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Measuring the Construction Risk Insurability through Fuzzy Inference System

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Abstract

Contractors face most of the construction risks among stakeholders, and insurance is a common method to mitigate these risks. However, not all risks are insurable. While prior studies have typically assessed risk insurability through a binary approach (insurable versus non-insurable) and lacked clear criteria, this study offers a novel perspective by evaluating the insurability of construction risks based on four criteria: 'accidental events,' 'quantifiable,' 'numerous and homogenous,' and 'evaluable.' This study develops a fuzzy-based model to assess the degree of the construction risk insurability, accounting for the uncertainty, imprecision, and vagueness inherent in evaluating insurability against a specific criterion and criteria combinations. The model is applied to assess the insurability of several construction risks, illustrating its practical application. This paper concludes by discussing the model's limitations and suggesting directions for future research.

Introduction

The construction industry is inherently unique, with projects operating in a dynamic and ever-shifting environment. The specific nature of construction projects raises numerous risks that stakeholders must actively manage [1-3]. These risks can significantly impact the project objectives, including budget, quality, and time. Ultimately, risks can adversely influence business profitability, customer satisfaction, and project success [4]. Therefore, proactively identifying, assessing, monitoring, and managing risks is crucial to project success. Since risks can only be mitigated, not eliminated, effective risk minimization strategies often involve sharing or allocating risks to appropriate parties. Strategically allocating risks can dramatically improve the likelihood of a project's success [4-6]. The fundamental principle is to assign risks to the party best positioned to manage and control risks' potential impact [7].

In construction projects, the contractor often faces more risks than the client. Accordingly, the contractor must have strategies to reduce these risks, and one strategy is transferring the risks to a third party, the insurance firm [8]. An agreed-upon insurance policy will bind the insurance firm (the insurer) and the contractor (the insured) legally [9]. As the insured party, the contractor may reasonably expect that most of the risks associated with construction activities will be covered under a construction insurance policy. However, an insurance policy usually only covers the risks mentioned as uninsured, leaving numerous 'unspecified' risks open to interpretation [10,11]. This situation creates a breeding ground for conflict and disputes between contractors and insurers, reducing the intended risk-mitigation benefits for both parties (e.g., delayed project finish) [12].

Studies on the insurability of construction risks are relatively scant, with much of it relying on empirical analyses of insurance claim databases. The current approach also often creates a dichotomy between insurable and uninsurable risks. For example, Perera et al. [13] and Halwatura [14] use insurance claim databases to identify characteristics of

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risks that are likely to be insured. Owusu-Manu et al. [9] and Hatmoko et al. [15] explore the perspectives of contractors and insurers by surveying which construction risks are deemed insurable or uninsurable. These studies reveal a significant disparity between the perspectives of contractors and insurers, with each group identifying different risks as insurable or uninsurable. Berliner [16] further argues that risk insurability is influenced by 'risk size,' a subjective factor that depends on the expert or assessor's perspective, which can introduce imprecision into the assessment.

Bunni [8] establishes four criteria for determining insurable risk: insurable risks must be accidental and fortuitous, have a quantifiable impact and damage, be homogenous and frequent, and possess an identifiable cause. However, no studies have directly assessed the insurability of risks solely within this framework. Therefore, this study seeks to bridge the gap between these differing perspectives by measuring the insurability of construction risks according to their fitness to these insurable risk criteria.

While this study adopts Bunni's criteria for evaluating construction risk insurability, several critical observations must be made. First, two extreme scenarios exist: one where all criteria are satisfied, classifying the risk as insurable, and another where none are met, rendering the risk uninsurable. However, between these extremes lies a gradual transition from one state to another based on various possible combinations. Second, the assessment of each of these four criteria cannot always be determined in a binary fashion, either 'yes' or 'no' for belonging to a set for two key reasons: first, the criteria often lack clear-cut boundaries, and second, evaluating whether a risk meets specific criteria frequently involves a spectrum of membership, ranging from complete exclusion to full inclusion within the set. Consequently, this study employs fuzzy set theory, introducing a novel approach by developing a model that more realistically and flexibly measures construction risk insurability. Furthermore, the model accounts for the uncertainty, imprecision, and vagueness inherent in evaluating insurability against a specific criterion and criteria combinations.

Fuzzy Inference Systems (FIS) are employed as an optimal method to address the inherent imprecision in expert judgments. FIS enhances the accuracy of the risk assessment process by applying fuzzification, processing the information through an inference system, and translating the results via defuzzification [17,18]. This approach aims to create a more consistent and reliable evaluation of construction risk insurability.

