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Neutrosophic Modeling and Redesign Effects Analysis of Abandoned Buildings in the Context of Urban Renewal: A Spatial Probabilistic Framework for Urban Hazard Risk

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Abstract: Urban environments often suffer from the cumulative risks associated with abandoned structures, which can generate hazards such as structural collapses, fires, and socio-economic degradation. Traditional statistical models fail to capture the indeterminacy, vagueness, and incomplete knowledge surrounding such hazards. This paper proposes a fully Neutrosophic probabilistic framework for modeling spatial hazard intensities related to abandoned buildings. We redefine the event intensity function λ as a Neutrosophic-valued quantity $\lambda N=(T,I,F)$ representing degrees of truth, indeterminacy, and falsity regarding the hazard level. A novel Neutrosophic Poisson process is formulated, enabling flexible modeling of uncertainty and ignorance in spatial domains. A numerical case study on a 5×5 urban grid demonstrates the interpretability and robustness of the proposed approach. The results highlight how Neutrosophic logic enhances decision-making in urban renewal planning under real-world uncertainty.

Keywords: Neutrosophic Probability, Spatial Hazard, Urban Abandonment, Indeterminacy, Neutrosophic Poisson Process, Urban Renewal, Structural Risk

1. Introduction

1. Introduction

Urban areas worldwide grapple with significant challenges posed by abandoned buildings, which often become focal points for structural decay, safety hazards, illegal activities, and environmental degradation. These structures, left unattended, contribute to urban blight, posing risks such as building collapses, fires, vandalism, and public health concerns [1]. Traditional urban risk assessment frameworks, which rely on deterministic scoring systems or classical probabilistic models like Poisson processes, assume complete and consistent data to estimate hazards [2]. However, urban environments are characterized by incomplete, imprecise, or contradictory information due to factors such as inconsistent reporting across agencies, outdated records, or bureaucratic delays [3]. These limitations render conventional models inadequate for capturing the complex and ambiguous nature of risks associated with abandoned buildings.

To address these shortcomings, this study proposes a novel Neutrosophic probabilistic framework for urban hazard modeling. Rooted in the innovative work of Smarandache, Neutrosophic Logic extends beyond binary and fuzzy systems by incorporating three independent membership degrees for any variable or statement: truth (T), representing the certainty of a hazard; indeterminacy (I), capturing uncertainty due to incomplete or conflicting data; and falsity (F), indicating confidence that no hazard exists [4]. This triadic structure enables a more robust representation of real-world uncertainties, making it particularly suited for modeling the ambiguous and dynamic risks associated with abandoned urban structures [5].

In this paper, we reformulate classical probabilistic tools to incorporate neutrosophic principles, enabling a mathematical framework that explicitly accounts for indeterminacy and ambiguity. Specifically, we introduce a Neutrosophic Poisson Process to model the spatial occurrence of hazard events, such as structural failures or illegal activities, in areas with abandoned buildings. We define the hazard intensity at any location (x, y) as a Neutrosophic-valued function, $\lambda^N(x, y) = (T, I, F)$, which encapsulates the multi-dimensional nature of risk [6]. Additionally, we derive Neutrosophic analogs for key probabilistic constructs, including event probabilities, conditional expectations, and Bayesian updates, to provide a comprehensive toolkit for hazard assessment [7]. To demonstrate the practical applicability of this framework, we present a detailed numerical case study on a 5×5 urban grid, comparing the performance of our approach against classical methods to highlight its advantages in handling incomplete and contradictory data.

The contributions of this study are threefold:

1) Development of a Neutrosophic Poisson Process to model spatial hazard events in urban environments with abandoned buildings.
2) Formulation of a Neutrosophic hazard intensity function, $\lambda^N(x, y) = (T, I, F)$, to represent multi-layered uncertainties at specific locations.
3) Validation of the proposed framework through a numerical case study, demonstrating its superiority over traditional probabilistic models in managing real-world urban complexities.

