reader is redirected to the plentiful literature available, see for instance [1] and [5] for BNs and [4] for GIS, among others. For the purpose of the present treatment it is sufficient to note that BNs and GIS answer two markedly different modelling needs. BNs offer capabilities for uncertainty modelling and decision making under uncertainty which are formally consistent with Bayesian probability theory and the Utilitarian principles to decision making. Use of the BN's features in risk analyses is well documented; see for instance [12] for a review of this field. GIS offers a platform for the storage of spatial datasets which are used in the modelling of geographically distributed problems and contexts.
The integration between these two systems was carried out based on the possibilities offered by the C++ dynamic libraries made available by the developers of the employed BNs software, Genie and Smile from the University of Pittsburgh, see [2], and the python environment of the employed GIS software, QGIS [10]. The SMILE dynamic libraries were exposed to .NET wrappers, which were in turn imported in the QGIS Python environment. In essence, this enables the software to communicate via the Python environment and share data. Through this set up, the GIS platform shares relevant variables for the risk analysis, such as topography and the environment processes of interest, and these are processed by the BN which, in turn, returns the required probabilistic assessment to the GIS

platform. Such concept is not novel, as previous implementations have been pioneered before [6].
Whilst the information contained in a GIS platform is fundamental in modelling the spatial characteristics of flooding and of the exposed infrastructure, risk-analytical models are needed to estimate damages and risks under different flooding scenarios. These models usually do not belong to a standard GIS suite and need to be integrated as external applications. One powerful example of a risk-based assessment tool is the BN model, which enables a probabilistic representation of hazards and offers methods to support decision making under uncertainty.

3. Case study: Sandy Storm

3.1. Short description of storm Sandy

Superstorm Sandy made landfall in the U.S. at around 8 p.m. of October 29, 2012 at New Jersey, with winds of 130 km/h. The storm took 286 lives and caused more than $68 billion dollars in property damage. While moving north-easterly, paralleling the Gulf Stream and still with hurricane status, Sandy experienced an “extra tropical transition”, this means “outside the tropics” or in this case, off the Gulf Coast of the US mainland. When tropical storms undergo this transition, the storm characteristics change. Tropical cyclones shift from a warm-core to a cold-core, but this transition isn’t necessarily smooth, and while Sandy was still a hurricane with a warm core- albeit smaller- the storm’s outer edges took on characteristics of an extra-tropical cyclone - .e.g., the intersection of a warm and a cold front, with cool air wrapping around the warm core, likely intensifying its low-level winds. A vast wind field emerged, with hurricane force winds along the small, central core; and a second maximum of high winds well to the north, with outer wind bands moving into Long Island and New York City, with winds nearing 90 mph as far north as Rhode Island. Superstorm Sandy also made landfall during high tide, making it even more catastrophic. The extreme winds combined with the high tide created some of the greatest sea-level heights ever recorded in many regions along the coast. The storm surge levels measured at The Battery in Lower Manhattan were the highest ever recorded at that location, nearly five feet above any previously measured value. This storm surge meant that considerable amounts of electric infrastructure near the coast was inundated; while inland, high precipitation in the form of both rain and snow wreaked havoc on the power distribution system.
Sandy was a hard hit for electrical infrastructure of the United States. The storm left more than 8.66 million customers without power. Among coastal states, 69 power plants and 102 electric substations were located in areas flooded due to storm tides. In the Long Island Power Authority’s (LIPA) service territory, damage occurred to 50 substations, 2,100 transformers, and 4,500 utility poles, and it took days and in some cases weeks or longer, to restore power to customers. Jersey Central Power & Light cut 65,000 trees to help restore power, fixed 34,000 downed wires and put up 6,700 new utility poles. In New York, Consolidated Edison has strung 60 miles of new electrical cable as a result of the storm [9].
Restoration efforts were high, with workers clocking 16 hour shifts to respond to 1.3 million reported power outages. All in all, more than 70,000 linemen and technicians were called in from 30 states and Canada to restore power. Utility workers treated as “first responders”, which granted utility trucks priority access to emergency fuel supplies and other resources.