Literature Review

Construction Risk Insurability

Construction insurance utilization involves numerous factors. Risk mitigation through insurance-based risk transfer is influenced by the contractor's trust in the insurer, their knowledge and experience with insurance, and their willingness to pay premiums [13,14,19-22]. However, it is crucial to acknowledge that not all risks, even those potentially covered by a Contractor's All Risk (CAR) policy, are insurable. CAR policies often effectively cover risks like theft of materials and tools, equipment damage, third-party property damage, and contractor payment delays [20,22-25]. Pramudya [10] examines construction risk insurance and identifies 76 prevalent risks across different construction types, e.g., buildings, infrastructure, housing, and ground construction. This study highlights a significant gap between contractors and insurers regarding the insurability of risks under CAR insurance policies.

Hatmoko et al. [15] deal with risk insurability among Indonesian contractors and insurers, revealing agreement on only 27 of 42 identified risks. Twelve are deemed insurable, fifteen are non-insurable, and fifteen remain elusive. Similarly, Owusu-Manu et al. [9], in their study of complex project deals in Ghana, identify 54 risks and find that most respondents consider project risks, such as construction design errors, payment delays, workplace accidents, property damage, fire, earthquakes, and storms insurable. It is worth noting that Owusu-Manu et al. [9] and Hatmoko et al. [15] employ a binary insurability assessment, i.e., insurable and non-insurable, which can potentially force nuanced risks into an inflexible categorization.

Insurable Risk Criteria

Bunni [8] contends that specific limitations are essential for viable insurance transactions, and these limitations implicitly define the criteria for insurable risk. Firstly, insurance fundamentally relies on probability, requiring an inherent degree of unpredictability ('accidental or fortuitous events,' coded as C1) in the insured subject matter. Secondly, insurable risks should ideally be quantifiable to enable the application of probability theories and the law of large numbers, underpinning accurate premium calculations ('quantifiable,' coded as C2). Thirdly, insurable risks conform to insurance market standards, with numerous and homogeneous insured objects facilitating effective risk selection methods (‘numerous and homogenous,’ coded as C3). Finally, an insurable risk should permit verification of loss occurrence, damage causation, and quantifiable damage assessment (‘evaluable,’ coded as C4).

Method

Figure 1 depicts the overall research framework. The initial phase involves identifying construction risks and formulating a questionnaire designed for contractors and insurers to evaluate these risks against insurable risk criteria. The second block introduces the development and implementation of a fuzzy model. This model analyzes questionnaire responses to determine the insurability of the identified risks based on their alignment with the defined insurable risk criteria.

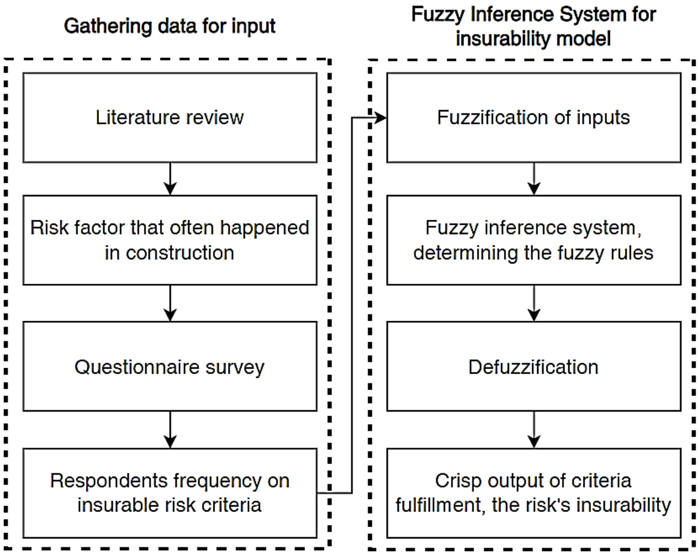

Figure 1. Overall Research Framework

Fuzzy Inference System

Previous studies frequently employ the FIS in risk management studies to interpret results, particularly regarding risk impact. The FIS proves valuable in analyzing respondents’ perspectives on risk assessment [26,27]. The FIS process typically involves three primary steps: (1) fuzzification, converting inputs into linguistic membership degrees (e.g., low, medium-low, medium-high, high); (2) fuzzy inference, applying fuzzy rules to map input relationships and determine output membership degrees; and (3) defuzzification, transforming the output membership degree into a precise numerical value using a chosen method. The FIS output indicates the extent to which risk factors align with insurable risk criteria from the respondents’ viewpoints, thus providing a measure of risk insurability. The methodology and procedures for Fuzzy Risk Insurability modeling in this study are described below:

1. Determining the membership for fuzzy input and output variables
   The precise quantification of subjective judgments can be difficult. Fuzzy modeling mechanisms, such as Triangular Fuzzy Numbers (TFNs) and Trapezoidal Fuzzy Numbers (TpFNs) TFNs and TpFNs are commonly used in construction management research due to their simplicity in concept and application. These fuzzy numbers are characterized by an upper limit, lower limit, and a most likely value, effectively representing respondents’ inputs within linguistic categories [28]. This study surveys respondents regarding specific risks and their alignment with insurability criteria. The frequency with which each insurable risk criterion is met across respondent groups serves as the model’s input. The frequencies of responses on *C1*, *C2*, *C3*, and *C4* are mapped to four linguistic memberships: *Low* (L), *Medium Low* (ML), *Medium High* (MH), and *High* (H). Table 1 and Figure 2 illustrate the corresponding fuzzy numbers. Equations (1) and (2) demonstrate the formulas used to calculate the membership degrees for TFNs and TpFNs, respectively.