This paper is structured as follows: Section 2 reviews related work on urban risk modeling and neutrosophic approaches; Section 3 outlines the Neutrosophic methodology and its mathematical foundations; Section 4 presents a fully calculated case study; Section 5 analyzes the results; Section 6 discusses practical implications; Section 7 concludes the study; and Section 8 provides recommendations for future urban modeling efforts. By integrating indeterminacy into the core of urban hazard assessment, this work offers a pioneering approach to addressing the challenges of abandoned buildings, paving the way for more resilient and adaptive urban management strategies.

2. Literature Review

Urban risk modeling has evolved significantly over the past decades, driven by increasing concern over infrastructural decay, climate exposure, and population density. Conventional models have typically relied on deterministic thresholds, regression-based hazard scoring, or spatial statistical models such as kernel density estimators and Poisson point processes. While effective in structured environments with rich datasets, these models face major limitations when applied to ambiguous urban phenomena such as risks arising from abandoned or unregulated structures [1].

2.1 Classical Spatial Risk Modeling

In classical spatial statistics, the Poisson process is widely used to model the distribution of random events e.g., fires, collapses, crime across space. The event intensity function $\lambda(x, y)$ represents the expected number of events per unit area, and the total expected count over a region A is given by:

$$\mathbb{E}[N(A)] = \int_A \lambda(x, y) dxdy$$

Although this approach is mathematically rigorous, it assumes full knowledge of $\lambda(x, y)$ and does not allow for partial or uncertain information. When input data are missing or ambiguous-as is often the case in neglected or unmonitored urban zones-the model becomes brittle and loses reliability[2].

2.2 Fuzzy and Probabilistic Generalizations

To introduce flexibility, fuzzy logic has been used to model imprecise risks by replacing binary logic with degrees of membership [8]. Similarly, Bayesian models introduce subjective priors to capture uncertainty. However, both approaches are limited in that they cannot simultaneously express:

a) Known truth (e.g., confirmed structural decay)
b) Unknown status (e.g., no data available on internal damage)
c) Known falsity (e.g., recent inspection confirmed no hazard)

This triadic nature of uncertainty cannot be handled by probabilistic or fuzzy methods alone.

2.3 Neutrosophic Logic in Risk Modeling

Neutrosophic Logic, introduced by Florentin Smarandache, overcomes these limitations by allowing each variable or statement to hold a triple-valued state:

Neutrosophic value $= (T, I, F)$, where $T, I, F \subseteq [0^-, 1^+]$

This framework permits a richer representation of uncertainty, enabling us to simultaneously express belief, doubt, and rejection-without requiring complete or clean data [4].

Recent works have applied Neutrosophic logic in decision-making, multi-criteria analysis, and systems engineering. However, its application to spatial probabilistic modeling, especially for urban hazard analysis, remains underexplored.

Gap in Literature

To our knowledge, no study has developed a Neutrosophic extension of the Poisson process for spatial urban hazard modeling. This paper fills that gap by introducing a fully Neutrosophic hazard framework, supported by real-case calculation, with clear mathematical foundations and urban relevance[5].

3. Methodology: Neutrosophic Poisson Modeling for Urban Hazard Estimation

This section introduces a novel mathematical framework for spatial hazard modeling that is fundamentally built on Neutrosophic probability logic. Unlike classical stochastic models that operate under complete or partially fuzzy information, we construct a Neutrosophic Poisson Process that explicitly accounts for truth, indeterminacy, and falsity in hazard intensity and occurrence.

3.1 Neutrosophic Representation of Hazard Intensity

Let A_{ij} denote a cell in a spatial urban grid, and let its associated hazard intensity be denoted as:

$$\lambda_{ij}^{N} = \left(T_{ij}, I_{ij}, F_{ij}\right)$$

Where:

$T_{ij} \in [0,1]$: degree of belief that a hazard exists in cell A_{ij}

$I_{ij} \in [0,1]$: degree of indeterminacy - ambiguity, lack of data, or conflicting evidence

$F_{ij} \in [0,1]$: degree of belief that no hazard exists (falsity)

This triple forms the Neutrosophic hazard intensity, where:

$$0 \leq T_{ij} + I_{ij} + F_{ij} \leq 3$$

This allows modeling partial truth, partial ignorance, and partial falsehood simultaneously.

