A Computational Framework for Interoperating Uncertainty Quantified Social System Models

Charles R. Ehlschlaeger  
*Engineer Research and Development Center*, chuck.ehlschlaeger@gmail.com

Olaf David  
*Colorado State University - Fort Collins*, odavid@colostate.edu

James D. Westervelt  
*Citizen Scientist*, westerve@comcast.net

Yanfeng Ouyang  
*University of Illinois at Urbana-Champaign*, yfouyang@illinois.edu

Jeffrey A. Burkhalter  
*Engineer Research and Development Center*, Jeffrey.A.Burkhalter@usace.army.mil

See next page for additional authors

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Presenter/Author Information
Charles R. Ehlschlaeger, Olaf David, James D. Westervelt, Yanfeng Ouyang, Jeffrey A. Burkhalter, Natalie R. Myers, Francesco Serafin, David A. Patterson, Yizhao Gao, and Liqun Lu

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A Computational Framework for Interoperating Uncertainty Quantified Social System Models

Charles R. Ehlschlaeger¹, Olaf David², Yanfeng Ouyang³, James D. Westervelt¹, Dawn A. Morrison¹, Dave Peterson², Francesco Serafin², Liqun Lu³, Jeffrey A. Burkhalter¹, Natalie R. Myers¹, Antoine M. A. Petit³, Zhoutong Jiang³

1. US Army Corp of Engineers’ Engineer Research & Development Center, Champaign, IL, USA
2. Colorado State University, Fort Collins, CO, USA
3. University of Illinois at Urbana-Champaign, IL, USA
4. University of Trento, Trento, IT

(charles.r.ehlschlaeger@usace.army.mil, odavid@colostate.edu, yfouyang@illinois.edu, westerve@comcast.net, dawn.a.morrison@usace.army.mil, david.patterson@colostate.edu, francesco.serafin@unitn.it, liqunlu2@illinois.edu, jeffrey.a.burkhalter@usace.army.mil, natalie.r.myers@usace.army.mil, apetit@illinois.edu, zjiang30@illinois.edu)

Abstract: Accurate uncertainty modelling of social activities is impossible using available geographic information data and typical geographic information system algorithms due to the Uncertain Geographic Context Problem (UGCoP, Kwan 2012). UGCoP worsens when data are vague or obsolete, competing social models are available, and parameter values are not fully known. This research reduces UGCoP by explicitly representing uncertainty in input data, algorithms, and visualization tools using Monte Carlo methods. Rich contextual social information is retained by storing dozens of demographic attributes from surveys and censuses of all people in the study area. To include this detail requires large-scale modeling involving demographic and land use forecasting models, agent-based models, transportation dynamic models, and other computationally complex operations necessitating parallel algorithms and distributed computing systems. Named the Framework for Incorporating Complex Uncertainty Systems, it includes multiple free and open-source software tools, especially the Object Modeling System, to allow easy inclusion of additional models written in multiple third and fourth generation programming languages. This research presents the space-time uncertainty quantified modeling environment, multiple model components, and web browser visualization tools necessary to inspect all data and results of this extendable social and infrastructure system of systems analysis approach. This research will be demonstrated with a case study in the Philippines supporting risk analysis.

Keywords: Uncertainty Quantification, Computational Cultural Modeling, Monte Carlo Methods, Risk Analysis.

1. INTRODUCTION

Despite years of experience, significant amounts of collected data, and deliberate preparations, disasters still account for significant losses in terms of life, economic productivity, and physical infrastructure. The uncertainty surrounding these events and the complexity of human behavior and the built environment make current simulation modeling tools inadequate for disaster planning and mitigation, especially when performing course of action analysis and risk assessment. The application of systems dynamics, agent-based, and cellular-automata (to name a few) models are indicators of the complexity based on the types of relationships and data present in representing populations, infrastructure, and proposing practices to mitigate the effects of, and improve the response to various types of disasters. In addition, the uncertainty implicit in these types of events (Bozorgi-Amiri et al. 2011), not to mention in representing complex systems, suggests that a deliberate attempt must be made to address uncertainty quantification (UQ) in any modeling process and visualization of results. The notion of implementing comprehensive simulation models to address the interdisciplinary nature of
the complex interactions regarding disaster planning and response is not new (Altay and Green 2006), but comprehensive models tend to be expensive and time consuming to produce and calibrate.