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-L}{M-L}, & L \le x \le M \\ \dfrac{U-x}{U-M}, & M \le x \le U \\ 0, & x < L \text{ or } x > U \end{cases} \tag{1}$$

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-L}{M_1-L}, & L \leq x \leq M_1 \\ 1, & M_1 \leq x \leq M_2 \\ \dfrac{U-x}{U-M_2}, & M_2 \leq x \leq U \\ 0, & x < L \text{ or } x > U \end{cases} \quad (2)$$

where $\mu_{\tilde{A}}(x)$ represents the membership degree of x at linguistic A, L is the lowest x on fuzzy numbers, M is x with the highest membership on fuzzy numbers, and U is the highest x on fuzzy numbers.

This study defines a 'risk fulfillment degree' (*DF*) that measures alignment with insurable risk criteria. The *DF* is a crisp value ranging from 0.00 (non-insurable) to 1.00 (fully insurable). Each insurable risk criterion is assigned a score from 1 (*Low*) to 4 (*High*). A maximal fulfillment degree and insurability (1.00) is achieved when a score of 4 is assigned to all criteria. Conversely, the lowest fulfillment degree and non-insurability (0.00) is indicated by a score of 1 across all criteria. Due to the possible combinations of scores between 16 and 4, there are 13 potential *DF* output variations. The *DF* range (0 to 1) is therefore linearly segmented into 13 singleton fuzzy numbers: (0.00, 0.08, 0.17, 0.25, 0.33, 0.42, 0.50, 0.58, 0.67, 0.75, 0.83, 0.92, 1.00).

Table 1. TFN and TpFN Fuzzy Numbers for Model Inputs

Linguistic Category	Membership Function	Corresponding Fuzzy Numbers
Low (L)	Trapezoidal	(0.00, 0.00, 0.2, 0.33)
Medium Low (ML)	Triangular	(0.00, 0.33, 0.66)
Medium High (MH)	Triangular	(0.33, 0.66, 1.00)
High (H)	Trapezoidal	(0.66, 0.8, 1.00, 1.00)

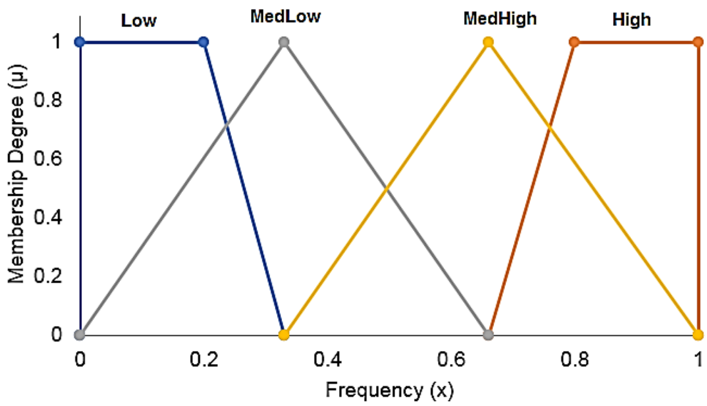

Figure 2. Model Input's Fuzzy Number

2. Constructing fuzzy rules for Inference System
The FIS employed in this study relies on a Mamdani-type inference system, using 'AND' and 'OR' fuzzy logic operators. The 'AND' operator determines the minimum value among inputs, while the 'OR' operator determines the maximum [29]. This study incorporates four inputs, each with four linguistic categories. Consequently, the FIS accommodates 4^4 (or 256) potential output combinations, managed through a comprehensive set of fuzzy rules.