3.2. Storm Surge and inland flood modelling

A storm surge analysis was carried out in order to identify surge heights and the water column that will be available to analyse the spatial propagation of water on land, water depths and the final inundation extent. An analysis of the track location in time, maximum wind speed, pressure drop, and the radius of maximum wind was carried out and were identified as the primary variables that drove the storm surge assessment. The storm surge was modelled with a dynamic numerical model that solves the non-linear shallow water equation with a finite differences algorithm. A computational domain of 6.5 km grid that covered a large of the Atlantic Ocean and Caribbean Sea was selected and a nested grid of 60m was used inside the impact area (where the hurricane made landfall). The GEBCO bathymetry was used as a basis and depth values were defined for every grid cell. To specify the wind forcing as a time-series for the hurricane’s space varying components, the hurricane track was specified into a grid with an explicit radius of maximum wind [13]. The resulting surge was validated against NOAA (National Oceanic and Atmospheric Administration) buoy measurements.
The flooding extent of the Sandy storm was simulated departing from the values obtained at each grid cell from the storm surge analysis. The flooding assessment was performed with a volume conservation, 2.5-dimensional flood routing model that distributes the time-stage control over a system of grid elements. The model governing equations are the continuity equation and the two-dimensional equations of motion (dynamic wave) [8]. A grid of 20 m resolution imposed over a digital terrain model

was defined inside the model and each was assigned a time-stage hydraulic control on unconfined floodplains. Multiple time-stage controls were introduced to the system for the inflow points and where distributed inside the computational domain. By setting the water stage at the surface, inflow to coastal areas was simulated with a discharge. The model numerically routed the designed hydrograph while predicting the area of inundation and simulating the flood wave attenuation. As the flood wave moved over the floodplain, flow over adverse slopes, attenuation, ponding and backwater effects were also simulated. In addition, the duration of the storm was modelled in real time. The resulting flooding extent compares well with observations over Long Island provided by FEMA (*Figure 2* and *Figure 3*).

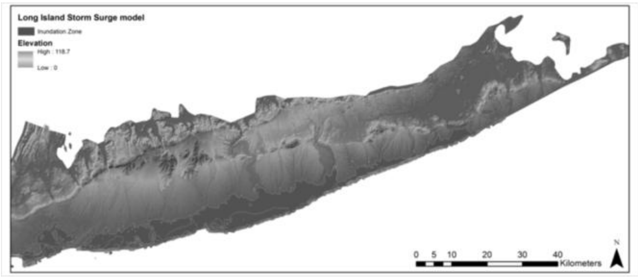

Figure 2. The area of inundation caused by the Sandy Storm in Long Island is revealed in shaded color.

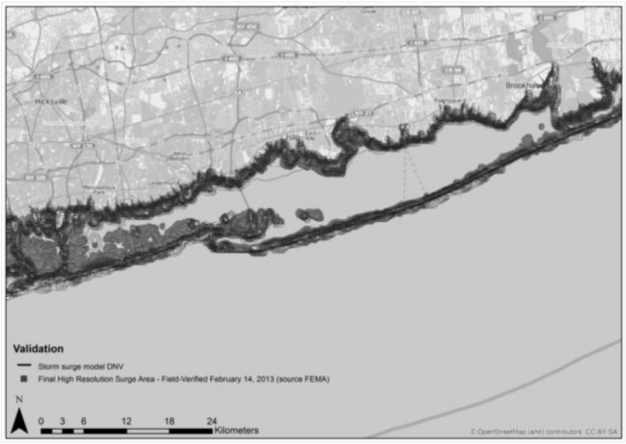

Figure 3. Comparison of the results obtained of modelling and validated using the FEMA information.

Based on this simulation and on geographical data of the substations within Long Island, we were able to match the substations that were reported flooded during the Sandy event. Flood exposure maps were also generated with the purpose of displaying and assessing what other relevant infrastructures can be potentially threatened in the future. These results can support decision making concerning flood protection and adaptation measures, as well as the creation of evacuation plans and emergency response.

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3.3. Preliminary risk assessment of electricity infrastructures – power grid

The analysis concludes with a risk-based quantification of flooding. As with any hazard, risk analysis is a necessary complement to the impact analysis illustrated earlier as it enables cost-benefit analysis of adaptation to climate extremes. By defining flooding-induced damages and losses to the electrical infrastructure in monetary terms, risk analysis offers a direct method to compare storm hardening costs with their benefits. In this context, benefits are intended as the reduction of future expected losses after the network is hardened. The final aim of such a risk-based assessment is to arrive at an optimal adaptation strategy among a possible portfolio of adaptation investments.