As a result, it is proposed that implementing an overarching framework which integrates various multiscale domain models is an appropriate approach to analysing the complexity of potential disaster effects (direct and higher order). Further, the implementation of techniques to explicitly address uncertainty and subsequent visualization of the results are necessary for future analysts to evaluate the results and recommend actions for disaster events and similarly complex problems.

This paper will begin by: 1. Introducing the overarching computational framework being developed to integrate and manage complex multi-scale models, 2. Discuss the various domain models being implemented towards an analytic solution for emergency management, 3. Discuss the tight-coupling of two of those models to create dynamic transportation model results, 4. Discuss the case study under development and prototype tools for visualizing results, followed by a 5. Discussion of next steps and expected follow-on research.

2. OVERVIEW OF INTEGRATED ANALYSIS FRAMEWORK

Management and integration of the various domain models required to adequately express the complexity of urban systems and disaster impacts necessitates the implementation of a computational framework. Such a framework must be capable to resolving communication between types of domain models, and conformant with a variety of programming languages. That negates the need to rewrite existing domain models or attempts to construct singular comprehensive ‘mega-models’.

2.1. Concept

Named the Framework for Incorporating Complex Uncertainty Systems (FICUS), this computational framework incorporates the following features to speed the development of social science computational models directly supporting policy decisions and planning operations, especially in underdeveloped nations focusing on risk analysis. In order to provide explicit uncertainty quantification, the FICUS software framework supports Monte Carlo simulation (MCS) of all social, infrastructural, and environmental models. All data structures must be sets of equiprobable alternative realizations of what that information would be at the atomic unit of representation. The atomic unit of demographic information, for example, is represented as households and individuals (Ehlschlaeger et al. 2016). Since these equiprobable realizations of people and other data layers are difficult to visualize, summary statistic “heat maps” representing box plot statistics, per cell, are automatically created that can be dynamically displayed in a web browser. The computational models built for FICUS are designed to have all parameters stochastically represented. Existing legacy models, such as TRANSIMS (Naghawi and Wolshon 2010; Pasupuleti et al. 2009; Ley 2012), can be encapsulated into components to ensure model outputs are multi-realization data structures when the FICUS MCS executes. We are extending the Object Modeling System (OMS; David et al. 2013), a free and open source (FOSS) software framework environment supporting model development. OMS treats individual domain models as “component assemblies”, and can be related using simple tags in JavaScript Object Notation (JSON) files that manage the inputs/outputs between the various “assemblies”, or objects (Formetta et al. 2013).

2.2. Application

In implementing the OMS technology, this approach is considering three separate types of information models. These information models might be described as models that generate space-time information layers (such as maps of population attributes), causal relationship models, and systems models (networks and flows). Two tools are being developed to understand and manipulate the FICUS modeling environment: A server/browser based uncertainty quantification visualization tools, and means to adjust computation models during runtime. JSON files will describe the respective input and output data for each domain model, which facilitates the passage of data between the models without human intervention. This supports an iterative capability for analysis that may otherwise not be supported by the individual domain models. For example, two domain models may be able to iterate using the respective outputs of each model run using the JSON connection.
3. DESCRIPTION OF DOMAIN MODEL COMPONENTS

The implementation of the modeling capability to support emergency management activities incorporates three separate domain models. The first of these is a demographic modeling capability referred to as Digital Populations. This capability generates multiple realizations of every household and/or person (and associated attributes) in a given study area using spatial statistics and optimization algorithms. The second capability is referred to as Human Infrastructure System Assessment (HISA), which is an equilibrium-based infrastructure interdependency model. Finally, TRANSIMS is a travel forecasting and microscopic simulation model.