These fuzzy rules account for all 256 possible input combinations. Due to the lack of information on Bunni's insurable risk criteria, this paper assigns equal weight to each criterion. As a result, the specific order of inputs does not impact the output. Additionally, input combinations with equal sums yield identical outputs. For example, input patterns of '*High, High, Low, Low*' (H, H, L, L) and '*Medium-High, Medium-High, Medium-Low, Medium-Low*' (MH, MH, ML, ML) both share the same sum value and thus map to an identical output (a 0.5 degree of fulfillment). The 256 rules are generated by using the 'AND' operation and are illustrated below:
Rules #1 IF (***C1*** is *H*) AND (***C2*** is *H*) AND (***C3*** is *H*) AND (***C4*** is *H*) THEN (***DF*** is 1)
Rules #2 IF (***C1*** is *H*) AND (***C2*** is *H*) AND (***C3*** is *H*) AND (***C4*** is *MH*) THEN (***DF*** is 0.92)
Rules #3 IF (***C1*** is *H*) AND (***C2*** is *H*) AND (***C3*** is *H*) AND (***C4*** is *ML*) THEN (***DF*** is 0.83)
Rules #4 IF (***C1*** is *H*) AND (***C2*** is *H*) AND (***C3*** is *H*) AND (***C4*** is *L*) THEN (***DF*** is 0.75)

Rules #5 IF (*C1* is *H*) AND (*C2* is *H*) AND (*C3* is *MH*) AND (*C4* is *H*) THEN (***DF*** is 0.92)
Rules #6 IF (*C1* is *H*) AND (*C2* is *H*) AND (*C3* is *MH*) AND (*C4* is *MH*) THEN (***DF*** is 0.83)
Rules #7 IF (*C1* is *H*) AND (*C2* is *H*) AND (*C3* is *MH*) AND (*C4* is *ML*) THEN (***DF*** is 0.75)
Rules #8 IF (*C1* is *H*) AND (*C2* is *H*) AND (*C3* is *MH*) AND (*C4* is *L*) THEN (***DF*** is 0.67)
…
Rules #249 IF (*C1* is *L*) AND (*C2* is *L*) AND (*C3* is *ML*) AND (*C4* is *H*) THEN (***DF*** is 0.33)
Rules #250 IF (*C1* is *L*) AND (*C2* is *L*) AND (*C3* is *ML*) AND (*C4* is *MH*) THEN (***DF*** is 0.25)
Rules #251 IF (*C1* is *L*) AND (*C2* is *L*) AND (*C3* is *ML*) AND (*C4* is *ML*) THEN (***DF*** is 0.17)
Rules #252 IF (*C1* is *L*) AND (*C2* is *L*) AND (*C3* is *ML*) AND (*C4* is *L*) THEN (***DF*** is 0.08)
Rules #253 IF (*C1* is *L*) AND (*C2* is *L*) AND (*C3* is *L*) AND (*C4* is *H*) THEN (***DF*** is 0.25)
Rules #254 IF (*C1* is *L*) AND (*C2* is *L*) AND (*C3* is *L*) AND (*C4* is *MH*) THEN (***DF*** is 0.17)
Rules #255 IF (*C1* is *L*) AND (*C2* is *L*) AND (*C3* is *L*) AND (*C4* is *ML*) THEN (***DF*** is 0.08)
Rules #256 IF (*C1* is *L*) AND (*C2* is *L*) AND (*C3* is *L*) AND (*C4* is *L*) THEN (***DF*** is 0)

3. Selecting the defuzzification method
Several defuzzification methods, maxima and derivatives, distribution and derivatives, and area methods are the often-used defuzzification methodologies [30]. This study employs distribution methods and derivatives, known as the centroid or center of gravity (COG) method for defuzzification. It can be calculated using Equation (3).

$$COG_{\tilde{A}(x)} = \frac{\sum_{x_{min}}^{x_{max}} x \cdot \mu_{\tilde{A}}(x)}{\sum_{x_{min}}^{x_{max}} \mu_{\tilde{A}}(x)} \tag{3}$$

where $COG_{\tilde{A}(x)}$ represents fuzzy A's centroid in crisp value, and $\mu_{\tilde{A}}(x)$ is the membership degree of x.

For demonstration purposes, this fuzzy model is tested on twelve risks across seven categories (Table 2). These risks are selected for their diverse characteristics: natural disasters are inherently unpredictable, while contractors can manage construction operational risks. In contrast, financial and regulatory risks are primarily controlled by external parties (banks and government), leaving construction stakeholders with limited influence.

Table 2. Selected Risks with Different Characteristic

Category	Risk
Site condition	Geological conditions (R1)
Natural disaster	Earthquakes, volcanic eruptions, and tsunamis (R2)
	Landslides (R3)
Human-caused disaster	Robbery and theft on-site (R4)
	War, civil war, and terrorism (R5)
	Accidental damage (R6)
Construction operational	Material or equipment availability (R7)
	Material waste by workers (R8)
	Third-party property damage (R9)
Competition	Competition from similar projects (R10)
Financial	Funding shortages and loan cancellations (R11)
Law and regulation	Changes in laws and government regulations (R12)

Results and Discussion

A survey is conducted to measure risk insurability by evaluating the fulfillment of insurable risk criteria from the contractor's and insurer's perspectives. The survey involves 31 contractors and 15 insurer respondents with over five years of experience. Their responses are normalized by dividing the number of agreements ('yes' responses) by the total number of respondents in each group (please see Table 3). The analysis highlights significant differences in risk perception between the two groups. For example, 70% of contractor respondents consider 'earthquakes, volcanic eruptions, and tsunamis' to fulfill the accidental event criterion (*C1*) and 20% consider them to exhibit quantifiable damage (*C2*). However, less than 10% assess these risks as frequently occurring (*C3*) or having identifiable causes (*C4*). Conversely, over 70% of insurers evaluate 'landslides' as fulfilling three criteria (*C1*, *C2*, and *C4*), with approximately 40% labeling it as frequently occurring (*C3*). This finding illustrates that the risk might get different insurability perceptions from each group.

