Natural Hazards
https://doi.org/10.1007/s11069-022-05712-1

ORIGINAL PAPER

# Assembly area risk assessment methodology for post-flood evacuation by integrated neutrosophic AHP-CODAS

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Received: 13 May 2022 / Accepted: 9 November 2022


## Abstract
Floods are one of the natural disasters that affect human life materially and morally. There are various measures to prevent flood damage. The evaluation of flood risk and assembly points is of great importance for flood risk preparation and disaster mitigation measures. This study presents a two-stage framework with a multi-criteria decision-making (MCDM) technique for flood and assembly point risk assessment problems. First of all, with a detailed literature review, the main and sub-criteria affecting the flood and assembly points are determined. Each criterion is evaluated with expert opinion. Then, the importance weights of the criteria are determined with the Interval-Valued Neutrosophic Analytical Hierarchy Process (IVN-AHP) methodology. The ranking of the twelve assembly points in Bartın according to their risks is obtained by the Interval-Valued Neutrosophic Combinative Distance-based Assessment (IVN-CODAS) method. The proposed risk assessment methodology is applied to the Merkez district of Bartın, Turkey, which is frequently exposed to floods. In this context, a risk assignment hierarchy consisting of 6 main criteria as Topographic, Access, Hydrological, Sociological, Humanitarian Aid and Infrastructure and a total of 24 sub-criteria is constructed. The most important main criterion is determined as Topographic. Although 'Topographic' is the most important main criterion, considering that there is no significant difference between this criterion and the others, it is suggested that each criterion should be considered when determining the location of an assembly point. The results demonstrate that the most important sub-criterion is "Proximity to flood risk area" with a final weight of 0.076 among 24 criteria. The result of the proposed methodology is tested by sensitivity analysis. A comparative analysis is also done to verify the efficiency of the proposed methodology. The proposed integrated methodology is intended to be a useful tool for disaster risk assessments and to guide decision makers.

**Keywords** Assembly point · Flood risk · Interval-valued neutrosophic numbers · AHP · CODAS

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Published online: 20 November 2022

## 1 Introduction

Natural and man-made disasters such as floods, earthquakes, and landslides, pose serious risks to humanity. Flood is defined as the overflow of lands due to excessive precipitation or snowfall (Liang et al. 2019). For Turkey, the flood is the second largest natural disaster after the earthquake, which has caused serious material and moral losses until now. Turkey, especially in the western Black Sea region, is frequently exposed to flood disasters due to its location, terrain, and adverse meteorological conditions. For this reason, it is necessary to identify risks to reduce damage to the economy and people. It is of great importance that people and authorized institutions follow a systematic flood risk management process against this devastating natural disaster (Plate 2002). Identifying suitable assembly points also contributes to the flood risk management process.

When the literature on flood disaster is reviewed, the determination of temporary shelters and flood risk assessment are the most popular topics. MCDM techniques are frequently used in flood disaster studies. MCDM is very effective in cases where more than one criterion affects each other, and these criteria are evaluated together. In (Aruldoss et al. 2013; Swain et al. 2020) and (Chen et al. 2015) create a flood risk map integrated the remote sensing and AHP with geographic information systems (GIS). Among the studies that deal with flood risk mapping or assessment problems, there are many studies using AHP and GIS techniques. These studies (Ramkar and Yadav 2021)–(Narendr et al. 2021) make flood risk assessments by dividing the regions into classes such as high, medium, and low. Islam et al. (Islam and Ghosh 2022) and Das (Das 2020) evaluate risk using AHP together with demographic, social, economic, and infrastructural factors. Morea et al. (Morea and Samanta 2020) and Karymbalis et. al (Karymbalis et al. 2021) use GIS-integrated AHP and weighted linear combination (WLC) using 9 independent flood criteria and effective parameters for water flow, respectively. Tiryaki and Karaca (Tiryaki and Karaca 2018) created a 5-class flood susceptibility map using GIS, MCDM, and optically stimulated luminescence (OSL), focusing on past and present floods. Tang et al. (Tang et al. 2017) used the probabilistic ordinal weighted average (OWA) to account for the uncertainty of the risk attitudes of decision makers in the criterion weights through Monte Carlo simulation.

The uncertainty factor is of great importance in risk assessment problems. There are studies that use the fuzzy MCDM technique to cope with this uncertainty as (Cai et al. 2021)–(Lee et al. 2015). Flood maps are generally created under the dimensions of vulnerability, hazard, exposure and vulnerability Unlike these, Ekmekcioglu et al. (Ekmekcioğlu et al. 2021a) prioritized the risk factor for the province of Istanbul, Jamrussri and Toda (Jamrussri and Toda 2018) calculated the evacuation times, and Lee et al. (Lee et al. 2015) proposed a set of group decision making (GDM) combining the VIKOR method and data fuzzification. The fuzzy logic technique is used to improve the evaluation of experts, since human judgment is imperfect under uncertainty (Sukcharoen et al. 2016).

Urban flood susceptibility maps or models provide important information in assessing potential hazards and planning the development of the city. Wang et al. (Wang et al. 2018) divided into six different risk factors the regions representing three aspects of flood risk sources (socioeconomic, land cover, and flood factors). In this context, urban flood risks are estimated in cities in developing countries and urban flood areas are mapped (Zia et al. 2021). A GDM is proposed to measure urban flood resilience by combining the three normalization, weighting, and criterion data (Zhu and Liu 2021).

In the current literature, the number of studies using machine learning and optimization techniques related to flood risk assessment and assembly points is less than those using MCDM techniques. Ali et al. (Ali et al. 2020), bivariate statistics and machine learning were hybridized and mapped with different physical–geographical factors. Kittipongvises et al. are using regression on the relationship between past flood experiences and flood preparedness of community residents (Kittipongvises et al. 2020). A deep neural network (DNN) is used for spatial prediction of floods, and the AHP method is used to generate flood exposure and vulnerability maps. Two hybrid artificial intelligence (AI) models are developed for the assessment of flood susceptibility (human health and financial impact) by combining AdaBoost and Bagging algorithms with the Decision Table (DT) (Pham et al. 2021). Flood-prone areas are determined using two different approaches, AHP and boosted classification tree (BCT) (Vojtek et al. 2021).

Different types of geospatial datasets such as morphological, hydrometeorological, demographic characteristics, infrastructure, and land uses are used in Wu et al. (2021) and (Hussain et al. 2021) to generate flood vulnerability maps. There are studies with different purposes, apart from flood risk and vulnerability mapping. For example, the objective is to identify water catchment areas with MCDM to reduce water scarcity problems (Behera et al. 2019). Meral and Eroglu (Meral and Eroğlu 2021), a basin precipitation map is prepared in order to use the city center and the agricultural plain as a basis for future flood management plans. In addition to flood risk assessment, there is a lack of literature on temporary shelter and assembly points. Assembly points are safe areas that people need to reach quickly during and after a disaster and do not pose a risk of disaster. Temporary shelters are preplanned and basic shelters that offer the best possible living conditions for temporary shelter of disaster victims after the initial turmoil has been overcome (Cinar et al. 2018). Studies on flood disasters mostly focus on the determination of optimum shelter points. For example, a multi-objective optimization model is proposed to minimize total cost, evacuation time, and number of open shelters in the shelter location problem (Praneetpholkrang and Kanjanawattana 2021). The DEMATEL method is used to examine the cause–effect relationships of the factors affecting shelter selection (Trivedi 2018) and to identify shelters (Boostani et al. 2018). Candidate shelters for pedestrian evacuation planning are evaluated (Lee et al. 2021). The optimal location of temporary shelters is found using local search modified particle swarm optimization (LMPSO) (Samany et al. 2021). In addition, potential shelters are identified and evaluated by incorporating traffic microsimulation modelling for mass evacuation (Alam et al. 2021). Similarly, Sadat et al. (Kanani-Sadat et al. 2019) integrated DEMATEL for flood susceptibility assessment in data-scarce areas with fuzzy theory and the uncertainty of experts' views.

Bathrellos et al. (Bathrellos et al. 2016) discussed a flood hazard assessment model for urban areas with GIS-based AHP for Athens. Bathrellos et al. (Bathrellos et al. 2017) identified areas suitable for urban development with a multiple hazard assessment map. Singh et al. (Singh et al. 2021) also calculated the flood hazard index using the GIS-based AHP technique. Pham et al. (Pham, et al. 2022) developed a flood vulnerability map with conditioning factors and evaluated the flood exposure of buildings using three machine learning techniques (neural network multilayer perceptron, deep learning neural network, Bayesian logistic regression) techniques. Similarly, Ye et al. (Ye et al. 2022) used five advanced machine learning techniques (light gradient boosting, extreme gradient boosting, categorical boosting, support vector machine, and random forest). It is used for precipitation-induced landslide susceptibility mapping. Hong et al. (Hong, et al. 2019) used MCDM and bivariate statistical techniques for estimating landslide susceptibility. MCDM techniques are frequently used in earthquake disasters as well as floods and landslides. One of these studies proposed a simultaneous hazard zoning mapping approach to earthquake-induced secondary effects (Karpouza et al. 2021). As a result, flood and assembly point risk assessment and management are critical for understanding flood-prone locations and taking appropriate measurements. Therefore, this study aims to determine flood risk criteria and priority ranking of assembly points according to risks using MCDM techniques for the Merkez district of Bartın.

Real-life problems often involve uncertainty because they cannot be described by deterministic models. For this reason, the fuzzy method is preferred for MCDM problems. Neutrosophic sets are used to avoid the inability of classical fuzzy and extensions. IVN-AHP expresses uncertainty and can effectively involve human thought in decision making. In addition, the IVN-AHP method completely and accurately reflects the thoughts of decision makers compared to classical AHP. IVN-CODAS, on the other hand, is an efficient and current method recommended for use in solving MCDM problems. A proposed methodology that uses neutrosophic CODAS proposes a very easy-to-use and very systematic way to represent complex, uncertain real-life MCDM problems (Ayyildiz 2022). Since the subjects of hazard analysis and assessment are very close to real-life problems and contain a lot of uncertainty, efficient results can be obtained with the IVN-AHP and IVN-CODAS methods.