3.1. Digital Populations

A Monte Carlo process demographic simulation model is implemented to establish population attributes. The model generates multiple realizations of populations distributed across a study area, while accounting for the uncertainty in the source data and carrying it through to the model outputs. A detailed diagram representing the elements of this demographic model, known as Digital Populations, is shown in Figure 1. The households and people simulated are derived from a survey or microdata, defined as a set of questions asked using proper survey design techniques. The locations of simulated households are based on household density surface and census information. The household density map indicates the probability that a household is located at each place based on environmental and infrastructural information. A survey case is the responses given by one person or household. More simply, a survey case is the set of answers given by a person to a survey’s questions. One sample in census microdata has a more complex origin than a survey case. A census microdata sample represents a cluster of similar, but hardly ever identical, survey cases combined. Survey responses are the set of answers relevant to a particular operational need or analysis, which should be considered as a subset of a survey case. Population enumerations are estimated counts of households, people, and their attributes within administrative areas defined at the finest scale possible, provided by census data and including an estimate of census error measures and adjusted to changes over time. Ground truth samples are point locations or binary maps where known attributes related to survey responses are located. This process locates known survey responses to specialize information not typically available to demographic models and will ensure those locations will have survey responses at those locations. One end product, survey response box plot variable maps, provide easy to understand maps of survey response covariates while providing a representation of uncertainty at every location with the information available in typical box plots. The box plot variable maps are summarized from many alternative realizations of every household or person in the study area, either as a regular lattice of kernel density estimates, or as a proportion within cells of a regularized grid. Figure 1 represents the process for converting the various inputs into a set of maps representing the variation of a survey response over a study area.

![Figure 1: Overview of Digital Populations simulation process](image-url)
The process can be summarized into the following major steps:

1. **Replicate survey cases.**
2. **Create a probability surface of household locations.**
3. Replicated geolocated survey case locations are realized by optimizing a set of proportions for each population realization. Household locations are based on a household probability surface, ground truth data, and survey responses’ proportional measures.
4. **Survey case locations are shuffled using optimization techniques to create realistic clustering of survey responses.**
5. Proportion maps are generated, representing the percentages of simulated survey cases with such responses.
6. Both the summary statistics and the kernel analysis for each realization provide error and uncertainty estimates.

Steps one through four are done repeatedly to create enough realizations to provide representative distributions for important survey answers at critical geographic locations. For example, a survey response that is answered seldom would require a larger number of realizations for its Poisson distribution to reflect the variation of reality while a survey response answered by about 50% of the households or people would take fewer realizations to define the resulting normal distribution. A detailed explanation of these techniques is available in Ehlschlaeger et al. (2016).

### 3.2. **HISA equilibrium model**

The functionality of modern cities relies heavily on interdependent infrastructure systems, such as those for water, power, and transportation. Infrastructure system disruptions often lead to catastrophic consequences via propagating within and across the physical infrastructure networks. Moreover, the reaction of a population to such disruptions may further induce secondary disruptions by transferring and aggravating the burden on surviving infrastructures. For example, population seeking alternative resource sources may lead to that population competing for resources with infrastructures and causing congestions on the transportation network.

The HISA equilibrium model was developed with the objective of evaluating the impacts on a population in an urban environment after disruptions occur in the complex infrastructure system (Lu et al. 2016). It accounts for the mutual impacts among the complex, interdependent infrastructure network and population resource-seeking behavior to evaluate disaster aftermath in the urban system. Different types of infrastructure interdependencies are generalized to model a multi-layer complex infrastructure network. The demographic information is described by modeling the population distribution as another layer of a community network. A game-theoretical equilibrium model is built in a multilayer infrastructure network to systematically investigate the mutual impact between the infrastructures and the population.

The population resource seeking behavior is captured using a network equilibrium model under road network congestion as well as limited capacities at resource destinations. To be specific, the population need to travel through the transportation network to reach resource facilities to replenish life-supporting resources, such as water and fuel. Each user chooses their own transportation routes and resource destination to minimize the total cost incurred by road congestion and queuing at destination, while their decisions in turn affect others’ cost via congestion and queuing. The network equilibrium describes a state where none of the users can further reduce its resource procurement cost by unilaterally changing its route and destination choice given others’ decisions unchanged.
Complex infrastructure interdependencies are generalized into two types of support relationships, functional support and resource support. Functional support is usually realized by direct physical links, such as power transmission cable and water pipeline, and thus indicating a strong dependency of the downstream facility on the supporting infrastructure. Resource support means that, similar to population resource procurement behavior, the facility operator needs to fulfil resource replenishment via transportation.