Table 3. Respondents Frequency of Risks against Insurable Risk Criteria

Risk	Relative Frequencies							
	Contractors				Insurers			
	C1	C2	C3	C4	C1	C2	C3	C4
Geological conditions (R1)	0.42	0.32	0.13	0.26	0.53	0.73	0.60	0.53
Earthquakes, volcanic eruptions, and tsunamis (R2)	0.71	0.19	0.06	0.10	0.80	0.73	0.40	0.73
Landslides (R3)	0.74	0.19	0.10	0.10	0.73	0.73	0.73	0.67
Robbery and theft on-site (R4)	0.45	0.26	0.29	0.19	0.67	0.60	0.73	0.60
War, civil war, and terrorism (R5)	0.65	0.10	0.10	0.10	0.33	0.33	0.13	0.27
Accidental damage (R6)	0.71	0.32	0.10	0.23	0.73	0.73	0.47	0.53
Material or equipment availability (R7)	0.10	0.42	0.26	0.48	0.07	0.07	0.27	0.27
Material waste by workers (R8)	0.10	0.29	0.52	0.19	0.27	0.13	0.00	0.27
Third-party property damage (R9)	0.52	0.42	0.16	0.19	0.80	0.73	0.67	0.67
Competition from similar projects (R10)	0.10	0.23	0.48	0.19	0.07	0.00	0.13	0.13
Funding shortages and loan cancellations (R11)	0.16	0.16	0.26	0.26	0.20	0.13	0.27	0.13
Changes in laws and government regulations (R12)	0.32	0.19	0.10	0.23	0.13	0.13	0.20	0.13

Input Transformation

The first step of applying FIS is transforming the input into membership degree through fuzzification, as described in Table 3. For example, the 'landslides' frequency reported by contractors at *C1* is 0.74. Based on Figure 2, the value of 0.74 belongs to the *Medium-High* and *High* categories. Thus, the membership degrees for *Low* and *Medium-Low* are 0, while those for *Medium-High* and *High* are calculated using Equations (1) and (2).

For *Low* category, $\mu_L(x_{R3-C1}) = x_{R3-C1} \geq 0.33 = 0$

$\mu_L(x_{R3-C1}) = 0.74 \geq 0.33 = 0$

For *Medium-Low* category, $\mu_{ML}(x_{R3-C1}) = x_{R3-C1} \geq 0.67 = 0$

$\mu_L(x_{R3-C1}) = 0.74 \geq 0.67 = 0$

For *Medium-High* category $\mu_{MH}(x_{R3-C1}) = \frac{U_{MH}-x_{R3-C1}}{U_{MH}-M_{MH}} = \frac{1-0.74}{1-0.67} = 0.77$

For *High* category, $\mu_H(x_{R3-C1}) = \frac{x_{R3-C1}-L_H}{M_{H-1}-L_H} = \frac{0.74-0.67}{0.8-0.67} = 0.56$

In summary, the membership degree of *C1* is 0 for *Low*, 0 for *Medium-Low*, 0.76 for *Medium-High*, and 0.59 for *High* (0.00, 0.00, 0.77, 0.56). By applying the same steps for other inputs (*C2*, *C3*, and *C4*), the membership degree for 'landslides' from the contractors' perspective is [*C1*: (0.00, 0.00, 0.77, 0.56); *C2*: (1.00, 0.58, 0.00, 0.00); *C3*: (1.00, 0.29, 0.00, 0.00); *C4*: (1.00, 0.29, 0.00, 0.00)]. Table 4 shows the calculated membership degrees based on the relative frequencies of contractors and insurers, which are then used as input.