As a result of the review of the literature, the following observations motivated this study. Current studies focus on issues such as flood risk, susceptibility, vulnerability mapping and assessment, and temporary shelter. In this way, the evaluation of post-flood assembly points emerges as an important field of study. Similarly, risk assessment studies are carried out taking into account a certain number of criteria. This work aims to comprehensively examine flood and assembly point risk factors. Studies have been mostly limited to the AHP technique. Therefore, this study presents a risk assessment framework by integrating the IVN-AHP method with the IVN-CODAS technique for the first time in the literature. To our knowledge, there is no study in the literature that deals with candidate assembly points and flood risk together. It should be noted that most studies on flood risk and shelter site selection use the AHP technique, which is the most well known of the MCDM techniques and takes into account a limited number of criteria. This situation constitutes the motivation for the study in terms of using a different decision-making technique. Unlike other flood studies, this study establishes and implements a new two-level IVN-AHP integrated IVN-CODAS methodology. With IVN-AHP, the importance weights of each criterion are determined, and then with IVN-CODAS, alternative assembly points are ranked according to their risks.

This study seeks answers to the following research questions by focusing on these gaps in the flood and assembly point literature. (i) What are the criteria that influence the assessment of the risk of both flood and assembly points? (ii) Which of the main and sub-criteria are more important as a result of the risk assessment process? (iii) Can a different decision-making technique yield effective results in assessing assembly points in terms of flood?

The main contribution of this study mainly includes both methodological and practical aspects.

(i) From a methodological point of view, a new integrated MCDM framework has been proposed for the assessment of the risk of flood and assembly points. To the author's knowledge, there are no studies extending IVN-AHP with integrated IVN-CODAS in the current flood risk assessment literature.
(ii) From a practical point of view, this study introduces the post-flood assembly point risk assessment problem to the literature. Risk assessment and assemblage point

studies are increasing, as Turkey is more exposed to flood disasters after the earthquake. However, there are limited studies on post-flood assembly risk assessment. This study focuses on post-flood assembly point risk assessment and uses a new MCDM framework, taking into account important criteria such as hydrological, topographic, sociological, accessibility, infrastructure, and humanitarian relief, which makes the framework more realistic

## 2 Methodology

In this study, the IVN-AHP and IVN-CODAS techniques are used together to determine the flood risk for the Merkez district of Bartın. Expert opinions are included in the process. Using the criteria weights obtained, twelve assembly points in Bartın are ranked according to their flood risk levels. Finally, the results are evaluated and discussed by sensitivity analysis. The steps of the proposed flood risk assessment methodology are shown in Fig. 1. The study area and levels of the proposed methodology are detailed in the following sections.

### 2.1 Evaluation criteria

The assessment of flood risk for assembly points is a complex and multidimensional decision problem. Considering more than one parameter complicates the risk assessment process. Therefore, we perform a detailed literature review to identify criteria that affect both flood and assembly points. The candidate criteria obtained are then finalized by a group of experts' judgment. As seen in Table 1, six main criteria and 25 sub-criteria have been determined for risk assessment.

**Hydrological (C1)** Water is one of the most basic parameters affecting floods (Msabi and Makonyo 2021). In addition, floods are a subject of the discipline of hydrology (Swain

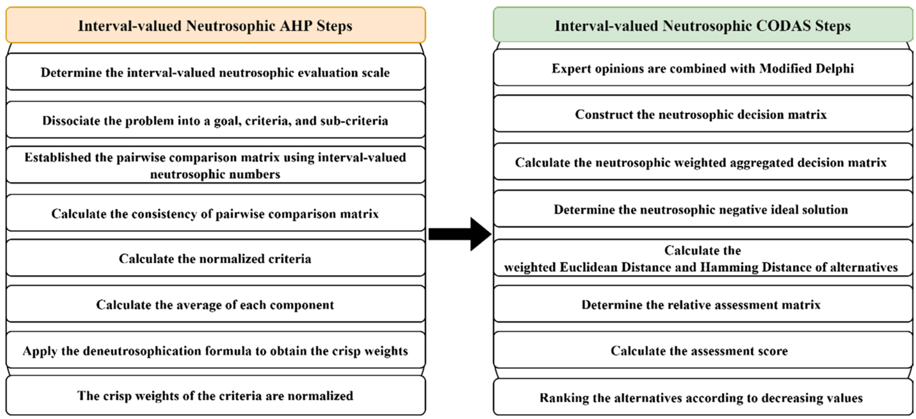


**Fig. 1** The steps of the proposed methodology

**Table 1** Flood and assembly point risk main criteria and sub-criteria

| Main criteria | Code | Sub-criteria | Sources |
|---|---|---|---|
| Hydrological (C1) | C11 | Drainage density | Liang et al. (2019); Plate (2002); Swain et al. (2020); Ramkar and Yadav (2021); Narimani et al. (2021); Souissi et al. (2020); Chakraborty and Mukhopadhyay (2019); Karymbalis et al. 2021); Tiryaki and Karaca (2018); Jamrussri and Toda (2018) |
| | C12 | Flow accumulation | |
| | C13 | Surface runoff | |
| Topographic (C2) | C21 | Elevation | Plate (2002); Narimani et al. (2021); Allafta and Opp (2021); Souissi et al. (2020); Koem and Tantanee (2020); Morea and Samanta (2020); Tang et al. (2017); Wang et al. (2018) |
| | C22 | Slope | |
| | C23 | Aspect | |
| | C24 | Distance from the river | |
| | C25 | Imperviousness | |
| Sociological (C3) | C31 | Population density | Plate (2002); Koem and Tantanee (2020); Narendr et al. (2021); Islam and Ghosh (2022); Tang et al. (2017); Cai et al. (2021) |
| | C32 | Education level | |
| | C33 | Housing typology | |
| | C34 | Road density | |
| Access (C4) | C41 | Proximity to the city center | Ekmekcioğlu et al. (2021b); Sukcharoen et al. (2016); Zia et al. (2021) |
| | C42 | Proximity to flood risk area | |
| | C43 | Proximity to main road | |
| Infrastructure (C5) | C51 | Condition of local road infrastructure | Fariza et al. 2020; Zhu and Liu 2021) |
| | C52 | Total floor area | |
| | C53 | Telecommunication facility | |
| | C54 | Water | |
| | C55 | Electricity | |
| Humanitarian Relief (C6) | C61 | Proximity to healthcare organization | Lee et al. (2015); Zia et al. (2021); Zhu and Liu (2021) |
| | C62 | Distance to shelter | |
| | C63 | Access to the police and fire station | |
| | C64 | Proximity to relief distribution center | |

et al. 2020). As a result of the literature review, it is seen that hydrological criteria are frequently used to create a flood risk map.

**Topographic (C2)** Topography includes issues related to surface features (Samany et al. 2021). The topography of an area plays an important role in exposure to flood hazards and sheltering in safe places.

**Sociological (C3)** Unlike other main criteria, the anthropological and sociological criteria are related to human and social science (Narendr et al. 2021). During or after the flood, many issues, such as the number of people in the region and the level of public awareness, are important.

**Access (C4)** Accessibility is an important criterion for the evacuation of people and the sending of relief materials in all disasters, including floods (Boostani et al. 2018). This criterion includes distance information to important places.

**Infrastructure (C5)** Infrastructure-related features mostly contain information about the road condition of the assembly point and the region (Trivedi 2018). This information particularly contributes to the determination of the assembly point.

**Humanitarian Relief (C6)** Humanitarian factors include distance information to important institutions such as hospitals, police, and fire stations. This main criterion is taken as a sub-criterion in many studies (Alam et al. 2021). In this study, the humanitarian aid factor is evaluated as the main criterion using the expert opinion.

There are 25 sub-criteria depending on the main criteria created as a result of the literature research. Each of the sub-criteria is confirmed by expert opinions. The explanation and importance of each sub-criteria are given in Table 2.

### 2.2 Neutrosophic sets and preliminaries

The concept of fuzzy logic introduced by Zadeh is a logical structure developed to deal with semantic uncertainty (Zadeh et al. 1996). Classical fuzzy set theory has been expanded over time with different approaches by researchers. Atanassov intuitionistic fuzzy set theory is an improved version of the classical fuzzy set (Atanassov 1989). In intuitionistic fuzzy sets degrees of truth membership and falsity membership as distinct from Zadeh. Compared to classical fuzzy set theory, more successful results have been obtained (Xu 2007). Following this approach, Smarandache introduced the more advanced version of the neutrosophic set (Smarandache 1998). In the neutrosophic set, in addition to the heuristic fuzzy set, the uncertainty membership value is also taken into account. At the same time, unlike fuzzy logic, a phenomenon is represented by three membership values, namely truth (T), uncertainty (I), and falsity (F). Neutrosophic sets are suitable for representing uncertainty and inconsistency since they carry more information than the fuzzy logic approach (Wang et al. 2010). After the introduction of the neutrosophic sets by Smarandache, various variations have been improved (Smarandache 1998). This section provides general information on neutrosophic clusters and range-valued neutrosophic numbers. Here $\widetilde{\widetilde{A}}$., denotes a neutrosophic set defined in E

**Table 2** Meaning of sub-criteria

| Code | Sub-criteria | Significance |
|---|---|---|
| C11 | Drainage density | It is the length of the stream per unit area of the basin. A low drainage density indicates that the area is durable or permeable |
| C12 | Flow accumulation | It shows the waterways in the entire area that contribute to the flow in a particular area. High flow accumulation means a higher risk of flooding |
| C13 | Surface runoff | It is the part of the precipitation that flows on the surface of the ground. More precipitation means that there may be more runoff |
| C21 | Elevation | It is the height of a region above sea level. Low-altitude places are more susceptible to floods |
| C22 | Slope | It is the height difference between two points. Increasing the slope can result in an increase in flood size |
| C23 | Aspect | It gives the position of the slopes against the sun. North-facing slopes receive more precipitation than south-facing slopes |
| C24 | Distance from the river | It gives the distance between the assembly points and the rivers. Proximity to the river increases the risk of floods |
| C25 | Imperviousness | It gives the level of water permeability of the ground surface |
| C31 | Population density | It refers to the number of people per $km^2$. Higher density increases exposure to floods |
| C32 | Education level | Indicates the level of awareness of the population |
| C33 | Housing typology | Determines the durability level of the buildings according to the types of housing |
| C34 | Road density | It denotes the road network per $km^2$. The sensitivity of the regions with intense road density is high |
| C41 | Proximity to the city center | The distance from the city center is important for access to resources |
| C42 | Proximity to flood risk area | The distance of the assembly points from areas at risk of flooding is critical |
| C43 | Proximity to main road | The proximity to the main road is important to shorten the arrival times to the assembly points |
| C51 | Condition of local road infrastructure | The robustness of the roads is critical to reaching assembly points |
| C52 | Total floor area | Indicates the human capacity that the assembly point can take |
| C53 | Telecommunication facility | The telecommunication infrastructure is needed for communication |
| C54 | Water | Since the transportation of polluted water as a result of floods causes disease, the location of the assembly points should be close to clean water |
| C55 | Electricity | Electricity is required for the operation of the devices |
| C61 | Proximity to healthcare organization | The proximity of assembly points to health facilities is important |
| C62 | Distance to shelter | It gives the distance to other assembly points. It is preferred that the total distance be minimal |

**Table 2** (continued)

| Code | Sub-criteria | Significance |
|---|---|---|
| C63 | Access to police and fire station | The distance of the assembly points from the police and fire stations is important for security |
| C64 | Proximity to relief distribution center | It gives information on how close the assembly points are to the relief distribution centers |

and represented by the truth membership function T, the uncertainty-membership function I, and the falsity membership function F (Bolturk and Karasan 2018).