The loss spectrum faced by utilities in the case of flooding is broad and particularly sensitive to the type of damage, the location of the damage, and the number of end users affected. Furthermore, the dynamics of flooding are highly dependent on local spatial features such as topography, terrain characteristics, land use and so forth. These reasons motivates the integration of risk-analytical modules and a GIS platform, which stores and handles the relevant geographic variables of a region, including the types of infrastructure present, population density and size, etc.

In this concluding step of the analysis, the concept of dynamically integrating BNs with GIS in risk analysis is explored. Here, the GIS provides the spatial inputs to the BNs module, which processes these inputs and return the risk levels at the location of interest. These risk estimates are then returned to the GIS platform which displays them spatially. Linking the information in this manner offers a powerful tool for decision making under uncertainty. Since BNs can present interdependencies among random variables that are used to describe real-world domains, this has a great potential for natural hazard and risk assessment.

The concept is applied in the context of adaptation against flooding of distribution substations located within the Nassau and Suffolk counties, with one BN created (*Figure 4*). For this demonstration, the damage analysis is modelled simply as a function of the flood height at the substation. Owing to this, monetary damages are estimated to be linearly increasing with the water height at the substation location, whose value is provided by the GIS platform. Furthermore, only raising the substation was considered as a possible adaptation measure. All these assumptions do not constitute a limit to the applicability of this tool, as more complex and realistic damage functions can be integrated and other adaptation measures such as flood proofing can be included and evaluated in the same network.

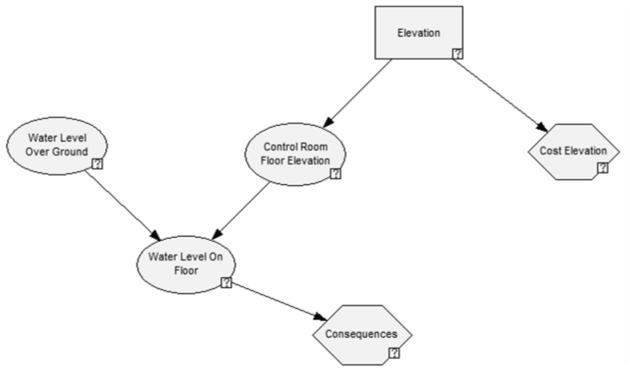

Figure 4. Bayesian Network used for simulating the probability of flooding at each substation.

Figure 5. Result of a risk thematic map obtained for the analysis.

Using the developed application, the expected monetary loss due to flooding was estimated (see *Figure 5*). This figure shows the realized implementation returns, for each substation analyzed, main characteristics of the substation such as identifier and location, the expected loss due to flooding and the risk-optimal adaptation elevation. The monetary values displayed are only for illustration, as the damage function they are derived from is fictitious and serves only the purpose of demonstrating the concept.

A BN model that consider the conditional parameters of the flooding event was implemented, see *Figure 4*. The model returns the probability of flooding of a substation at a given location. The BN models this probability as solely a function of the elevation of the site where the substation is located relative to the elevation of the surge. Once the height of the flood was calculated from the modelling, it is included inside a GIS platform and automatically processed by the Bayesian inference engine. The engine is called directly within the GIS via the Bayesian network software and the results are directly displayed on a map, see *Figure 5*. A display showing the probability of flood depending for the different substations considered is obtained.

4. Conclusions and recommendations

The BN and GIS interaction offers a powerful tool for decision making under uncertainty that can be used displayed in a spatial manner. Since BNs can present interdependencies among random variables that are used to describe real-world domains, this has a great potential for natural hazard and risk assessment.

The concept was applied in the context of adaptation against flooding of distribution substations located in Long Island. At the present status of the analysis, the damage is modelled as a function of the flood height at the substation site. Owing to this, monetary damages are estimated to be linearly proportional to the water height at the substation location, whose value is provided by the GIS platform. Furthermore, raising the substations was considered as a possible adaptation measure.

Using the developed application, the expected monetary loss due to flooding of the considered was estimated. The realized implementation returns, for each substation analysed, main characteristics of the substation such as identifier and location, the expected loss due to flooding and the risk-optimal adaptation elevation. In the future, more complex and realistic damage functions can be easily integrated and other adaptation measures such as flood proofing can be formally included and evaluated in the same network.

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