Table 4. Membership Degree by Contractors and Insurers for Inputs

Code	C1	C2	C3	C4
Membership Degree by Contractors (L, ML, MH, H)				
R1	(0.00, 0.74, 0.26, 0.00)	(0.08, 0.97, 0.00, 0.00)	(1.00, 0.39, 0.00, 0.00)	(0.26, 0.77, 0.00, 0.00)
R2	(0.00, 0.00, 0.87, 0.32)	(1.00, 0.58, 0.00, 0.00)	(1.00, 0.19, 0.00, 0.00)	(0.10, 0.29, 0.00, 0.00)
R3	(0.00, 0.00, 0.77, 0.56)	(1.00, 0.58, 0.00, 0.00)	(1.00, 0.29, 0.00, 0.00)	(0.10, 0.29, 0.00, 0.00)
R4	(0.00, 0.65, 0.35, 0.00)	(0.56, 0.77, 0.00, 0.00)	(0.32, 0.87, 0.00, 0.00)	(0.19, 0.58, 0.00, 0.00)
R5	(0.00, 0.06, 0.94, 0.00)	(1.00, 0.29, 0.00, 0.00)	(1.00, 0.29, 0.00, 0.00)	(0.10, 0.29, 0.00, 0.00)
R6	(0.00, 0.00, 0.87, 0.32)	(0.08, 0.97, 0.00, 0.00)	(1.00, 0.29, 0.00, 0.00)	(0.23, 0.68, 0.00, 0.00)
R7	(1.00, 0.29, 0.00, 0.00)	(0.00, 0.74, 0.26, 0.00)	(0.56, 0.77, 0.00, 0.00)	(0.48, 0.55, 0.45, 0.32)
R8	(1.00, 0.29, 0.00, 0.00)	(0.32, 0.87, 0.00, 0.00)	(0.00, 0.45, 0.55, 0.00)	(0.19, 0.58, 0.00, 0.00)
R9	(0.00, 0.45, 0.55, 0.00)	(0.00, 0.74, 0.26, 0.00)	(1.00, 0.48, 0.00, 0.00)	(0.19, 0.58, 0.00, 0.00)
R10	(1.00, 0.29, 0.00, 0.00)	(0.81, 0.68, 0.00, 0.00)	(0.00, 0.55, 0.45, 0.00)	(0.19, 0.58, 0.00, 0.00)
Membership Degree by Insurers (L, ML, MH, H)				
R1	(0.00, 0.40, 0.60, 0.00)	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.20, 0.80, 0.00)	(0.00, 0.40, 0.60, 0.00)
R2	(0.00, 0.00, 0.60, 1.00)	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.80, 0.20, 0.00)	(0.00, 0.00, 0.80, 0.50)
R3	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.00, 1.00, 0.00)
R4	(0.00, 0.00, 1.00, 0.00)	(0.00, 0.20, 0.80, 0.00)	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.20, 0.80, 0.00)
R5	(0.00, 1.00, 0.00, 0.00)	(0.00, 1.00, 0.00, 0.00)	(1.00, 0.40, 0.00, 0.00)	(0.50, 0.80, 0.00, 0.00)
R6	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.60, 0.40, 0.00)	(0.00, 0.40, 0.60, 0.00)
R7	(1.00, 0.20, 0.00, 0.00)	(1.00, 0.20, 0.00, 0.00)	(0.50, 0.80, 0.00, 0.00)	(0.50, 0.80, 0.00, 0.00)
R8	(0.50, 0.80, 0.00, 0.00)	(1.00, 0.40, 0.00, 0.00)	(1.00, 0.00, 0.00, 0.00)	(0.50, 0.80, 0.00, 0.00)
R9	(0.00, 0.00, 0.60, 1.00)	(0.00, 0.00, 0.80, 0.50)	(0.00, 0.00, 1.00, 0.00)	(0.00, 0.00, 1.00, 0.00)
R10	(1.00, 0.20, 0.00, 0.00)	(1.00, 0.00, 0.00, 0.00)	(1.00, 0.40, 0.00, 0.00)	(1.00, 0.40, 0.00, 0.00)
R11	(1.00, 0.60, 0.00, 0.00)	(1.00, 0.40, 0.00, 0.00)	(0.50, 0.80, 0.00, 0.00)	(1.00, 0.40, 0.00, 0.00)

Fuzzy Rules Applications

The regulated 256 fuzzy rules cover all the possibilities of input combinations. For example, based on the insurers' input, 'landslide' has inputs of [*C1*, *C2*, *C3*, *C4*] = [(0.00, 0.00, 0.80, 0.50); (0.00, 0.00, 0.80, 0.50); (0.00, 0.00, 0.80, 0.50); (0.00, 0.00, 1.00, 0.00)]. These inputs are then loaded to all of the fuzzy rules. Since the fuzzy rules only use the 'AND' operation, each combination's minimum (lowest) membership is selected. This step is described in Table 5.