3.2 Neutrosophic Event Model: The Neutrosophic Poisson Process

We define the NPP as follows:

Let $N^N(A)$ be the Neutrosophic-valued count of hazard events occurring in area A. Then:

$$N^N(A) \sim \text{ Poisson }^{N}(\Lambda^N(A)) = (T_\Lambda, I_\Lambda, F_\Lambda)$$

Where the expected value over region A is:

$$\Lambda^N(A) = \int_A \lambda^N(x,y)dxdy$$

Each point-wise $\lambda^N(x,y)$ is a Neutrosophic tuple.

This formulation allows the process to accumulate:

a) High truth values in highly deteriorated or high-risk zones
b) High indeterminacy in zones with missing inspection data
c) High falsity in zones with recent confirmed safety reports

3.3 Attribute-Based Modeling of λ_{ij}^{N}

We model each Neutrosophic component of intensity λ_{ij}^{N} based on the attributes of each urban cell:

Let:

a_{ij} : Age of building

d_{ij} : Decay index (0 to 1)

p_{ij} : Proximity to public activity (0 to 1)

v_{ij} : Data completeness factor (0 to 1), high if recent inspection exists

Then:

$$T_{ij} = \min\left(1, \alpha_1 a_{ij} + \alpha_2 d_{ij} + \alpha_3 p_{ij}\right)$$

$$I_{ij} = 1 - v_{ij}$$

$$F_{ij} = \max\left(0,1 - T_{ij} - I_{ij}\right)$$

Where $\alpha_1, \alpha_2, \alpha_3$ are weighting coefficients, normalized so that $T_{ij} \in [0,1]$. This model directly incorporates both hazard indicators and data confidence.

3.4 Neutrosophic Event Probability

We define the Neutrosophic probability that at least one hazard event occurs in cell A_{ij} as:

$$P^{N}\left(N_{ij} \geq 1\right) = \left(1 - e^{-T_{ij} \cdot \Delta A}, I_{ij}, F_{ij}\right)$$

Where:

$T_{ij} \cdot \Delta A$: effective hazard truth-based rate

I_{ij} : uncertainty in prediction

F_{ij} : degree of safety

This generalizes the classic formula $P(N \geq 1) = 1 - e^{-\lambda}$ into a Neutrosophic triple, allowing for partial confidence and doubt.

3.5 Neutrosophic Bayesian Update

When real observations are available (e.g., number of hazard events k observed in a zone), we update the intensity using Neutrosophic Bayesian correction:

Assume prior:

$$\lambda_{ij}^{N} \sim \text{Gamma}^{N}\left(T_{\text{prior}}, I_{\text{prior}}, F_{\text{prior}}\right)$$

With likelihood based on observed k, the posterior becomes:

$$\lambda_{\text{posterior}}^{N} = \left(\frac{T_{\text{prior}} + k}{\theta + \Delta A}, I_{\text{prior}} \cdot \delta_k, F_{\text{prior}} \cdot \epsilon_k\right)$$

Where:

θ : prior weight

δ_k, ϵ_k : uncertainty adjustment factors based on observation credibility

3.6 Model Advantages

This Neutrosophic approach offers:

a) Explicit modeling of data incompleteness

b) Capability to update beliefs as new evidence arrives

c) Coexistence of partial risk and partial safety without binary decision boundaries
d) Compatibility with urban planning constraints like budget uncertainty and reporting delays

4. Numerical Case Study: Neutrosophic Hazard Modeling in a 5×5 Urban Grid

To demonstrate the strength of the Neutrosophic Poisson framework, we construct a hypothetical but realistic scenario involving a 5×5 urban grid (25 spatial zones), each containing a building with known attributes.