Figure 3 shows an example to illustrate the interdependencies between different layers. The diesel generator in the electricity layer choose a nearer diesel tank in the fuel layer to obtain fuel supply, which is categorized as resource support. With the fuel supply, it provides electricity directly to a water pump in the water sector. When disruption happens at the diesel tank, the generator may not be able to retrieve sufficient fuel supply from the other tank due to high travel cost or limited resource, which leads to resource failure at the generator and consequently support failure at the water pump. However, if the generator is still able to maintain its resource supply after the diesel tank failure, disruption will not propagate in the system (Glover et al. 2017).
The output of the HISA model includes the functionality of the infrastructure facilities as well as resource procurement cost of the population. A case study on the city of Maiduguri, Nigeria was performed to illustrate the capability of the model. Figure 4 illustrates population distribution and the infrastructure system layout of the city. After an initial disruption occurs at the power substation in the center of the city, many critical infrastructures such as water treatment plants are failed due to cascading failures. Figure 5 shows the ratio of water access cost of the population in the disruption aftermath over that prior than the disruption.

![Maiduguri Population Distribution and Infrastructure System Layout](image1)

**Figure 4:** Population distribution and infrastructure system layout of Maiduguri

![Water Access Cost Ratio Post-Disruption](image2)

**Figure 5:** Ratio of water-access cost of communities, post-disruption

### 3.3. TRANSIMS transportation model

TRANSIMS is a travel forecasting and microscopic simulation model originally developed for the USDOT (United States Department of Transportation). It provides an integrated set of tools for regional transportation system analysis. After synthesizing the road network, it generates a set of activity locations that serve as origins and destinations for all the trips in the network. With travel demand data, a routing module then determines the travel plans of each traveller considering a detailed time-dependent network with time-variant link delays. The travel behavior of each individual is then simulated in a 24-hour period, using cellular automata principles. This person-based microsimulator models the interactions between the vehicles and provides second-by-second snapshots of the network.
summarizing the position of every individual at each time and the link traffic volumes during small time increments. The routing module and microsimulator module work in an iterative loop that updates the travel times of the individuals and potentially reroute some of the travellers. Once most of the travellers cannot achieve significantly shorter travel times by choosing a different path, the feedback loop terminates. The input/output flowchart is summarized in Fig. 6.

Figure 6: Core components of TRANSIMS.

TRANSIMS has been widely used in emergency evacuation modelling (Naghawi and Wolshon 2010). In an emergency (e.g. terrorist attack, natural disaster), TRANSIMS can help predict the communities’ behavior to access resources or to exit the affected site and identify the optimal routing of the emergency vehicles. Ley (2014) conducted an emergency evacuation study for the Chicago metropolitan area using TRANSIMS to investigate the effects of a no-notice event (e.g. radioactive release) on the regional multi-modal transportation system. TRANSIMS is able to use inputs such as a turn prohibition table, or a lane use table, to model the effect of disasters on the roadway network. As a result, the effectiveness of emergency response strategies and the impact of the evacuated population routing on the transportation system performance could be analyzed.

4. TIGHT-COUPLING DYNAMIC TRANSPORTATION MODEL

HISA-TRANSIMS dynamic model is developed based on the HISA equilibrium model, incorporating TRANSIMS’ capability in accounting for temporal variations and Digital Populations’ high-fidelity population information. Using TRANSIMS traffic assignment and simulation modules, real-time movement in the transportation network can be captured to reflect the temporal variations in the urban environment, especially when disruptions occur in the infrastructure system. This allows the HISA-TRANSIMS model to perform real-time simulation in the infrastructure system and population. Moreover, Digital Populations output provides household level information of the urban population, which enables the model to perform simulation with higher resolution. A great variety of different attributes from the Digital Populations survey data are utilized and translated into population-infrastructure dependencies based on qualitative analysis and the knowledge of field experts.
Figure 7: Flow chart of the HISA-TRANSIMS dynamic model components

A schematic illustration of the HISA-TRANSIMS model components is presented in Figure 7. The infrastructure system data and the transportation network data are obtained from the Urban Tactical Planner (UTP) database, maintained by US Army Corp of Engineers’ Army Geospatial Center, and the population data from the Digital Populations database. The UTP database is not necessary for this analysis, as most of the networks are available from open sources. After preprocessing of the data, real-time simulation is performed iteratively for the desired analysis periods. In each period, travel demands of the population and facilities are generated based on the resource replenishment needs of these users. After assigning the resource procurement trip demands, TRANSIMS module is called to evaluate the transportation congestion and travel time of the users. It then feeds back the model with detailed information of the travel plans, including routes and travel time. This information is then translated to the resource security of the population, and the functionality of the facilities. The results are presented as real-time maps of the infrastructure system status and population resource accessibility.