Table 5. Combination and Fuzzy Rule Used for R4 based on Insurers Perspective

Rule No.	Input Combination	*C1*	*C2*	*C3*	*C4*	Calculated Membership (MIN μ)	Output (*DF*)
1	[H, H, H, H]	0.50	0.50	0.50	0.00	0.00	1.00
2	[H, H, H, MH]	0.50	0.50	0.50	1.00	0.50	0.92
3	[H, H, H, ML]	0.50	0.50	0.50	0.00	0.00	0.83
…	…	…	…	…	…	…	…
85	[MH, MH, MH, H]	0.80	0.80	0.80	0.00	0.00	0.75
86	[MH, MH, MH, MH]	0.80	0.80	0.80	1.00	0.80	0.67
…	…	…	…	…	…	…	…
254	[L, L, L, MH]	0.00	0.00	0.00	1.00	0.00	0.17
255	[L, L, L, ML]	0.00	0.00	0.00	0.00	0.00	0.08
256	[L, L, L, L]	0.00	0.00	0.00	0.00	0.00	0.00

Defuzzification

The crisp value of applied fuzzy rules is obtained through defuzzification. This study applies the COG or centroid method to transform the fuzzy number into a crisp value that describes the degree of fulfillment of insurable risk criteria. The calculation is performed using Equation (3) as follows.

$$COG_{\mu\,(DF_{R4})} = \frac{\sum_{x_{min}}^{x_{max}} DF_{R4} \cdot \mu_{\,(DF_{R4})}}{\sum_{x_{min}}^{x_{max}} \mu_{\,(DF_{R4})}}$$

$$COG_{\mu\,(DF_{R4})} = \frac{(0 \times 1) + (0.5 \times 0.92) + (0 \times 0.83) + \cdots + (0 \times 0.083) + (0 \times 0)}{(0 + 0.5 + 0 + \cdots + 0 + 0)}$$

$$COG_{\mu\,(DF_{R4})} = \frac{3.3667}{4.3} \approx 0.77$$

The degree of insurable risk criteria fulfillment (*DF*) illustrates the insurability measurement of the identified risk. The result of *DF* is presented in Table 6. The fulfillment degree among insurers ranges from 0.04 to 0.77. Contractors' evaluations of the risks yield a fulfillment degree ranging from 0.19 to 0.33, indicating a narrower range compared to insurers. This variation is understandable, as insurers more frequently assess the risk and its insurability than contractors. The narrow range of fulfillment scores reflects contractors' hesitancy or uncertainty in evaluating the suitability of risks against insurable risk criteria. Several risks are considered more insurable by contractors showing higher DFs than insurers (e.g., 'competition from similar projects'). The difference between *DF* by contractor and insurers varies from -0.25 to 0.44, where the minus sign indicates that *DF* by contractor is higher than insurers and vice versa.

Based on Table 6, most risks associated with natural disasters are highly insurable, particularly from the perspective of insurers. For instance, 'earthquakes, volcanic eruptions, tsunamis, and landslides' score above 0.75 according to insurers and 0.32 according to contractors. Natural disaster risks are typically unpredictable, unlike other risks that may be managed within the contractor's control.

The contractor places greater importance on certain risks than the insurer when evaluating the fulfillment of insurable risk criteria. These risks include 'the availability of material or equipment,' 'material waste caused by workers,' and 'competition from similar projects.' Table 3 shows that 'material or equipment availability' is determined by approximately 93% of insurers as not fulfilling the criteria for accidental events (*C1*) and quantifiable damage (*C2*). Additionally, about 73% of insurers consider this risk to be infrequent (*C3*) and with non-identifiable causes (*C4*). In comparison, 42% of contractors deem the risk to fulfill the quantifiable damage (*C2*), and 48% agree that the risk's cause is identifiable (*C4*). Similarly, 'material waste by workers' is perceived by over 73% of insurers as non-accidental events, unquantifiable damage, rarely occurring, and having non-identifiable causes. However, around 52% of contractors consider that 'material waste by workers' and 'actual volume differences from the contract' frequently occur (*C3*).

Furthermore, more than 87% of insurers believe that 'competition from similar projects' does not meet the criteria for insurable risks, while 48% of contractors agree that the risk frequently occurs (*C3*). Based on the model's measurement, contractors assign this risk a *DF* score exceeding 0.29, whereas insurers assign it a *DF* score of less than 0.13, indicating a low level of insurability.

Based on the model's findings, insurers consider risks associated with contractor control and regulatory factors to have limited insurability, for example, 'material or equipment availability,' 'material waste by workers,' 'competition from similar projects,' 'funding shortages and loan cancellations,' and 'changes in laws and government regulations.' Regarding risk transfer, assigning risks to the party with the most control over how risks may impact the situation is optimal. Since many of these risks can be effectively managed by the contractor, insurers perceive them to have low insurability.

Both contractor and insurer respondents seem to share a concurrent perception of 'war, civil war, and terrorism' and 'funding shortages and loan cancellations.' Both risks' *DF* difference shows a low value of approximately 0.01. Notably, based on Table 3, 65% of contractors perceive 'war, civil war, and terrorism' as accidental events. Approximately 90% of contractors agree that the damage of this risk is unquantifiable, rarely occurs, and has non-identifiable causes. On the other hand, only 33% of insurers consider this risk an accidental event with quantifiable damage. In comparison, more than 73% of insurers deem it to occur rarely and to have non-identifiable causes. Similarly, over 74% of contractors and 73% of insurers agree that 'funding shortages and loan cancellations' are classified as non-accidental events, resulting in unquantifiable damage, rarely occurring, and having non-identifiable causes.