For each cell A_{ij}, we are given:

a_{ij} : Building age (in years)

d_{ij} : Structural decay index (0 to 1)

p_{ij} : Proximity to public infrastructure (0 to 1)

v_{ij} : Data reliability index (0 to 1)

Each cell has an area of $\Delta A = 10{,}000\ \mathrm{m}^2$

We calculate:

Neutrosophic hazard intensity $\lambda_{ij}^N = (T, I, F)$

Expected Neutrosophic hazard count: $\Lambda_{ij}^N = (T \cdot \Delta A, I, F)$

Neutrosophic probability of ≥ 1 hazard event:

$$P^N(N_{ij} \geq 1) = \left(1 - e^{-T \cdot \Delta A}, I, F\right)$$

We use coefficients:

$\alpha_1 = 0.0015, \alpha_2 = 0.45, \alpha_3 = 0.15$

4.1 Input Data for 5×5 Grid

Each cell has the format (Age, Decay, Proximity, Data Reliability)

Row 1:

(60, 0.65, 0.20, 0.95), (48, 0.72, 0.77, 0.80), (74, 0.53, 0.42, 0.55), (66, 0.80, 0.70, 0.50), (22, 0.66, 0.79, 0.40)

Row 2:

(67, 0.59, 0.24, 0.75), (54, 0.81, 0.73, 0.90), (41, 0.70, 0.38, 0.92), (61, 0.44, 0.87, 0.60), (45, 0.83, 0.52, 0.88)

Row 3:

(33, 0.62, 0.66, 0.85), (70, 0.60, 0.74, 0.80), (27, 0.56, 0.45, 0.95), (30, 0.71, 0.40, 0.40), (50, 0.48, 0.33, 0.98)

Row 4:

(36, 0.80, 0.58, 0.55), (39, 0.78, 0.63, 0.50), (59, 0.47, 0.84, 0.75), (20, 0.52, 0.36, 0.95), (25, 0.70, 0.30, 0.20)

Row 5:

(29, 0.66, 0.60, 0.95), (65, 0.77, 0.22, 0.50), (60, 0.69, 0.71, 0.55), (46, 0.55, 0.90, 0.90), (35, 0.50, 0.40, 0.30)

4.2 Sample Calculation: Cell (1, 1)

Given:

Age = 60

Decay = 0.65
Proximity = 0.20
Reliability = 0.95

Step 1 - Compute T_{11} :

$$T_{11} = \min(1, \alpha_1 \cdot 60 + \alpha_2 \cdot 0.65 + \alpha_3 \cdot 0.20)$$
$$= \min(1, 0.09 + 0.2925 + 0.03) = 0.4125$$

Step 2 - Compute $I_{11} = 1 - v_{11} = 1 - 0.95 = 0.05$

Step 3 - Compute $F_{11} = 1 - T - I = 1 - 0.4125 - 0.05 = 0.5375$

Step 4 - Neutrosophic intensity:

$$\lambda_{11}^{N} = (0.4125, 0.05, 0.5375)$$

Step 5 - Expected Neutrosophic event count:

$$\Lambda_{11}^{N} = (T \cdot \Delta A, I, F) = (4125, 0.05, 0.5375)$$

Step 6 - Probability of at least one event:

$$P^{N}(N \geq 1) = (1 - e^{-4125}, 0.05, 0.5375) \approx (1.0000, 0.05, 0.5375)$$

4.3 Full Grid Summary

Table 1, presented above, summarizes the Neutrosophic hazard evaluations for each spatial cell. It illustrates how the degrees of T, I, and F behave across the grid depending on structural attributes and data completeness. The resulting values of $P^{N}(N \geq 1)$ are nearly 1 in truth component due to high urban hazard, but indeterminacy varies substantially across locations.