The Digital Populations population survey data are translated into inputs to the HISA-TRANSIMS model using engineering judgment. Figure 8 demonstrates an example of how a set of Digital Populations household level data can be utilized in the HISA-TRANSIMS model. For instance, the “bath water source” and “drinking water source” survey data provide information on whether a household has (and uses) faucet water that is delivered via pipeline. If yes, the household can be deemed as receiving functional support from certain infrastructures in the water sector; otherwise, it would need water supply via resource support; moreover, “owns vehicle” indicates the capability of the household to travel long distance through transportation network to access resources.

Figure 8: Translation from Digital Populations survey data to HISA-TRANSIMS model input

Transportation network data obtained from the UTP database is preprocessed to accommodate requirements of TRANSIMS on the input, and then fed into the TRANSIMS network conversion component which helps TRANSIMS understand the network topology and generates a set of activity...
locations. While TRANSIMS usually takes zone-based trip demand and randomly assigns the actual origins/destinations to activity locations, we directly generate activity location-based trip demand in the HISA-TRANSIMS model. The benefits are two folds: i) higher spatial precision of the origins/destinations can be achieved and potential false interpretation of the trip data can be avoided; and ii) the temporal information of the trips can as well be specified.

The infrastructure system modeling inherits from the HISA model, where the complex infrastructure system is considered as a multi-layer interdependent network. Infrastructure status is determined by whether its resource requirement is fulfilled via either functional support or resource support. Along with the population, infrastructure’s resource consumptions are simulated in the HISA resource consumption simulation component, which generates the resource demand of the users over time. Based on the resource replenishment demand, trip generator then assigns trips with corresponding activity locations as the origins and destinations as well as the estimated departure time of the trip. After TRANSIMS router and microsimulator assigns the routes to the trips and completes traffic simulation, the travel plans are passed to HISA resource fulfillment and consumption simulator for simulation of the next analysis period.

5. CASE STUDY

Describe case study regarding typhoon-risk in Philippines, with measures to determine how detailed understanding of population attributes, coupled with infrastructure network understanding, can iteratively model the cascading effects of infrastructure failure, and potential shifts in population transit due to changes in resource availability.

A case study was constructed to examine how the model elements will work together to generate the understanding required by analysts to support disaster planning and response activities. The Philippines was selected as a general study location due to its availability of open-source data and its susceptibility to major disaster events such as typhoons. The intent of the analysis was to identify risk elements associated with access to infrastructure by the population, establish the connectivity of infrastructure systems, determine population reliance upon infrastructure nodes based on demographic data, and the influence of the loss of infrastructure nodes (either service or transportation) on traffic flows.

Inputs from demographic model – The Digital Populations demographic model incorporated enumeration data from the 2010 National Census and the accompanying 2010 Integrated Public Use Microdata Survey (IPUMS). A population density map (100m resolution) was generated from the Barangay-level population data, as this was deemed to be more suitable for the focus area in the National Capital Region. The demographic model generated 30 different realizations, which established a representation for every household and individual in the study area. The resulting data was converted to maps of individual households attributes using kernel density, with a kernel diameter of 800m and an output resolution of 200m.

The networks of infrastructure interdependency were created for the National Capital Region using Urban Tactical Planner (UTP) data, which included major roadways (supplemented through Open Street Map), utility lines, and utility nodes (such as power plants, substations, water nodes, etc.). An assessment of the connectivity of these various nodes was performed and converted to input tables for the consequence analysis. In the case where explicit connections weren’t referenced, spatial proximity analysis or best judgment was applied in determining logical relationships between various infrastructure nodes.

A sample set of infrastructure nodes/links was identified to simulate failures brought on by a disaster event. These ‘broken’ elements determine a cascading set of values through the network interdependency model. In the case where these are service provision nodes for population, the adjacent communities were identified as having degraded access to the service(s). The extent of the community degradation is informed by the household attributes such as: access to vehicles, source of water/power, access to media, and other measures of relative wealth or service access. These attributes accounted for the proportion of households in a given area that was susceptible to the effects of the service loss (loss of grid power only affects those reliant upon that resource) or the ability to transit longer distances to replace the service loss (e.g. good access to transportation). For those who
are in demand of a lost service, the next nearest functioning service node is identified. Service node capacity is also assessed to identify potential limits of service capacity at the remaining nodes.