A surface model of *DF* can be generated using two frequency inputs, as shown in Figure 3, with *C1* and *C2* as examples. Since every criterion is assumed to be equally weighted, and the fuzzy rules are generated linearly, as mentioned previously, the conducted surface represents the *DF* value of any two frequency inputs, such as *C1* and *C3*, *C2* and *C4*, or *C3* and *C4*. A single input of 1.00 for one criterion results in a maximum *DF* value of 0.5. The second criterion of 0.5 increases the value of *DF*, resulting in a *DF* of about 0.6.

Table 6. The Overall Result of Insurability Measurement

Risk	Degree of Fulfillment		
	Contractors	**Insurers**	**Difference**
Geological conditions (R1)	0.28	0.64	0.37
Earthquakes, volcanic eruptions, and tsunamis (R2)	0.32	0.75	0.43
Landslides (R3)	0.33	0.77	0.44
Robbery and theft on-site (R4)	0.29	0.69	0.40
War, civil war, and terrorism (R5)	0.29	0.28	-0.01
Accidental damage (R6)	0.32	0.64	0.32
Material or equipment availability (R7)	0.33	0.13	-0.20
Material waste by workers (R8)	0.29	0.11	-0.18
Third-party property damage (R9)	0.33	0.76	0.43
Competition from similar projects (R10)	0.29	0.04	-0.25
Funding shortages and loan cancellations (R11)	0.19	0.18	0.00
Changes in laws and government regulations (R12)	0.26	0.13	-0.13

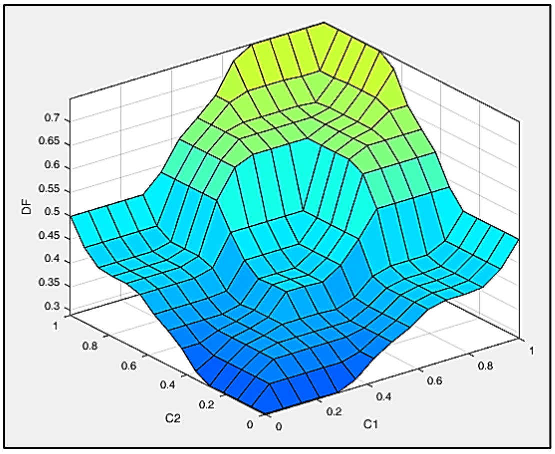

Figure 3. *DF* Surface According to Two Inputs: C1 and C2

Conclusions

The contractor is the party most exposed to risks among the stakeholders involved in a construction project. Managing these risks often involves considering the use of construction insurance as a strategy measure. This study develops a fuzzy-based model designed to assess the insurability of risks by evaluating their fulfillment against four criteria for insurability. The model incorporates the perspectives of both contractors and insurers, converting their assessments of risk into linguistic membership degrees through fuzzification. This process involves 256 fuzzy rules resulting in 13 singleton fuzzy numbers output, which are then defuzzified using the centroid method.

The model is tested on 12 construction risks, each with different characteristics. The fuzzy model's outcomes reveal that, according to insurers, risks associated with unpredictable accidents, such as on-site theft, accidental damage, and third-party property damage, exhibit moderately high insurability. Natural disaster risks demonstrate higher insurability, including earthquakes, volcanic eruptions, tsunamis, and landslides. In contrast, risks perceived to be within the contractor's control and related to construction management are evaluated as having low fulfillment of insurable criteria. Nevertheless, contractors may perceive these risks as having slightly higher insurability than insurers. In real-world construction insurance applications, contractors need to recognize that not all risks they encounter are insurable. Understanding the criteria that determine a risk's insurability is crucial, as it allows contractors to implement more advanced risk management strategies to minimize the impact of those risks.

The developed model has limitations, which can pave the way for future research. The model assumes equal weighting for each insurable risk criterion, though it is acknowledged that specific criteria may influence insurability more than others. Therefore, a thorough examination of the impact of each criterion on risk insurability can enhance the robustness of the model. For example, the Analytical Hierarchy Process can be used to determine the weight of each insurable risk criterion, which can lead to changes in the assessment of risk insurability. Additionally, incorporating dataset creation and applying machine learning techniques can potentially elevate the research to an advanced level for the evolution of new insurable risk criteria. Another limitation is that the model does not account for the potential existence of necessary and sufficient conditions for determining whether a risk is insurable. Future research could focus on investigating this aspect in greater detail.

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