**Definition 1:** Let E be a universe. A neutrosophic set $\tilde{\tilde{A}}$ in E is characterized by a truth-membership function $T_A$, an indeterminacy-membership function $I_A$, and a falsity-membership function $F_A$ (Saaty 1988; Bolturk and Kahraman 2018).

$I_A(x) and F_A(x)$ are real standard or nonstandard subset of$]^{-}0, 1[^{+}$. A neutrosophic set $\tilde{\tilde{A}}$ can is presented:

$$\tilde{\tilde{A}} = \left\{ \left\langle x, \left(T_A(x), I_A(x), F_A(x)\right) \right\rangle : x \int E, \left(T_A(x), I_A(x), F_A(x) \int ]^{-}0, 1[^{+}\right) \right\} \tag{1}$$

There is no restriction on the sum of $T_A(x)$, $I_A(x) and F_A(x)$, so that $0^{-} \leq T_A(x) + I_A(x) + F_A(x) \leq 3^{+}$.

**Definition 2** An interval-valued neutrosophic set (IVNS) $\tilde{\tilde{N}}$ in E is characterized by a truth-membership function $T_N(x)$ an indeterminacy-membership function $I_N(x)$ and a falsity-membership function $F_N(x)$ (Karaşan et al. 1029).

$$T_N(x) = \left[T_N^L(x), T_N^U(x)\right] \subseteq [0, 1] \tag{2}$$

$$I_N(x) = \left[I_N^L(x), I_N^U(x)\right] \subseteq [0, 1] \tag{3}$$

$$F_N(x) = \left[F_N^L(x), F_N^U(x)\right] \subseteq [0, 1] \tag{4}$$

Thus $\tilde{\ddot{N}}$ can be given:

$$\tilde{\ddot{N}} = \left\{x, \left[T_N^L(x), T_N^U(x)\right], \left[I_N^L(x), I_N^U(x)\right], \left[F_N^L(x), F_N^U(x)\right] xE\right\} \tag{5}$$

**Definition 3** For deneutrosophication, proposed by Bolturk et al. (Bolturk and Karasan 2018) interval-valued neutrosophic number (IVNN) is given below:

$$\mathfrak{D}(x) = \left( \frac{\left(T_N^L(x) + T_N^U(x)\right)}{2} + \left(I_N^U(x)\right)\left(1 - \frac{\left(I_N^L(x) + I_N^U(x)\right)}{2}\right) - \left(1 - F_N^U(x)\right)\left(\frac{F_N^L(x) + F_N^U(x)}{2}\right) \right) \tag{6}$$

where $\tilde{\ddot{x}}_j = \left[T_x^L, T_x^U\right], \left[I_x^L, I_x^U\right], \left[F_x^L, F_x^U\right]$

**Definition 4** Let $\tilde{\ddot{N}}_1 = \left[T_{N_1}^L, T_{N_1}^U\right], \left[I_{N_1}^L, I_{N_1}^U\right], \left[F_{N_1}^L, F_{N_1}^U\right]$ and $\tilde{\ddot{N}}_2 = \left[T_{N_2}^L, T_{N_2}^U\right], \left[I_{N_2}^L, I_{N_2}^U\right], \left[F_{N_2}^L, F_{N_2}^U\right]$ be two IVNNs. For those two numbers, some main operations are given:

$$\lambda\left(\tilde{\ddot{N}}_1\right) = \left[1 - \left(1 - T_{N_1}^L\right)^{\lambda}, 1 - \left(1 - T_{N_1}^U\right)^{\lambda}\right], \left[\left(I_{N_1}^L\right)^{\lambda}, \left(I_{N_1}^U\right)^{\lambda}\right], \left[\left(F_{N_1}^L\right)^{\lambda}, \left(F_{N_1}^U\right)^{\lambda}\right], \lambda > 0 \tag{7}$$

$$\left(\tilde{\ddot{N}}_1\right)^{\lambda} = \left[\left(T_{N_1}^L\right)^{\lambda}, \left(T_{N_1}^U\right)^{\lambda}\right], \left[\left(I_{N_1}^L\right)^{\lambda}, \left(I_{N_1}^U\right)^{\lambda}\right], \left[1 - \left(1 - F_{N_1}^L\right)^{\lambda}, 1 - \left(1 - F_{N_1}^U\right)^{\lambda}\right], \lambda > 0 \tag{8}$$

$$\tilde{\ddot{N}}_1 \oplus \tilde{\ddot{N}}_2 = \left[T_{N_1}^L + T_{N_2}^L - T_{N_1}^L T_{N_2}^L, T_{N_1}^U + T_{N_2}^U - T_{N_1}^U T_{N_2}^U\right], \left[I_{N_1}^L I_{N_2}^L, I_{N_1}^U I_{N_2}^U\right], \left[F_{N_1}^L F_{N_2}^L, F_{N_1}^U F_{N_2}^U\right] \tag{9}$$

$$\tilde{\ddot{N}}_1 \otimes \tilde{\ddot{N}}_2 = \left[T_{N_1}^L T_{N_2}^L, T_{N_1}^U T_{N_2}^U\right], \left[I_{N_1}^L + I_{N_2}^L - I_{N_1}^L T_{N_2}^L, I_{N_1}^U + I_{N_2}^U - I_{N_1}^U I_{N_2}^U\right], \left[F_{N_1}^L + F_{N_2}^L - F_{N_1}^L F_{N_2}^L, F_{N_1}^U + F_{N_2}^U - F_{N_1}^U F_{N_2}^U\right] \tag{10}$$

**Definition 5** Let $\tilde{\ddot{N}}_1 = \left[T_{N_1}^L, T_{N_1}^U\right], \left[I_{N_1}^L, I_{N_1}^U\right], \left[F_{N_1}^L, F_{N_1}^U\right]$ is an IVNN. A score function of $\tilde{\ddot{N}}_1$ is given as follows (Xu et al. Oct. 2017)**:**

$$S\left(\tilde{\ddot{N}}_1\right) = \frac{\left(2 + T_{N_1}^L - I_{N_1}^L - F_{N_1}^L\right) + \left(2 + T_{N_1}^U - I_{N_1}^U - F_{N_1}^U\right)}{6} \tag{11}$$

where $S\left(\tilde{\ddot{N}}_1\right) \in [0, 1]$.

**Definition 6** Let $\tilde{\ddot{N}}_1 = \left[T_{N_1}^L, T_{N_1}^U\right], \left[I_{N_1}^L, I_{N_1}^U\right], \left[F_{N_1}^L, F_{N_1}^U\right]$ and $\tilde{\ddot{N}}_2 = \left[T_{N_2}^L, T_{N_2}^U\right], \left[I_{N_2}^L, I_{N_2}^U\right], \left[F_{N_2}^L, F_{N_2}^U\right]$ be two IVNNs. For those two numbers, Euclidean distances and Hamming distances of these numbers are defined as follows:

$$E_i = \sqrt{\left(T_a^L - T_b^L\right)^2 + \left(T_a^U - T_b^U\right)^2 + \left(I_a^L - I_b^L\right)^2 + \left(I_a^U - T_b^U\right)^2 + \left(F_a^L - F_b^L\right)^2 + \left(F_a^U - F_b^U\right)^2} \tag{12}$$

$$H_i = \left(\left|T_a^L - T_b^L\right| + \left|T_a^U - T_b^U\right| + \left|I_a^L - I_b^L\right| + \left|I_a^U - I_b^U\right| + \left|F_a^L - F_b^L\right| + \left|F_a^U - F_b^U\right|\right) \tag{13}$$

## 2.3 Interval-valued neutrosophic analytical hierarchy process

AHP is a decision analysis technique that was developed by Thomas Saaty in the 1970s (Saaty 1988) and provides effective use in solving MCDM problems (Nabeeh et al. 2019). Although classical AHP is frequently used in MCDM problems, it does not reflect the concept of uncertainty (Tumsekcali et al. Dec. 2021). The IVN-AHP method has been developed to fully and accurately reflect the thoughts of decision makers (Yalcin Kavus et al. 2022). IVN-AHP expresses uncertainty and can effectively involve human thought in decision making (Bolturk and Kahraman 2018). Different studies such as (Abdel-Basset et al. 2018)–(Kahraman et al. 2020) used neutrosophic AHP and IVN-AHP methodology. In this study, the weights of the criteria affecting the flood and the assembly point were calculated using the IVN-AHP methodology. The steps of IVN-AHP are given below (Gulum et al. 2021):

*Step 1*. Determine the neutrosophic evaluation scale.

*Step 2*. Dissociate the problem into a goal, criteria, and sub-criteria.