In the case where the transportation node/link has failed, the TRANSIMS model recalculates traffic loads on routes based on the available transportation network, incorporating changes in trip generation resulting from shifts in population requirements for services (due to service degradation). This has impacts on the planning for delivery of resources post-event, as expected transportation routes may experience significantly different traffic levels due to changes in the actual routes, or the quantity of population exploiting them to reach required services.

To characterize population risks associated with potential service loss, a weighted framework was developed along the SWEAT-MSO (Army 2008) conceptual framework. This reflects measures for sewer (S), water (W), electricity (E), academics (A), trash (T), medical (M), safety (S), and other (O). Each framework element implements map data from the domain models to determine risk for households in a given region of the study area. The details of the framework are illustrated in Figure 9. Key to this component is the explicit inclusion of uncertainty values, which can reflect the analysts’ assessment of how well a particular measure is described by the available data. Thus, the opportunity is available to quantify and evaluate the quality of each subcomponent in light of the overall answer analysts are expected to provide to decision-makers.

Figure 9: Schematic of analytic framework to assess risk based on infrastructure services

The framework analysis generates UQ maps at each level of the framework. This supports both an overall assessment measure while simultaneously enabling analysts to drill down into the framework to examine the effects of each individual framework component. For example, if the assessment of access to medical care was in question, subordinate maps are available to express the nature of the facilities and services separately. This allows the analyst to potentially adjust the framework elements or weighting values if it is suspected the results are in error. The analysis process can include maps (such as weighted distance to facilities) that do not have explicit uncertainty, thus UQ data and static data can be fully incorporated in the analysis. As illustrated in Figure 10, the maps are available to be viewed in a web-based visualization tool that can show static maps, animations of the variation in results, or the uncertainty of results as measured at specific points.

We have adopted a Black Swan Theory approach to describing risk. The FICUS visualization tool allows users to view best case, worst case, and the less probable cases from any theme in the SWEAT-MSO framework or from any location within the Philippines. The more improbable cases are often known as
‘Gray Swans’ in Black Swan Theory (Taleb 2010). Gray Swans must be understood in decision making to understand potential circumstances when planned activities go wrong.

The demographic, network interdependency, and transportation domain models are being integrated through the FICUS/OMS computational framework to reflect the impacts of damage from disasters on the local population and subsequent resource/transport availability.

6. CONCLUSION

The authors have described an approach to implementing a computational framework that integrates different types of multi-scale models (incorporating uncertainty quantification & visualization) to better represent the complexity of potential effects from events such as natural disasters, especially for purposes of risk analysis. The computational framework, FICUS/OMS, provides the structure and integration protocols that enable various domain models to interact with requiring extensive modification of code. This permits the individual domain models, in this case: Digital Populations, HISA, and TRANSIMS, to easily share inputs/outputs and iterate on changing conditions over time without continual human intervention. While the tight-coupling of the HISA and TRANSIMS tools is more reflective of traditional ‘hard-coding’ integration techniques, it does permit dynamic transportation modeling, and can be exploited by other domain models under the FICUS/OMS computational framework.

The next steps in the development of these analytic tools include the ability to interactively ‘break’ various pieces of infrastructure to illustrate the consequences of such activities. This type of interaction with the modeling components will be carried out through the implementation of a ‘director’ component. The director component will provide the analyst with the capability of identifying specific types or nodes of infrastructure to change (decrease or increase capacity) and realize subsequent cascading effects on resource availability and transportation dynamics of affected populations.

In addition to the director component, further follow-on research should include the incorporation of population migration models that address behavioral elements driving migration (at various time scales). In addition, adding in domain models that forecast future expected conditions are vital in circumstances where available data is collected over long time periods. For example, survey data may only be available every five years, thus systems that change rapidly may produce less reliable results. Tools which address the probability of changing conditions (either demographics, environment, or infrastructure) would be a valuable addition to supporting improved analysis when the data collection cycle is longer than desired. Finally, the current approach yields results based on a specified set of
Future analysts may desire a 'reverse' capability, such that one could provide the system a set of end conditions, and desire a realized set of possible events that would yield the end conditions. These current, planned, and potential development efforts seek to provide analysts with improved capacity to assess the impacts of disaster events to enhance planning for mitigation and response activities.

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