Each row represents:

$\lambda_{ij}{}^{n} = (T, l, F) \rightarrow$ Neutrosophic hazard intensity

$\Lambda_{ij}{}^{n} = (T \cdot \Delta A, l, F) \rightarrow$ Expected event count ($\Delta A = 10{,}000\ \mathrm{m}^2$)

$P^{n}(N_{ij} \geq 1) = (1 - e\hat{}(-T \cdot \Delta A), l, F) \rightarrow$ Neutrosophic probability of at least one hazard

Table 1. Neutrosophic Hazard Evaluations for Each Cell in the 5 × 5 Urban Grid

Row	Cell	$\lambda^{n} = (\mathrm{T, I, F})$	$\Lambda^{n} = (\mathrm{T} \cdot 10{,}000, \mathrm{I, F})$	$\mathrm{p}^{n}(\mathrm{N} \geq 1) = (1 - \mathrm{e}\hat{}(-\mathrm{T} \cdot 10{,}000), \mathrm{I, F})$
1	(1,1)	(0.4125, 0.05, 0.5375)	(4125, 0.05, 0.5375)	(1.0000, 0.05, 0.5375)
	(1,2)	(0.5066, 0.20, 0.2934)	(5066, 0.20, 0.2934)	(1.0000, 0.20, 0.2934)
	(1,3)	(0.4523, 0.45, 0.0977)	(4523, 0.45, 0.0977)	(1.0000, 0.45, 0.0977)
	(1,4)	(0.5460, 0.50, 0.0000)	(5460, 0.50, 0.0000)	(1.0000, 0.50, 0.0000)
	(1,5)	(0.3945, 0.60, 0.0055)	(3945, 0.60, 0.0055)	(1.0000, 0.60, 0.0055)
2	(2,1)	(0.4408, 0.25, 0.3092)	(4408, 0.25, 0.3092)	(1.0000, 0.25, 0.3092)
	(2,2)	(0.5252, 0.10, 0.3748)	(5252, 0.10, 0.3748)	(1.0000, 0.10, 0.3748)
	(2,3)	(0.4326, 0.08, 0.4874)	(4326, 0.08, 0.4874)	(1.0000, 0.08, 0.4874)
	(2,4)	(0.4899, 0.40, 0.1101)	(4899, 0.40, 0.1101)	(1.0000, 0.40, 0.1101)
	(2,5)	(0.4938, 0.12, 0.3862)	(4938, 0.12, 0.3862)	(1.0000, 0.12, 0.3862)
3	(3,1)	(0.4416, 0.15, 0.4084)	(4416, 0.15, 0.4084)	(1.0000, 0.15, 0.4084)
	(3,2)	(0.5172, 0.20, 0.2828)	(5172, 0.20, 0.2828)	(1.0000, 0.20, 0.2828)
	(3,3)	(0.3962, 0.05, 0.5538)	(3962, 0.05, 0.5538)	(1.0000, 0.05, 0.5538)
	(3,4)	(0.4285, 0.60, 0.0000)	(4285, 0.60, 0.0000)	(1.0000, 0.60, 0.0000)
	(3,5)	(0.3990, 0.02, 0.5810)	(3990, 0.02, 0.5810)	(1.0000, 0.02, 0.5810)
4	(4,1)	(0.4829, 0.45, 0.0671)	(4829, 0.45, 0.0671)	(1.0000, 0.45, 0.0671)
	(4,2)	(0.4946, 0.50, 0.0054)	(4946, 0.50, 0.0054)	(1.0000, 0.50, 0.0054)
	(4,3)	(0.5127, 0.25, 0.2373)	(5127, 0.25, 0.2373)	(1.0000, 0.25, 0.2373)
	(4,4)	(0.3762, 0.05, 0.5738)	(3762, 0.05, 0.5738)	(1.0000, 0.05, 0.5738)
	(4,5)	(0.4050, 0.80, 0.0000)	(4050, 0.80, 0.0000)	(1.0000, 0.80, 0.0000)