*Step 3*. Create the pairwise comparison matrix ($\tilde{\ddot{P}}$) using IVNNs.

$$\tilde{\ddot{P}} = \begin{bmatrix} [T_{11}^L, T_{11}^U], [I_{11}^L, I_{11}^U], [F_{11}^L, F_{11}^U] & [T_{12}^L, T_{12}^U], [I_{12}^L, I_{12}^U], [F_{12}^L, F_{12}^U] & \cdots & [T_{1n}^L, T_{1n}^U], [I_{1n}^L, I_{1n}^U], [F_{1n}^L, F_{1n}^U] \\ [T_{11}^L, T_{11}^U], [I_{11}^L, I_{11}^U], [F_{11}^L, F_{11}^U] & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ [T_{n1}^L, T_{n1}^U], [I_{n1}^L, I_{n1}^U], [F_{n1}^L, F_{n1}^U] & \cdots & & [T_{nn}^L, T_{nn}^U], [I_{nn}^L, I_{nn}^U], [F_{nn}^L, F_{nn}^U] \end{bmatrix} \tag{14}$$

*Step 4.* Calculate the consistency of the pairwise comparison matrix. For this purpose, the consistency ratio (CR) proposed by Saaty (Xu et al. Oct. 2017) is calculated using score values.

$$S\left(\tilde{\ddot{N}}_1\right) = \frac{\left(2 + T_{N_1}^L - I_{N_1}^L - F_{N_1}^L\right) + \left(2 + T_{N_1}^U - I_{N_1}^U - F_{N_1}^U\right)}{6} \tag{15}$$

Then, the consistency index (CI) of the matrix is calculated.

$$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n} - 1} \tag{16}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{17}$$

$\lambda_{\max}$ is the largest eigenvalue of the pairwise comparison matrix. The random index (RI) depends on the order of the matrix (n). RI is determined by the table (Xu et al. Oct. 2017). The CR should be less than 0.1.

*Step 5.* Calculate the normalized criteria.

$$\tilde{\ddot{N}}_{ij} = \left[\frac{T_{kj}^L}{\sum_{k=1}^n T_{kj}^U}, \frac{T_{kj}^U}{\sum_{k=1}^n T_{kj}^U}\right], \left[\frac{I_{kj}^L}{\sum_{k=1}^n I_{kj}^U}, \frac{I_{kj}^U}{\sum_{k=1}^n I_{kj}^U}\right], \left[\frac{F_{kj}^L}{\sum_{k=1}^n F_{kj}^U}, \frac{F_{kj}^U}{\sum_{k=1}^n F_{kj}^U}\right]; j = 1, 2, \ldots, n \tag{18}$$

*Step 6.* Calculate the average of each component for each criterion.

$$\tilde{\ddot{W}}_j = \left[\frac{\sum_{k=1}^n \frac{T_{1j}^L}{\sum_{k=1}^n T_{kj}^U}}{n}, \frac{\sum_{k=1}^n \frac{T_{1j}^U}{\sum_{k=1}^n T_{kj}^U}}{n}\right], \left[\frac{\sum_{k=1}^n \frac{I_{1j}^L}{\sum_{k=1}^n I_{kj}^U}}{n}, \frac{\sum_{k=1}^n \frac{I_{1j}^U}{\sum_{k=1}^n I_{kj}^U}}{n}\right], \left[\frac{\sum_{k=1}^n \frac{F_{1j}^L}{\sum_{k=1}^n F_{kj}^U}}{n}, \frac{\sum_{k=1}^n \frac{F_{1j}^U}{\sum_{k=1}^n F_{kj}^U}}{n}\right] \tag{19}$$

*Step 7.* Apply the deneutrosophication formula to obtain the crisp weights of the criteria.

*Step 8.* The crisp weights of the criteria are normalized $\left(w_j\right)$.

### 2.4 Interval-valued neutrosophic CODAS

The CODAS (Combinative Distance-based Assessment) method was presented to the literature by Keshavarz-Ghorabaee et al. as an alternative new approach to solve MCDM problems. The method is based on the preference of the alternative that is farther from the negative ideal solution (Keshavarz Ghorabaee et al. 2016).

Real-life problems often involve uncertainty because they cannot be described by deterministic models. For this reason, the fuzzy method is preferred for MCDM problems. Keshavarz Ghorabaee et al. proposed a fuzzy extension of the CODAS method to solve MCDM problems (Keshavarz Ghorabaee et al. 2016). To avoid the incapableness of classical fuzzy and its extensions, neutrosophic sets prove their superiority (Bolturk and Karasan 2018). Different studies such as (Bolturk and Karasan 2018, 2019; Karaşan et al. 2019) used IVN-CODAS methodology. The IVN-CODAS steps are given below:

*Step 1.* Expert opinions are combined with Modified Delphi.

The Modified Delphi method can be used when multiple expert opinions are needed on a specific topic. The Delphi method collects and analyses the opinions of anonymous experts who communicate on specific topics through written interviews, discussion, and feedback (Ayyildiz et al. 2020). Multiple experts share their knowledge and opinions until they reach a consensus (Gumus 2009).

*Step 2.* Construct the neutrosophic decision-making matrix $\left(\widetilde{\ddot{X}}\right)$:

$$\widetilde{\ddot{X}}\left[\widetilde{\ddot{x}}_{ij}\right]_{n\times m} = \begin{bmatrix} \widetilde{\ddot{x}}_{11} & \cdots & \widetilde{\ddot{x}}_{1m} \\ \vdots & \ddots & \vdots \\ \widetilde{\ddot{x}}_{n1} & \cdots & \widetilde{\ddot{x}}_{nm} \end{bmatrix} \tag{20}$$

where $\widetilde{\ddot{x}}_{ij} = \left[T_{ij}^L, T_{ij}^U\right], \left[I_{ij}^L, I_{ij}^U\right], \left[F_{ijl}^L, F_{ij}^U\right]$ denotes the neutrosophic evaluation score of $i$th ($i \in \{1, 2, \dots, n\}$) alternative with respect to $j$th criterion ($j \in \{1, 2, \dots, m\}$).

*Step 3.* Calculate the neutrosophic weighted aggregated decision matrix ($\widetilde{R}$):

$$\widetilde{\ddot{R}}_j = \left[\widetilde{\ddot{r}}_{ij}\right]_{n\times m} \tag{21}$$

$$\widetilde{\ddot{r}}_{ij} = w_j \otimes \widetilde{\ddot{x}}_{ij} \tag{22}$$

where $w_j$ denotes the weight of $j^{th}$ criterion.

*Step 4.* Determine the neutrosophic negative ideal solution $\left(\dddot{NS}\right)$:

$$\widetilde{\dddot{NS}} = \left[\widetilde{\dddot{ns}}_j\right]_{1\times m} \tag{23}$$

$$\widetilde{\dddot{ns}}_j = \min_i \widetilde{\dddot{r}}_{ij} \tag{24}$$

where $\min_i \widetilde{\ddot{r}}_{ij} = \left\{\widetilde{\ddot{r}}_{ij} \middle| \mathfrak{D}\left(\widetilde{\ddot{r}}_{ij}\right) = \min_i \left(\mathfrak{D}\left(\widetilde{\ddot{r}}_{ij}\right)\right), i \in \{1, 2, \dots, n\}\right\}$ for Benefit criteria.

$$\widetilde{ns}_j = \max_i r_{ij} \tag{25}$$

where $\max_i \widetilde{\ddot{r}}_{ij} = \left\{\widetilde{\ddot{r}}_{ij} \middle| \mathfrak{D}\left(\widetilde{\ddot{r}}_{ij}\right) = \max_i \left(\mathfrak{D}\left(\widetilde{\ddot{r}}_{ij}\right)\right), i \in \{1, 2, \dots, n\}\right\}$ for Cost criteria.

*Step 5.* Calculate the weighted Euclidean Distance $\left(ED_i\right)$ and weighted Hamming Distance $\left(HD_i\right)$ of alternatives from the neutrosophic negative ideal solution:

$$ED_i = \sum_{j=1}^{m} d_E\left(\widetilde{\ddot{r}}_{ij}, \widetilde{\dddot{ns}}_j\right) \tag{26}$$

$$\mathrm{HD}_i = \sum_{j=1}^{m} d_D\left(\widetilde{\dddot{r}}_{ij}, \widetilde{\dddot{ns}}_j\right) \tag{27}$$

*Step 6.* Determine the relative assessment matrix (RA):

$$RA = \left[p_{ik}\right]_{n\times n} \tag{28}$$

$$p_{ik} = \left(ED_i - ED_k\right) + \left(t\left(ED_i - ED_k\right) \times \left(HD_i - HD_k\right)\right) \tag{29}$$

where $k \in \{1, 2, \ldots, n\}$ and $t$ is a threshold function that is defined as follows:

$$t(x) = \begin{cases} 1 & \text{if } |x| \geq \tau \\ 0 & \text{if } |x| < \tau \end{cases} \tag{30}$$

The threshold parameter ($\tau$) of this function can be set by the decision maker. In this study, we use $\tau = 0.4$ in our calculations.

*Step 7.* Calculate the assessment score $\left(AS_i\right)$ of each alternative:

$$\mathrm{AS}_i = \sum_{k=1}^{n} p_{ik} \tag{31}$$

*Step 8.* Rank the alternatives according to the increasing values of the assessment scores and select the alternative with the minimum assessment score as the safest place.

## 3 Results

In this study, the problem of determining and evaluating risk factors affecting the flood and the location of the assembly point is emphasized. Bartin is one of the provinces that are frequently exposed to floods (Tunay and Ateşoğlu 2019). As a result of flood analyses in Tunay and Ateşoğlu (2019); Turoğlu 2007) it is emphasized that Bartın region is risky in terms of the flood. As the flood disaster causes serious material and moral losses, the determination of the flood risk and the selection of assembly points are very important. For this reason, the Merkez district in Bartin Province is chosen for the application of the proposed method.

First, the literature is reviewed to identify risk criteria that affect flood and assembly points. Then the importance weights of each risk criterion are obtained using IVN-AHP. There are 12 assembly points determined by AFAD located in the Merkez district of Bartin Province. To evaluate these assembly points in terms of flood risk, the opinions of 4 experts (Ayyildiz et al. 2020) are combined with Modified Delphi. The interviews with experts are conducted face to face. These experts are selected from different institutions. In addition, experts are people who have done academic studies on floods or have a technical background. After the importance weights of the criteria are calculated, the IVN-CODAS method is applied. Experts score 12 counties based on relevant criteria and then counties are ranked by IVN-CODAS, from the most risky to least in terms of assembly point and flood risk. The methodology and results are analyzed in detail by sensitivity analysis.

### 3.1 Study area

The western Black Sea basin, where the Bartın Stream basin is located, is a region where floods are frequently experienced. More than 20 floods have occurred since 1970. Finally, the General Directorate of Meteorology announced on its official website on August 10,

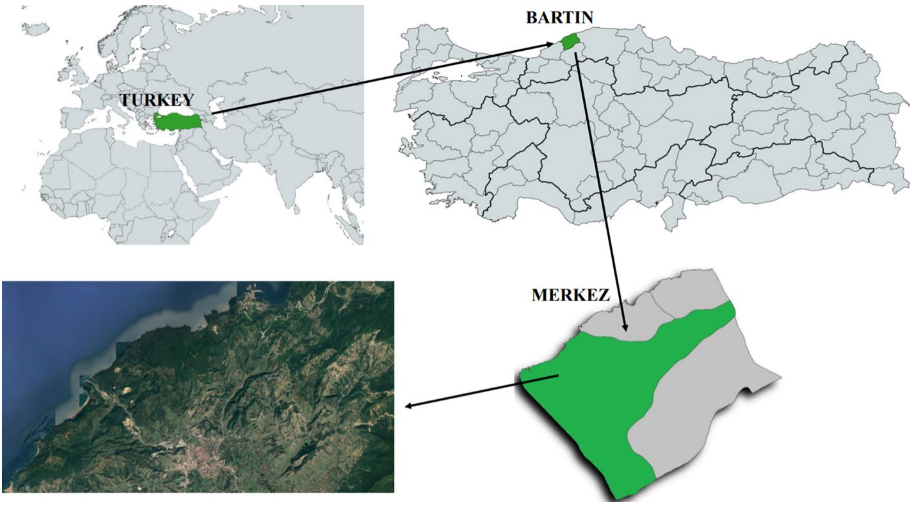


**Fig. 2** The location of the Merkez district of Bartın

2021, that the amount of precipitation per square meter in some regions of Bartın, Kastamonu, and Sinop provinces was recorded as 2/3 of the total precipitation in a year ("Sel felaketinin yaşandığı bazı bölgelerde 48 saatteki yağış miktarı, 1 yıllık toplam yağışın 3'te 2'sini buldu". xxxx). Bartın is chosen as the study area in light of this information. In the Western Black Sea region of Turkey, Bartın is located at the confluence of two major rivers in the city center. It is between 41° 53′- 41° 20′ north latitudes and 32° 06′—32° 54′ east longitude, as in Fig. 2. Bartın has a total of 4 districts including the Merkez district. Its area is 2,330 $km^2$. The area of Bartın is covered 46% by forests, 35% by agricultural areas, 7% by pastures and pastures, and 12% by areas not suitable for culture and settlements. The forests that occupy a large place in the vegetation usually consist of broad and coniferous trees. Most of the transportation to Bartın is provided by road. The total length of the road is 281 km, of which 142 km is on state roads and 139 km on provincial roads. There is no highway in the province. According to data from the Bartın Governorship, the population of the Merkez district of the Bartın province is approximately 200 thousand people. Most of the population is over 65 years. The population of Bartın is 49.56% male and 50.44% female. Bartın, a city where the majority are civil servants and craftsmen, trails other cities in terms of educational level. The altitude of the Merkez is 25 m (Ercanoglu 2005). It has a typical maritime climate. Bartın, which receives precipitation in almost every season, receives more precipitation, especially in the autumn and winter months. The average temperature in the summer months is 21° C, and the average temperature in the winter months is 6° C. Relative humidity in Bartın, which has a very humid climate, varies between 75 and 85%. Although the average precipitation in the summer months varies between 50 and 60 kg/m$^2$, the average precipitation in the winter months is between 200 and 220 $kg/m^2$. The annual precipitation average is between 1000 and 1200 kg/m$^2$ (Ercanoglu 2005). In the province located in the Western Black Sea basin, flood events are experienced regionally. It is one of the provinces most affected by the flood events that occurred in 1998.

The flood risk assessment is carried out for 12 assembly points determined by AFAD in the central district of Bartın province in Fig. 5. Disaster management departments in Turkey generally consider places such as schools, sports facilities, and community centers

**Table 3** Expert's information

| Expert no | Institution | Profession | Experience |
|---|---|---|---|
| 1 | AFAD | Geomatic Engineer | 10–15 |
| 2 | Bartin Municipality | Civil Engineer | 5–10 |
| 3 | Yildiz Technical University | Industrial Engineer | 20 + |
| 4 | Bartin University | Forest Engineer | 15–20 |

as potential assembly points or temporary shelters, as they first consider them as candidate facilities when identifying flood shelters. These areas have a good source of life, such as water, electricity, and natural gas.

Expert opinion is a technique frequently used in determining and selecting criteria in MCDM problems. With this technique, the knowledge of experts in the field is used (Kanani-Sadat et al. 2019). In this article, 4 experts from different fields were selected to determine the factors (and their relationships) affecting the flood and the assembly point. Information about experts is given in Table 3. Experts make a pairwise comparison between two different criteria. With this comparison, they present their opinion on the importance of dependencies between criteria defined through linguistic variables.

**Table 4** Linguistic terms for criteria evaluation

| Linguistic terms | | $T^L$ | $T^U$ | $I^L$ | $I^U$ | $F^L$ | $F^U$ |
|---|---|---|---|---|---|---|---|
| Absolutely More Important | AMI | 0.9 | 0.95 | 0 | 0.05 | 0.05 | 0.15 |
| Strongly More Important | SMI | 0.8 | 0.9 | 0.05 | 0.1 | 0.1 | 0.2 |
| More Important | MI | 0.7 | 0.8 | 0.15 | 0.25 | 0.2 | 0.3 |
| Weakly More Important | WMI | 0.6 | 0.7 | 0.25 | 0.35 | 0.3 | 0.4 |
| Equal Importance | EI | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Weakly Less Important | WLI | 0.4 | 0.5 | 0.55 | 0.65 | 0.5 | 0.6 |
| Less Important | LI | 0.3 | 0.4 | 0.65 | 0.75 | 0.6 | 0.7 |
| Strongly Less Important | SLI | 0.2 | 0.3 | 0.75 | 0.85 | 0.7 | 0.8 |
| Absolutely Less Important | ALI | 0.1 | 0.2 | 0.9 | 0.95 | 0.8 | 0.9 |

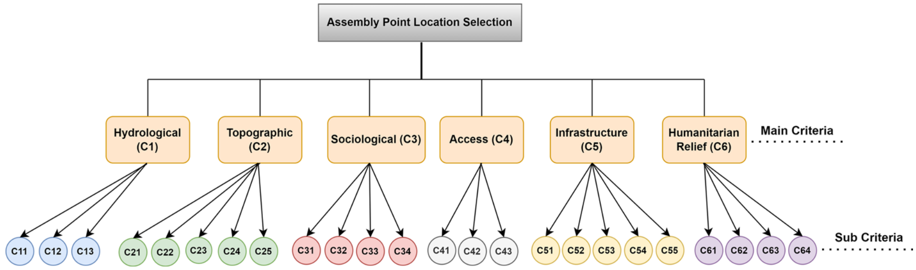


**Fig. 3** Hierarchical structure of the problem

**Table 5** Pairwise comparison of the main criteria

| E-1 | C1 | C2 | C3 | C4 | C5 | C6 | E-2 | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| C1 | EI | WMI | WMI | MI | EI | WMI | **C1** | EI | WLI | LI | SLI | LI | EI |
| C2 | WLI | EI | WMI | WMI | LI | EI | **C2** | WMI | EI | WMI | EI | SMI | MI |
| C3 | WLI | WLI | EI | WLI | LI | EI | **C3** | MI | WLI | EI | LI | WMI | WMI |
| C4 | LI | WLI | WMI | EI | EI | EI | **C4** | SMI | EI | MI | EI | SMI | SMI |
| C5 | EI | MI | MI | EI | EI | WMI | **C5** | MI | SLI | WLI | SLI | EI | WMI |
| C6 | WLI | EI | EI | EI | WLI | EI | **C6** | EI | LI | WLI | SLI | WLI | EI |
| E-3 | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **E-4** | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** |
| C1 | EI | WLI | AMI | SMI | SMI | AMI | **C1** | EI | LI | WLI | LI | EI | WLI |
| C2 | WMI | EI | AMI | SMI | AMI | AMI | **C2** | MI | EI | MI | EI | SMI | WMI |
| C3 | ALI | ALI | EI | LI | EI | EI | **C3** | WMI | LI | EI | WLI | WMI | WLI |
| C4 | SLI | SLI | MI | EI | WMI | WMI | **C4** | MI | EI | WMI | EI | SMI | WMI |
| C5 | SLI | ALI | EI | WLI | EI | WMI | **C5** | EI | SLI | WLI | SLI | EI | WLI |
| C6 | ALI | ALI | EI | WLI | WLI | EI | **C6** | WMI | WLI | WMI | WLI | WMI | EI |

## 3.2 Determination of the criteria weights

*Step 1.* The selection criteria for the assembly point site are evaluated by four experts through face-to-face interviews. Experts use linguistic terms to express their opinions on criteria. Table 4 presents the linguistic terms used in the evaluation of criteria and their interval-valued neutrosophic equivalents valued at intervals (Karaşan et al. 1029).

The hierarchical structure of the criteria is constructed for the post-flood assembly point location selection problem, as shown in Fig. 3.

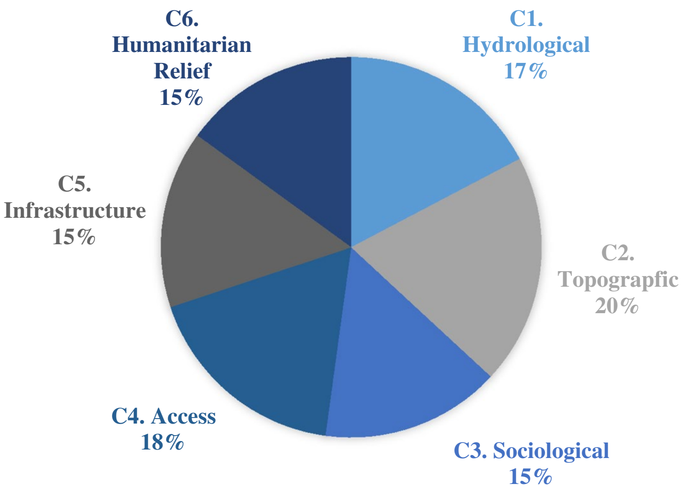


**Fig. 4** Weights of the main criteria

**Table 6** Weights of the main criteria for experts

| Main Criteria | E-1 | E-2 | E-3 | E-4 |
|---|---|---|---|---|
| C1. Hydrological | 0.188 | 0.139 | 0.219 | 0.146 |
| C2. Topographic | 0.163 | 0.195 | 0.234 | 0.193 |
| C3. Sociological | 0.153 | 0.175 | 0.119 | 0.164 |
| C4. Access | 0.157 | 0.201 | 0.163 | 0.189 |
| C5. Infrastructure | 0.184 | 0.149 | 0.139 | 0.133 |
| C6. Humanitarian Relief | 0.154 | 0.142 | 0.127 | 0.176 |

Pairwise comparison matrices for the main criteria are constructed for four anonymous experts using the linguistic terms given in Table 4. Table 5 presents pairwise comparisons of the main criteria created by four experts.

The matrices are checked for consistency. If any of the pairwise comparison matrix based on expert evaluation is determined as inconsistent, the relevant expert is asked to re-evaluate the criteria to make the matrix consistent. The consistency ratios are determined as 0.08, 0.09, 0.09, and 0.03 for Expert-1 (E-1), Expert-2 (E-2), Expert-3 (E-3), and Expert-4 (E-4), respectively. Since these values are less than 0.1, all pairwise comparison matrices for the main criteria can be considered consistent.

After determining that the matrices are consistent, IVN-AHP steps are applied to these matrices and the main criteria weights are determined for each expert as given in Table 6.

Then, to determine the final weights of the main criteria, the weights of four different experts are aggregated. Figure 4 shows the final weights of the main criteria.

As seen in Fig. 4, the topographic criterion has the highest weight. However, it is seen that all the main criteria do not have perceptible dominance when compared to each other. This means that each of the six criteria that affect the flood and the assembly point has similar importance. Also, the humanitarian relief criterion, which was not included in other studies as the main criterion before, is considered as significant as other criteria by the experts.

In this study, we evaluate the criteria for the post-flood assembly point location selection problem in hierarchical structure. After determining the main criteria weights, the experts evaluate the sub-criteria for each main criterion. For example, the pairwise comparison matrix for the sub-criteria of "C1. Hydrological" is constructed based on the

**Table 7** Pairwise comparison matrix of Expert-1 for C1. Hydrological

| | **C11** | **C12** | **C13** |
|---|---|---|---|
| C11 | EI | WMI | LI |
| C12 | WLI | EI | SLI |
| C13 | MI | SMI | EI |

**Table 8** Pairwise comparison matrix of Expert-4 for C6. Humanitarian Relief

| | **C61** | **C62** | **C63** | **C64** |
|---|---|---|---|---|
| C61 | EI | WMI | SMI | WMI |
| C62 | WLI | EI | MI | EI |
| C63 | SLI | LI | EI | LI |
| C64 | WLI | EI | MI | EI |

**Table 9** Consistency ratios

| | E-1 | E-2 | E-3 | E-4 |
|---|---|---|---|---|
| For the sub-criteria of Hydrological | 0.07 | 0.00 | 0.07 | 0.00 |
| For the sub-criteria of Topographic | 0.09 | 0.03 | 0.06 | 0.06 |
| For the sub-criteria of Sociological | 0.09 | 0.08 | 0.07 | 0.04 |
| For the sub-criteria of Access | 0.03 | 0.00 | 0.03 | 0.07 |
| For the sub-criteria of Infrastructure | 0.01 | 0.09 | 0.08 | 0.06 |
| For the sub-criteria of Humanitarian Relief | 0.08 | 0.06 | 0.04 | 0.03 |

**Table 10** Sub-criteria weights

| Sub-Criteria | E-1 | E-2 | E-3 | E-4 | Final Weight | Priority Rank-ing |
|---|---|---|---|---|---|---|
| Drainage density | 0.322 | 0.268 | 0.364 | 0.366 | 0.058 | 3 |
| Flow accumulation | 0.260 | 0.366 | 0.398 | 0.366 | 0.060 | 2 |
| Surface runoff | 0.417 | 0.366 | 0.238 | 0.268 | 0.055 | 4 |
| Elevation | 0.171 | 0.278 | 0.237 | 0.247 | 0.046 | 7 |
| Slope | 0.231 | 0.165 | 0.237 | 0.210 | 0.041 | 10 |
| Aspect | 0.168 | 0.150 | 0.118 | 0.110 | 0.026 | 22 |
| Distance from the river | 0.224 | 0.163 | 0.225 | 0.222 | 0.041 | 13 |
| Imperviousness | 0.206 | 0.244 | 0.184 | 0.211 | 0.041 | 11 |
| Population density | 0.266 | 0.316 | 0.285 | 0.315 | 0.045 | 8 |
| Education level | 0.176 | 0.149 | 0.167 | 0.171 | 0.025 | 24 |
| Housing typology | 0.311 | 0.284 | 0.253 | 0.249 | 0.042 | 9 |
| Road density | 0.247 | 0.252 | 0.295 | 0.265 | 0.040 | 15 |
| Proximity to city center | 0.249 | 0.247 | 0.312 | 0.260 | 0.047 | 6 |
| Proximity to flood risk area | 0.376 | 0.506 | 0.400 | 0.417 | 0.076 | 1 |
| Proximity to main road | 0.376 | 0.247 | 0.288 | 0.322 | 0.054 | 5 |
| Condition of local road infrastructure | 0.201 | 0.245 | 0.238 | 0.225 | 0.034 | 18 |
| Total floor area | 0.236 | 0.214 | 0.253 | 0.240 | 0.036 | 17 |
| Telecommunication facility | 0.220 | 0.182 | 0.157 | 0.179 | 0.028 | 20 |
| Water | 0.168 | 0.194 | 0.195 | 0.177 | 0.028 | 21 |
| Electricity | 0.175 | 0.166 | 0.157 | 0.179 | 0.026 | 23 |
| Proximity to healthcare organization | 0.270 | 0.246 | 0.260 | 0.295 | 0.040 | 14 |
| Distance to shelter | 0.285 | 0.307 | 0.246 | 0.259 | 0.041 | 12 |
| Access to police and fire station | 0.179 | 0.186 | 0.233 | 0.186 | 0.029 | 19 |
| Proximity to relief distribution center | 0.266 | 0.261 | 0.260 | 0.259 | 0.039 | 16 |

opinions of Expert-1 and the pairwise comparison matrix for the sub-criteria of "C6. Humanitarian Relief" is constructed based on Expert-4 opinions shown in Table 7 and Table 8.

After constructing the pairwise comparison matrix for sub-criteria of all main criteria for each expert, the matrices are tested for consistency. Table 9 presents the consistency ratios for the sub-criteria comparison matrix for each expert.

As presented in Table 9, all pairwise comparison matrices for the sub-criteria are determined as consistent. Then the IVN-AHP steps are repeated for each matrix, and the sub-criteria weights are determined as given in Table 10.

The final weights of each criterion are given in Table 10. The most prioritized criteria affecting the flood risk value of an assembly point are calculated as the proximity to flood risk area sub-criterion. Contrary to this, the education-level criterion has the lowest priority ranking. The reason may be the thought that being close to a flood-risk area is more critical than being a conscious individual. In general, sub-criteria that depend on the main criteria of hydrology and access are given priority. In addition, sub-criteria related to infrastructure have lower levels of importance.

### 3.3 Comparison of districts by IVN-CODAS

Twelve different assembly points in Bartın, Turkey, are evaluated as post-flood assembly points according to determined criteria. In this study, the aim is to determine the risk scores of the assembly points. All assembly points are determined by the Turkish Ministry of Interior Disaster and Emergency Management Presidency (AFAD). Figure 5 shows the assembly points.

Firstly, the experts evaluated the assembly points with respect to the criteria determined using the linguistic terms given in Table 11 through the questionnaire. Modified

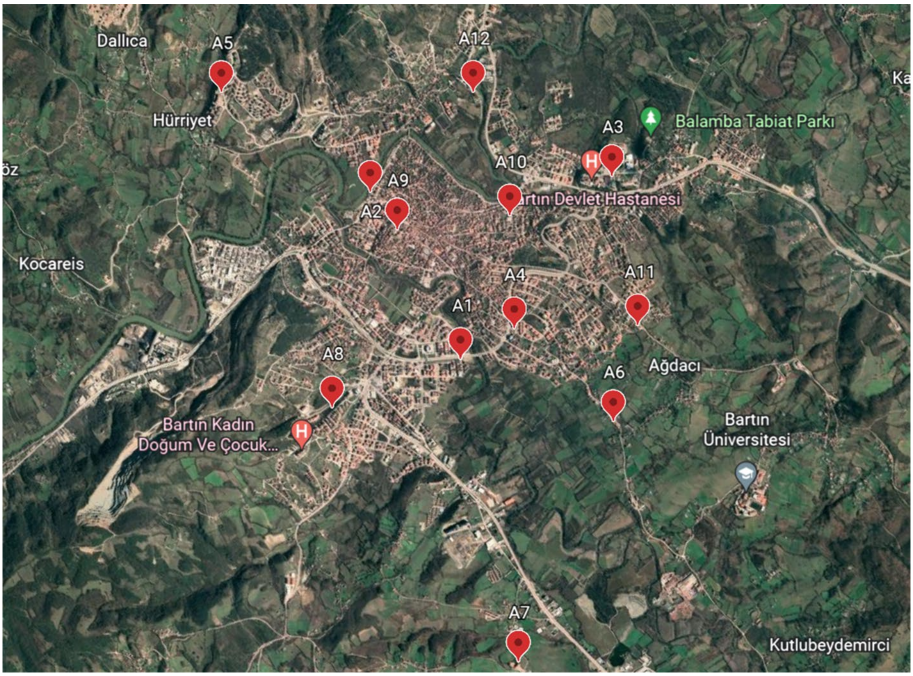


**Fig. 5** Assembly points in Bartın

**Table 11** Scale for scoring decision matrix

| Linguistic Terms | | $T^L$ | $T^U$ | $I^L$ | $I^U$ | $F^L$ | $F^U$ |
|---|---|---|---|---|---|---|---|
| Certainly Low Risk | **CL** | 0.05 | 0.2 | 0.4 | 0.6 | 0.85 | 1 |
| Very Low Risk | **VL** | 0.15 | 0.3 | 0.3 | 0.5 | 0.75 | 0.9 |
| Low Risk | **L** | 0.25 | 0.4 | 0.2 | 0.4 | 0.65 | 0.8 |
| Below Average Risk | **BA** | 0.35 | 0.5 | 0.1 | 0.3 | 0.55 | 0.7 |
| Average Risk | **A** | 0.45 | 0.6 | 0 | 0.2 | 0.45 | 0.6 |
| Above Average Risk | **AA** | 0.55 | 0.7 | 0.1 | 0.3 | 0.35 | 0.5 |
| High Risk | **H** | 0.65 | 0.8 | 0.2 | 0.4 | 0.25 | 0.4 |
| Very High Risk | **VH** | 0.75 | 0.9 | 0.3 | 0.5 | 0.15 | 0.3 |
| Certainly High Risk | **CH** | 0.85 | 1 | 0.4 | 0.6 | 0.05 | 0.2 |

**Table 12** Alternative evaluation matrix

| | **C11** | **C12** | **C13** | **C21** | **C22** | **C23** | **C24** | **C25** | **C31** | **C32** | **C33** | **C34** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A-1 | AA | A | L | L | A | VL | VL | L | VH | L | H | H |
| A-2 | CH | CH | L | BA | CH | CH | CL | L | CH | L | CL | H |
| A-3 | BA | CL | VL | A | CL | CL | CL | VL | A | A | CL | BA |
| A-4 | BA | VL | BA | A | L | A | VL | VL | VH | A | CL | BA |
| A-5 | L | CL | CL | VL | CL | CL | CL | VL | VH | L | BA | H |
| A-6 | AA | A | L | VL | H | A | CL | L | BA | A | CL | BA |
| A-7 | BA | VL | L | VL | BA | L | L | VL | L | A | CL | BA |
| A-8 | L | CL | L | BA | CL | CL | H | VL | AA | L | BA | AA |
| A-9 | L | CL | CL | VL | CL | CL | VL | VL | CH | VL | L | VH |
| A-10 | A | BA | VL | A | BA | L | CL | L | CH | L | CL | CH |
| A-11 | L | CL | VL | VL | CL | CL | CL | VL | A | BA | CL | BA |
| A-12 | AA | H | BA | VL | H | BA | VL | L | L | A | CL | L |
| | **C41** | **C42** | **C43** | **C51** | **C52** | **C53** | **C54** | **C55** | **C61** | **C62** | **C63** | **C64** |
| A-1 | VL | VH | CL | VH | BA | VL | VL | A | VL | VL | VL | VL |
| A-2 | VL | CH | CL | H | VL | VL | VL | A | VL | VL | VL | VL |
| A-3 | AA | L | L | BA | VL | VL | L | A | CL | VL | VL | VL |
| A-4 | L | A | CL | BA | BA | VL | L | AA | VL | VL | VL | CL |
| A-5 | AA | CL | L | BA | VL | VL | L | A | L | VL | BA | BA |
| A-6 | BA | L | CL | BA | BA | A | BA | H | VL | BA | L | CL |
| A-7 | AA | VL | CL | A | VL | A | VL | A | VL | A | BA | BA |
| A-8 | L | CL | VL | BA | A | VL | VL | A | CL | VL | VL | VL |
| A-9 | VL | CL | VL | L | A | VL | VL | A | VL | VL | VL | VL |
| A-10 | VL | A | VL | H | A | VL | BA | A | VL | VL | VL | VL |
| A-11 | BA | CL | VL | L | VL | VL | BA | A | VL | VL | VL | VL |
| A-12 | AA | A | CL | BA | CL | A | AA | H | L | VL | L | BA |

**Table 13** Distances from negative ideal solutions

| | A-1 | A-2 | A-3 | A-4 | A-5 | A-6 | A-7 | A-8 | A-9 | A-10 | A-11 | A-12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Euclidean | 0.840 | 1.281 | 0.698 | 0.839 | 0.460 | 0.993 | 0.888 | 0.614 | 0.386 | 0.820 | 0.491 | 1.094 |
| Hamming | 1.858 | 2.617 | 1.581 | 1.886 | 1.067 | 2.260 | 2.005 | 1.408 | 0.833 | 1.796 | 1.115 | 2.466 |

Delphi is employed to consolidate expert opinions to construct an alternative evaluation matrix.

The consolidated alternative evaluation matrix is presented in Table 12. The linguistic terms are converted into IVN numbers using the scale given in Table 11.

After constructing the alternative evaluation matrix, the weighted neutrosophic matrix is constructed using the final weights given in Table 10. Negative ideal solutions are determined for each criterion, and both Euclidean and Hamming distances are calculated from the negative ideal solutions for each location, as given in Table 13.

Then, the relative assessment matrix is constructed based on the distances given in Table 13. Table 14 presents the matrix. $\tau$ is determined as 0.4 in this step. The assessment scores and rankings for alternatives are also presented in Table 14.

As seen in Table 14, the point with the highest flood risk of the assembly points is determined as A-2. After A-2, the risk decreased slightly. The biggest factor in the risk for A-2 point with the highest risk is its location very close to the river. The assembly point with the lowest risk is A-9 with a score of 13.831. In addition to being close to the city center, the fact that it is at a low risk point in terms of topography supports this result.

### 3.4 Sensitivity analysis

Sensitivity analysis is performed to test the validity and stability of the proposed hybrid framework. For this purpose, threshold ($\tau$) value for IVN-CODAS is changed between 0 and 0.5 increasing by 0.05. For each value of $\tau$ the assessment scores of alternative locations are calculated and noted. Table 15 presents the alternative assessment scores for different $\tau$ values (scenarios).

Then, based on the scores given in Table 15, the final rankings of alternative locations are determined as presented in Fig. 6.

According to Fig. 6, the final ranking order of the alternatives remains the same for eleven different scenarios, except the last scenario where $\tau = 0.05$. In this scenario, only the rankings of A-1 and A-4 are changed. A-1 decreases from 7 to 8, while A-4 increases to 7 from 8. To summarize, Fig. 6 clearly shows the stability of the proposed hybrid framework. As a result, A-3 is always the most desirable and A-2 is the worst alternative. As a result of the analysis, A-8 is the most appropriate location to be post-flood assembly point and A-2 is the worst option. Sensitivity analysis shows that the proposed hybrid framework is robust and efficient in solving complex MCDM problems.

### 3.5 Validation analysis

The proposed integrated neutrosophic logic-based MCDM approach utilized in the assembly area risk assessment problem is conducted to a validation analysis to examine its

**Table 14** Relative assessment matrix and final scores of alternatives

| | A-1 | A-2 | A-3 | A-4 | A-5 | A-6 | A-7 | A-8 | A-9 | A-10 | A-11 | A-12 | Risk Score | Ranking |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A-1 | 0.00 | -1.20 | 0.14 | 0.00 | 0.38 | -0.15 | -0.05 | 0.23 | 1.48 | 0.02 | 0.35 | -0.25 | 0.940 | 7 |
| A-2 | 1.20 | 0.00 | 1.62 | 1.17 | 2.37 | 0.29 | 0.39 | 1.88 | 2.68 | 1.28 | 2.29 | 0.19 | 15.357 | 12 |
| A-3 | -0.14 | -1.62 | 0.00 | -0.14 | 0.24 | -0.30 | -0.19 | 0.08 | 0.31 | -0.12 | 0.21 | -0.40 | -2.059 | 5 |
| A-4 | 0.00 | -1.17 | 0.14 | 0.00 | 0.38 | -0.15 | -0.05 | 0.23 | 1.51 | 0.02 | 0.35 | -0.26 | 0.984 | 8 |
| A-5 | -0.38 | -2.37 | -0.24 | -0.38 | 0.00 | -1.73 | -1.37 | -0.15 | 0.07 | -0.36 | -0.03 | -2.03 | -8.966 | 2 |
| A-6 | 0.15 | -0.29 | 0.30 | 0.15 | 1.73 | 0.00 | 0.11 | 0.38 | 2.03 | 0.17 | 1.65 | -0.10 | 6.282 | 10 |
| A-7 | 0.05 | -0.39 | 0.19 | 0.05 | 1.37 | -0.11 | 0.00 | 0.27 | 1.67 | 0.07 | 0.40 | -0.21 | 3.367 | 9 |
| A-8 | -0.23 | -1.88 | -0.08 | -0.23 | 0.15 | -0.38 | -0.27 | 0.00 | 0.23 | -0.21 | 0.12 | -1.54 | -4.305 | 4 |
| A-9 | -1.48 | -2.68 | -0.31 | -1.51 | -0.07 | -2.03 | -1.67 | -0.23 | 0.00 | -1.40 | -0.11 | -2.34 | -13.831 | 1 |
| A-10 | -0.02 | -1.28 | 0.12 | -0.02 | 0.36 | -0.17 | -0.07 | 0.21 | 1.40 | 0.00 | 0.33 | -0.27 | 0.573 | 6 |
| A-11 | -0.35 | -2.29 | -0.21 | -0.35 | 0.03 | -1.65 | -0.40 | -0.12 | 0.11 | -0.33 | 0.00 | -1.95 | -7.508 | 3 |
| A-12 | 0.25 | -0.19 | 0.40 | 0.26 | 2.03 | 0.10 | 0.21 | 1.54 | 2.34 | 0.27 | 1.95 | 0.00 | 9.165 | 11 |

**Table 15** Assessment scores for different scenarios

| | 0 | 0.05 | 0.1 | 0.15 | 0.2 | 0.25 | 0.3 | 0.35 | 0.4 | 0.45 | 0.5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A-1 | 2.082 | 2.194 | 2.194 | 1.917 | 2.318 | 1.867 | 2.475 | 1.732 | 0.940 | 1.699 | 0.674 |
| A-2 | 16.478 | 16.478 | 16.478 | 16.478 | 16.327 | 16.327 | 15.970 | 15.970 | 15.357 | 13.867 | 13.047 |
| A-3 | -2.940 | -2.940 | -3.114 | -2.317 | -1.894 | -2.874 | -2.195 | -2.943 | -2.059 | -2.059 | -2.059 |
| A-4 | 2.398 | 2.401 | 2.401 | 2.097 | 2.471 | 1.993 | 2.573 | 1.803 | 0.984 | 1.716 | 0.663 |
| A-5 | -11.975 | -11.927 | -12.161 | -12.161 | -11.820 | -11.306 | -11.306 | -11.306 | -8.966 | -8.028 | -8.028 |
| A-6 | 8.746 | 8.746 | 8.746 | 8.696 | 7.456 | 7.456 | 7.135 | 7.135 | 6.282 | 6.282 | 6.282 |
| A-7 | 4.424 | 4.158 | 3.950 | 4.205 | 3.781 | 4.242 | 3.644 | 3.644 | 3.367 | 2.429 | 2.429 |
| A-8 | -6.039 | -6.039 | -5.865 | -6.158 | -6.498 | -5.755 | -5.157 | -5.157 | -4.305 | -4.305 | -3.247 |
| A-9 | -15.669 | -15.669 | -15.436 | -15.154 | -15.154 | -14.579 | -14.579 | -13.831 | -13.831 | -12.868 | -10.791 |
| A-10 | 1.095 | 1.247 | 1.455 | 1.240 | 1.703 | 1.315 | 1.984 | 1.303 | 0.573 | -0.390 | 0.431 |
| A-11 | -11.020 | -11.068 | -11.068 | -11.058 | -11.058 | -10.592 | -10.592 | -8.397 | -7.508 | -7.508 | -7.508 |
| A-12 | 12.421 | 12.421 | 12.421 | 12.215 | 12.366 | 11.906 | 10.049 | 10.049 | 9.165 | 9.165 | 8.107 |

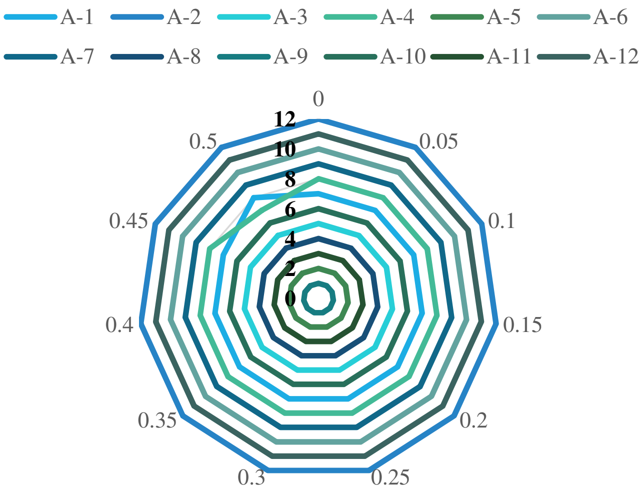


**Fig. 6** The results of the sensitivity analysis

validity and reliability. In this validation analysis, the impact of changing the alternative assessment methodology on the results is examined. In order to find the ideal location for an assembly area, a comparison analysis is carried out to confirm the efficacy and reliability of the proposed hybrid approach. The results are then compared, and the methodology's validity is discussed. To compare the IVN-CODAS results, the same IVN-AHP-determined criteria weight set is applied, and alternative locations are assessed using the IVN-TOPSIS approach. The following describes the IVN-TOPSIS methodology's steps (Gulum et al. 2021):

*Step 1:* The decision matrix is constructed.

*Step 2:* The neutrosophic weighted normalized decision matrix is calculated using crisp weight for each criterion determined by IVN-AHP.

*Step 3:* The IVN positive ideal solution $\widetilde{\dddot{S}}^{+}$, and the IVN negative ideal solution $\widetilde{\dddot{S}}^{-}$ are determined.

$$\widetilde{\dddot{S}}^{+} = \left[\max_j(T_j^L), \max_j(T_j^U)\right], \left[\min_j\left(I_j^L\right), \min_j\left(I_j^U\right)\right], \left[\min_j\left(F_j^L\right), \min_j\left(F_j^U\right)\right] \tag{32}$$

$$\widetilde{\dddot{S}}^{-} = \left[\min_j(T_j^L), \min_j(T_j^U)\right], \left[\max_j\left(I_j^L\right), \max_j\left(I_j^U\right)\right], \left[\max_j\left(F_j^L\right), \max_j\left(F_j^U\right)\right] \tag{33}$$

*Step 4:* The Euclidean distances of each alternative from positive ideal solutions $\left(D_i^{PIS}\right)$ and negative ideal solutions $\left(D_i^{NIS}\right)$ are determined.

*Step 5:* Revised closeness $\left(\varepsilon_i\right)$ is computed for each alternative.

$$\varepsilon_i = \frac{D_i^{NIS}}{\left(D_i^{NIS} + D_i^{PIS}\right)} \tag{34}$$

*Step 6:* Alternatives are ranked according to their revised closeness in ascending order (lower is safer).

**Table 16** Result of IVN-TOPSIS

| Alternative | $D_i^{PIS}$ | $D_i^{NIS}$ | $\varepsilon_i$ | Rank |
|---|---|---|---|---|
| A-1 | 9.464 | 3.340 | 0.261 | 6 |
| A-2 | 10.331 | 2.176 | 0.174 | 4 |
| A-3 | 8.491 | 4.033 | 0.322 | 8 |
| A-4 | 8.577 | 4.083 | 0.323 | 9 |
| A-5 | 11.005 | 1.460 | 0.117 | 1 |
| A-6 | 8.370 | 4.297 | 0.339 | 10 |
| A-7 | 7.352 | 5.143 | 0.412 | 12 |
| A-8 | 10.104 | 2.341 | 0.188 | 5 |
| A-9 | 11.166 | 1.983 | 0.151 | 2 |
| A-10 | 7.827 | 4.979 | 0.389 | 11 |
| A-11 | 10.409 | 2.126 | 0.170 | 3 |
| A-12 | 9.226 | 3.394 | 0.269 | 7 |

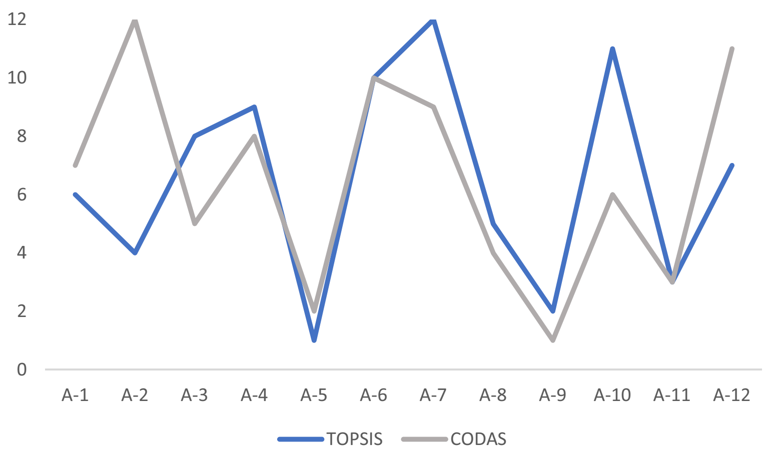


**Fig. 7** The rankings of the alternatives for comparison

After constructing the evaluation matrix for alternatives with experts, the positive and negative solutions are determined and final score of each alternative is calculated as given in Table 16.

The best option is A-5 because it has the lowest $\varepsilon_i$ score (0.117), according to the IVN-TOPSIS results. A-9 and A-11 are the next two, scoring 0.151 and 0.170, respectively. According to the outcome of the IVN-CODAS application in a separate ranking, these three alternatives are determined to be the best three alternatives. The results of IVN-CODAS and IVN-TOPSIS are compared in Fig. 7.

Figure 7 illustrates how the IVN-TOPSIS ranking of alternatives is comparable to IVN-CODAS result. Although the ranking methodology has changed, the order of the alternatives has not changed significantly. The proposed hybrid methodology's result is consistent with TOPSIS under neutrosophic environment, one of the most widely used MCDM approaches, according to the comparative study.

## 4 Discussion

This study aims to conduct a risk assessment of post-flood assembly points for the Merkez district of Bartın province, located in the northern region of Turkey. While previous research focused heavily on flood risk assessment and mapping (Narendr et al. 2021; Wang et al. 2018; Zhu and Liu 2021), this study conducts a risk assessment for post-flood assembly areas. In this context, first of all, the IVN-AHP approach is presented to find the important weights of the main and sub-criteria affecting the flood and assembly point. Then, candidate assembly points are evaluated using the IVN-CODAS method.

When this study is compared with studies on a similar topic, Bathrellos et al. (Bathrellos et al. 2016, 2017) produced flood, landslide, and seismic hazard assessment maps using AHP and GIS. As a result of the applied methodology, the regions were classified according to five different flood hazards between very low and very high. However, they have taken into account a limited number of criteria when making these classifications. In our study, we evaluate 24 criteria that affect both flood and assembly points. With IVN-CODAS, which we have not seen before in the flood and assembly point literature, we have ranked assembly points according to their risks. Aman and Aytac (2022) aimed to identify the safest assembly areas in Istanbul's Bağcılar district against the expected Marmara earthquake in the near future. The AHP result showed that not all open/green areas or areas determined by the municipality would be safe for post-earthquake assembly areas. In this study, our aim is to find the most suitable area by evaluating the risks of candidate assembly points for the Merkez district of Bartın province, which is constantly exposed to floods. In the ranking obtained as a result of IVN-CODAS, it has been shown that some candidate assembly points determined by AFAD will be highly affected by the flood disaster and these points will not be an effective assembly area in the event of a flood disaster.

The importance weights of the main risk parameters with the IVN-AHP method resulted in Topographic (0.20), Access (0.18), