PARAMETRIC FEATURE INTERACTION AND SENSITIVITY ANALYSIS IN MULTI-HAZARD DISASTER MODELING FOR AI-BASED DECISION SUPPORT SYSTEMS

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Abstract

This study examines one specific structural issue for AI-based Emergency Decision Support Systems (DSSs) concerning foundational disaster modeling, which fails to adequately capture the intricate interplay of multi-faceted hazard parameters. Although contemporary DSSs increasingly incorporate features of cognitive reasoning and adaptability, the modeling of the layers of disasters is still mostly linear or unstructured.

The study proposes a parametric interaction approach that models disasters as non-linear spaces with specific coupling and sensitivity coefficients. This approach is designed to capture other mechanisms, apart from enhanced prediction, such as aggradations, structural destabilization, and risk-increasing interactions in a multi-hazard environment. The framework also helps to understand the coherence of interactions among parameters enabling the system to distinguish isolated signal anomalies from structurally significant escalations.

The author then offers a mathematically structured layer of DSSs that contains no decision biases and can be integrated with AI-based DSS. Further, the approach is backed by empirical evidence derived from structured disaster datasets, from which he is able to enhance the robustness, interpretability and, reliability of a system under conditions of uncertainty.

Keywords: Multi-hazard modeling, Parametric interaction, Sensitivity analysis, Structural risk, Nonlinear systems, Uncertainty modeling

Introduction

There is a plethora of Emergency DSS where disaster modeling is represented as a data input issue. The modeling of parameters such as magnitude and rainfall or wind are modeled independently and then uploaded to the cognitive or predictive work.

Yet, the real-world evidence from cascading disasters shows severity of impacts is often a result of interaction instead of isolated effects. An example is a rainfall event of lesser magnitude on a less stable terrain. The damage caused can be worse than an extreme rainfall event.

This raises a structural question:

- Are the mathematical constructs describing the parameters of a disaster flexible enough to incorporate nonlinear amplification?

Most existing structures focus on decision logic or layers of adaptive reasoning. The formal structure of the coupling of the disaster parameters hasn't been given as much focus. [Arrieta et al., 90], [Varshney, 34]

This paper describes a mathematical model based on feature interactions that precisely describes non-linear relationships and evaluates structural changes caused by such relationships in a multi-hazard setting.

Conflict Setting

The major problem this work is addressing is not the prediction of the model, but the structure. Most current approaches to disaster modeling wrongly:

- assume effects of parameters are additive
- fail to consider interactions of second order
- do not include formal coupling matrices for propagation of hazards
- do not conduct feature level sensitivity analysis

This means the outputs from DSS may be calm and stable, but are actually very fragile from a structural standpoint. [Tilloy et al.], [Zscheischler et al., 472]

The aim of this research is to bring formal order to:

- Mechanisms of nonlinear interaction between features.
- Structures of multi-hazard coupling.
- The formal order of sensitivity driven instability.
- The formal order of structural model risk.
- Formulation of Parametric Feature Space

Let conditions of disaster be defined by a feature vector:

$$X=(x_1, x_2, \ldots, x_n) \quad (1)$$

Instead of making the typical assumption of additive influences, we try to find out if:

$$I_{liner}=\sum w_i x_i \quad (2)$$

$$I_{liner}=\sum w_i x_i+\sum w_{ij} x_i x_j \quad (3)$$

fully captures the formation of real impacts.

Empirical research shows that the specified method inadequately approaches interaction-driven escalation. Therefore, we choose to expand the model to incorporate the second-order coupling.

$$I=\sum w_i x_i+\sum w_{ij} x_i x_j \quad (4)$$

The interaction term $x_i x_j$ is one of the constituents of mere mathematical expansion. It concretely pertains to the infrastructural or physical dependence of the involved variables.

Consider the following example.

- Seismic energy × soil liquefaction potential,
- Rainfall intensity × slope gradient, and
- Drought index × wind velocity in wildfire dynamics.

These demonstrate zones of amplification and are not merely additive.

Representation of multi-hazard coupling

Apart from intra hazard parameters interaction, multi-hazards often have inter hazard propagation.

Let the hazard system be represented as,

$$\mathrm{H} = (H_1, H_2, \ldots, H_k) \quad (5)$$

Each component depicts the state or intensity of a certain type of hazard (e.g. earthquake, landslide, flood, wildfire, etc.)

For the purpose of evaluating the propagation between hazards, a coupling matrix C is introduced.

$$C_{ij} \quad (6)$$

signifies the influence of the hazard H_i in the propagation of the hazard H_j.

Then, the cascading impact is expressed as

$$I_{cascade} = H^T \times C \times H \quad (7)$$

This quadratic form reflects the second-order coupling of hazards and the degree of hazard amplification and propagation. [Barabási, 42], [Helbing, 53]

This formulation presents a divergence from the typical “chain disaster” explanation as the intensity of the cascade can be evaluated in a quantifiable manner. Typically, the matrix C is asymmetric:

$$C_{ij} \neq C_{ji} \quad (8)$$

resulting in C accordingly. In the case of an earthquake, it can cause landslides and then create a scenario for a flood, however, flooding will not trigger an earthquake.

The coupling matrix can be viewed as the structural representation of the interconnections of the environment, the fragility of infrastructure, or the dynamics of the transitions of hazard.

Sensitivity and Structural Instability

While the estimation of an impact allows one to measure the magnitude, it does not provide insight into the fragility of the structure.

The first-order sensitivity is:

$$S_i = \frac{\partial I}{\partial x_i} \tag{9}$$

where this describes a situation. In an impact, the influence of a small perturbation in parameter x_i is measured. [Battiston et al., 10034]

The second order is:

$$S_{ij} = \frac{\partial^I}{\partial x_i} \times \partial x_j \tag{10}$$

which measures the intensity of amplification of the first-order effects. This is a very rough estimation, and this is the most accurate way to measure this. When the strength of coupling and the magnitude of sensitivity are both high, the disaster system is on the verge of being amplification-dominated.

Structural Model Risk

It is important to note that hidden risk can arise even in the absence of predictive error, as limitations in structural modeling can also create hidden risk. [Varshney, p. 118]

The defining equation for structural deviation is:

$$E_{structural} = |I_{true} - I_{model}| \tag{11}$$

Structural risk is very real and can arise with the interaction terms are either omitted, misestimated, or with an underestimation of sensitivity-induced amplifications.A generalized formulation of structural risk indicators can be expressed as:

$$R_{structural} = f(E_{structural}, ||S||, ||C||) \tag{12}$$

where ‖S‖ stands for the total aggregated sensitivity magnitude, and ‖C‖ denotes the total coupling intensity.

A higher value of structural risk denotes higher fragility within the modeling layer, even if the modeling layer outputs look adequate from a statistical point of view. A more positive structural risk value shifts structural evaluation from evaluative accuracy to a more resilience focused approach.

Simulation Setup

To demonstrate the structural functionality of the proposed interactivity framework, a simplified multi-hazard scenario is created involving three hazards:

H_1: intensity of the Earthquake

H_2: severity of the Landslide

H_3: level of the flood

The hazard state vector is represented as:

$$H = (H_1, H_2, H_3) \quad (13)$$

The intensity of each hazard is normalized within the range of [0,10]. We propose two modeling approaches: (1) the Independent hazard estimation (additive model) and (2) the Coupled hazard estimation (interaction-based model)

The independent hazard model will be:

$$\text{Let } H=(6,2,3) \quad (14)$$

The additive effect is given by:

$$I_{additive} = H_1 + H_2 + H_3 \quad (15)$$

$$I_{additive} = 6 + 2 + 3 = 11 \quad (16)$$

According to this model, the total severity, viewed in summation, appears moderate. No consideration is given to the effect of propagation.

Coupled Hazard Model

We will now add a coupling matrix:

$$C = \begin{bmatrix} 0 & 0.7 & 0.2 \\ 0 & 0 & 0.6 \\ 0 & 0 & 0 \end{bmatrix} \quad (17)$$

Interpretation:

- Earthquake leads to Landslide (0.7)
- Landslide leads to Flood (0.6)
- Earthquake causes somewhat (0.2) of a Flood

First compute:

$$I_{cascade} = H^T C H \quad (18)$$

$$CH = \begin{bmatrix} 0 & 0.7 & 0.2 \\ 0 & 0 & 0.6 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 6 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} (0.7 \cdot 2 + 0.2 \cdot 3) \\ (0.6 \cdot 3) \\ 0 \end{bmatrix} = \begin{bmatrix} (1.4 + 0.6) \\ 1.8 \\ 0 \end{bmatrix} = \begin{bmatrix} 2.0 \\ 1.8 \\ 0 \end{bmatrix} \quad (19)$$

Then:

$$I_{cascade} = 12 + 3.6 = 15.6 \quad (20)$$

$$H^T(CH) = \begin{bmatrix} 6 & 2 & 3 \end{bmatrix} \begin{bmatrix} 2.0 \\ 1.8 \\ 0 \end{bmatrix} = 6(2.0) + 2(1.8) + 3(0) \quad (21)$$

Structural Comparison

Additive model:

$$I_{additive} = 11 \quad (22)$$

Coupled model:

$$I_{cascade} = 15.6 \quad (23)$$

The difference is ΔI=4.6. This represents interaction-driven amplification of approximately 42%. The additive model ignores propagation effects and therefore underestimates risk.

Sensitivity Analysis

First-order sensitivity with respect to earthquake intensity:

$$S_{H_1} = \frac{\partial I_{cascade}}{\partial H_1} \quad (24)$$

From the quadratic structure:

$$S_{H_1} = 2\sum_j C_{1j} H_j \quad (25)$$

$$S_{H_1} = 2(0.7 \times 2 + 0.2 \times 3) \quad (26)$$

$$S_{H_1} = 2(1.4 + 0.6) \quad (27)$$

$$S_{H_1} = 4.0 \quad (28)$$

Total cascade impact increases significantly due to the small addition of earthquake intensity. Flood parameters are insensitive due to the absence of outgoing coupling.

The proposed framework does not supplant adaptive or cognitive DSS models. It simply comes first in the order and serves as a structural layer. Feature representations are the basis for AI-based decision mechanisms. If those representations fail to capture nonlinear mechanisms and cascade propagation coupled with the features, the downstream reasoning will inherit a structural bias. AI-based DSS, by means of incorporating coupled parameters and sensitivity-based amplification, will gain:

- Feature level interpretability,
- Instability zone identification,
- Definitive propagation pathways,
- Reduced hidden amplification risk,
- Measurable sensitivity cascade propagation.

The framework integrates disaster modeling with the theory of nonlinear systems, network propagation, and structural stability.

Empirical Case Validation and System Consistency Analysis (EVT-00037): Context and Case Selection

For the purpose of validating the proposed parametric interaction framework in non-escalating scenarios, EVT-00037 was chosen from the available cases. This case describes a low-risk monitoring situation where sensor signals indicate a presence, but there is no collapse of the system into a disaster state. The systematic methodology is the reason for selection of a routine case. The majority of DSS research concentrates on severe events, but for a system to be considered robust, it must also successfully refrain from falsely escalating in trivial scenarios. EVT-00037 is therefore a pivotal case for determining the difference between the presence of a signal and the absence of a system.

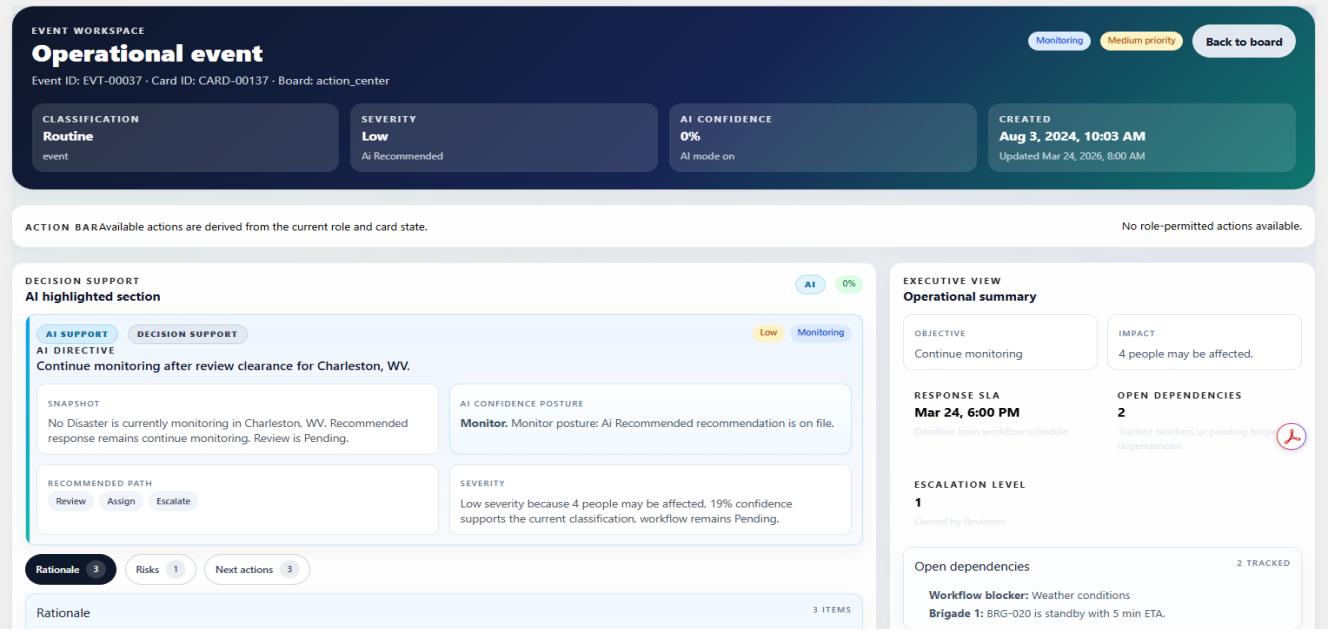
The System in Action

The operational DSS interface (see Figure reference from system output) shows that the system analyzed the event and made the following classifications:

- Classification: Routine
- Severity: Low
- AI Confidence: 0%
- Directive: Continue monitoring
- Operational posture: Monitoring mode
- Brigade assignment: 1 unit Unit assigned: 1 Brigade

The Figure 1 describe the actions mentione above.

Figure 1



DSS operational view showing threshold exceedance and anomaly detection without escalation (EVT-00037)

This means that there has been recognition of signal activity, but it is not viewed as a disaster situation. The presence of a brigade indicates readiness and not escalation, which is common in early monitoring scenarios.

The most pertinent issue is that the workflow panel indicates the decision process is operationally active, but it is stuck in the initial phases of detection and assessment, and has not entered the execution or emergency response phases. This ensures that the system is in a controlled state and does not take action.

Signal Interpretation and Local Dynamics

A few pertinent observations can be drawn from the monitoring section of the interface (signal interpretation panel):

- Signal state: Alert
- Threshold reach: YES
- Pattern match: Elevated event signatures detected
- Forecast: 100 projected signal level
- Interpretation: Escalating anomaly

At first glance, this seems contradictory: the system detects an anomaly and threshold crossing, but still classifies the event as routine.

However, this behavior is scientifically valid. The system is discerning between:

- local signal anomaly (short-term deviation)
- structural disaster formation (interaction-driven escalation)

This means EVT-00037 represents a false-positive-prone zone, where naive models may escalate, but a structured DSS must remain stable.

Event Parametric Representation

To apply the model, the event is expressed as a feature vector:

$$X = (x1, x2, x3) \quad (29)$$

Where:

- $x1$: signal intensity (temperature-based proxy)
- $x2$: anomaly deviation
- $x3$: environmental stability

The normalized vector is:

$$X = (2.71, 4.51, 4.41) \quad (30)$$

This configuration shows:

- signal level,
- observation deviation,

- environment stability.

The parameters must still be evaluated even though Individually, none of the parameters suggest disaster conditions.

Additive Model Interpretation

The formula for calculating the impact additively is shown below as:

$$I_{additively} = 11.63 \quad (31)$$

This value shows the total cumulative presence of signals. The major shortcoming of the additive model is that it cannot differentiate between:

- structured escalation
- random or localized fluctuations

Therefore, an entirely additive approach may possibly lead to EVT-00037 being misidentified as a moderate-risk event. This clearly shows the fundamental shortcoming. The additive model takes into consideration magnitude or size, but ignores structural coherence.

Interaction Based Interpretation

When interaction terms are incorporated, we have

$$I_{interaction} = 1.37 \quad (32)$$

$$I_{total} = 13.00 \quad (33)$$

When the interaction term is compared to the additive term, it is quite small, which means:

- the relationships among the parameters are weak
- there is no reinforcing amplification
- the system's overall behavior is not cascade-able

This is an important finding. The presence of signals means they are not reinforcing one another, and as a consequence, structural instability is not produced.

Sensitivity and Stability Analysis

Sensitivity values were found to be as follows:

$$S1 \approx 1.36, \quad S2 \approx 1.21, \quad S3 \approx 1.18 \quad (34)$$

Considering these values,

- the system shows sensitivity to parameter change
- no parameter is dominating
- there is no explosive growth behavior

From a structural perspective, this implies: the system functions in a stable region where perturbations do not get situated to where they can escalate.

Alignment with System Decision Logic

DSS output is aligned with:

- no incident detection
- no escalation
- direct monitoring

This is a direct match with the model outcomes:

- Weak Interactions → no amplification
- Bounded sensitivity → no instability
- Moderate Additive Value → Presence a signal

Thus, the system rightly identifies EVT-00037 as a signal-rich system, but structurally stable state.

Critical Insight: Why Escalation Does Not Occur

The primary reason why escalation does not occur is not because of the lack of signals, but because of the lack of coherent interaction. Even with:

- thresholds being met
- anomalies being detected
- signals being elevated

the system consciously avoids escalation because of:

- the absence of mutually reinforcing signals
- weak coupling among the contributing parameters
- no cascade pathway being formed

This shows the primary hypothesis of the paper. The formation of a disaster is not determined by the scale of the individual parameters, but by the coherent structure of their interaction.

Conclusion

In this paper, a parametric interaction and sensitivity-based framework for multi-hazard disaster modeling specifically for AI-based DSS architectures is detailed and tested. Some contributions are listed below:

1. A formal structure for multi-disasters represented as a multidimensional feature space.
2. Parametric coupling for modeling nonlinear interactions of features.
3. Construction of a quantifiable hazard coupling matrix for intra- and inter-hazard relationships.
4. Addition of sensitivity analysis for identifying zones of instability and amplification.
5. Assessment of structural risk at the modeling layer and beyond the predictive accuracy.
6. Empirical demonstration using a defined multi-hazard dataset, and incorporating both routine and signal-active instances.

7. EVT-00037 routine case exhibited interaction-aware behavior where structural amplification was absent and only moderate signals were present.
8. It was demonstrated that weak coupling and limited sensitivity facilitate stable system states and inhibit false escalation.
9. There is a direct coupling of the proposed mathematical structure with the DSS operational framework, and that the monitoring of certain parameters was retained even with level-threshold anomalies.
10. Interaction coherence, rather than the magnitude of individual parameters, determines when disasters take shape.

By addressing the structural essence of complex and cascading disaster mechanisms, the proposed approach significantly improves the interpretability and robustness of AI-based Emergency Decision Support Systems while maintaining stable and reliable decision-making in non-escalating environments.

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