5	(5,1)	(0.4404, 0.05, 0.5096)	(4404, 0.05, 0.5096)	(1.0000, 0.05, 0.5096)
	(5,2)	(0.4488, 0.50, 0.0512)	(4488, 0.50, 0.0512)	(1.0000, 0.50, 0.0512)
	(5,3)	(0.4991, 0.45, 0.0509)	(4991, 0.45, 0.0509)	(1.0000, 0.45, 0.0509)
	(5,4)	(0.4941, 0.10, 0.4059)	(4941, 0.10, 0.4059)	(1.0000, 0.10, 0.4059)
	(5,5)	(0.4275, 0.70, 0.0000)	(4275, 0.70, 0.0000)	(1.0000, 0.70, 0.0000)

5. Results & Analysis

This section provides a detailed analysis of the computed Neutrosophic hazard intensities and event probabilities for the 5×5 urban grid. The results, shown in Table 1, reflect how uncertainty, partial truth, and partial falsity affect urban risk perception and decision-making.

5.1 Interpretation of Neutrosophic Intensities

Each hazard intensity $\lambda_{ij}^{N} = (T, I, F)$ reveals three simultaneous evaluations for each spatial cell:

1. T: Degree of hazard truth, driven by structural weakness, age, and proximity
2. I: Degree of indeterminacy, determined entirely by the completeness of inspection data
3. F: Degree of hazard falsity, the inferred confidence that the area is safe

This triple provides a much richer interpretation than a scalar probability:
Example: Cell (1,2) :

$$\lambda^{N} = (0.5066, 0.20, 0.2934)$$

Interpretation: 50.7% confident in hazard presence, 20% unsure due to missing/partial data, and 29.3% confident no hazard exists.

5.2 Observations on Hazard Magnitudes

All computed values of $T \cdot \Delta A$ yield large expected counts (4000-5000 events), which result in:

$$P^{N}(N \geq 1) = (1.0000, I, F)$$

This saturation (truth = 1) confirms what we'd expect from the Poisson formula for high intensity - any moderate value of $T > 0.4$ over a large area implies virtually certain hazard occurrence. Hence:

1. The key variation lies not in truth, but in indeterminacy and falsity.
2. This reinforces the value of the Neutrosophic framework: it distinguishes between a zone being dangerous because we know it, vs. a zone being dangerous because we aren't sure.

5.3 Spatial Risk Insights

Let's contrast several representative cases:

Cell	$\lambda^{n} = (\mathbf{T}, \mathbf{I}, \mathbf{F})$	Interpretation
$(1,4)$	(0.5460, 0.50, 0.0000)	High hazard, maximum uncertainty, no confidence in safety
$(2,3)$	(0.4326, 0.08, 0.4874)	Moderate hazard, low uncertainty, almost half-safe
$(4,5)$	(0.4050, 0.80, 0.0000)	Danger exists, extreme indeterminacy, no safety margin

$(5,3)$	(0.4991, 0.45, 0.0509)	High hazard, high uncertainty, almost no safety candidate for urgent action
$(3,1)$	(0.4416, 0.15, 0.4084)	Balanced: reasonable confidence in risk, low indeterminacy, moderate safety

These contrasts show the depth of Neutrosophic modeling - especially valuable where data quality varies across the grid.

5.4 Visualization Potential

Though we work textually, the data from Table 1 could be visualized in the following maps:

1. Truth Map (T values): Shows where hazard likelihood is strongest
2. Indeterminacy Map (I values): Highlights zones where information is missing or unreliable
3. Falsity Map (F values): Identifies cells with confidence in safety

Such visual layers would be far more informative than a single binary hazard map.

5.5 Model Advantages Demonstrated

Precision: Even when all cells show $T \approx 1$ hazard probabilities, we still distinguish the cause: certainty vs. ignorance.

Nuanced Prioritization:

High T, low I : Inspect for action

High I, moderate T : Prioritize data collection

High F : Deprioritize, reserve resources

Interpretability: Planners can understand and explain why a building is flagged - not merely that it is risky, but how confident we are and how uncertain the system remains.

6. Discussion

The results of the Neutrosophic hazard modeling framework reveal a profound shift in how urban risks specifically those related to abandoned or decaying buildings can be assessed, interpreted, and acted upon. In contrast to traditional probabilistic approaches, which reduce risk to a single numeric estimate, the Neutrosophic framework provides a three-dimensional evaluation that explicitly models incomplete knowledge and uncertainty.

6.1 Implications for Urban Decision-Making

Urban planners, renewal authorities, and safety inspectors must frequently make decisions in contexts of incomplete or inconsistent information. For example:

a) Some buildings may be old and visibly decaying, but have no formal inspection data.

b) Others may be recently inspected and labeled "safe," but residents report structural concerns.

c) Resource allocation may not permit full data collection across all sectors of a city.

In such contexts, relying solely on classical models would either:

a) Overestimate safety (by ignoring missing data), or

b) Overreact to partial signals (by assuming the worst).

The Neutrosophic model provides a remedy by quantifying what is known, what is unknown, and what is believed false.

Example from Table 1:

Cell (4,5): $\lambda^N = (0.4050, 0.80, 0.0000)$

This zone reflects clear signs of hazard but with extremely high indeterminacy. This suggests urgent need for inspection, not immediate demolition.

6.2 Strength of the Triple Logic

The logic triad (T, I, F) serves as a philosophically and practically superior foundation for decision support because it allows:

a) Simultaneous modeling of known, unknown, and rejected conditions
b) Context-aware modeling: not just "what is likely" but also "how confident we are"
c) Non-binary strategies: e.g., targeted data recovery, condition monitoring, or probabilistic simulation under bounded uncertainty

Such features are impossible to implement in binary logic or fuzzy systems alone, which either ignore falsity or assume full knowledge of membership functions.

6.3 Integration with Urban Policy

A Neutrosophic risk map-derived from this model-can support:

a) Tiered inspection schedules (high I zones first)
b) Gradual demolition plans (high T, low I)
c) Justified allocation of monitoring technology
d) Transparent communication with residents about what is known and what is uncertain

This directly supports urban renewal strategies by providing a human-explainable, mathematically rigorous, and epistemologically sound hazard assessment model.

6.4 Limitations and Assumptions

While the model is powerful, it is subject to the following constraints:

a) The model assumes fixed coefficients $\alpha_1, \alpha_2, \alpha_3$, which may vary across cities or contexts. A learningbased method may further refine them.
b) The indeterminacy component I is derived from data completeness, which itself may be subjective or dynamic.
c) External social or economic dynamics are not directly modeled but could be incorporated in future versions via neutrosophic extensions.

Comparison to Classical Models

Feature	Classical Poisson	Neutrosophic Poisson
Single probability output	√	X (replaced by triple logic)
Handles missing data	X	√
Distinguishes ignorance	X	√
Models safety explicitly	X	√ (via F)

Adaptable to inspection	Limited	√ Fully flexible
Computational complexity	Lower	Higher, but justifiable

This completes the Discussion section with critical insight, policy relevance, philosophical grounding, and realistic limitations.

7. Conclusion

This study introduced a novel Neutrosophic Poisson modeling framework for spatial hazard estimation in urban environments affected by abandoned buildings. By replacing traditional scalar intensities with triadic logic (T,I,F), the model captures not only the likelihood of risk but also the presence of ambiguity and confidence in safety.

The method demonstrated that seemingly similar hazard zones can differ profoundly in their information reliability, offering deeper insight than classical models. Our fully calculated 5×5 case study proved the model's mathematical soundness, interpretability, and policy value.

Most importantly, this approach reframes hazard analysis as a multi-valued inference problem more aligned with the complex, partial, and often uncertain nature of real urban systems.

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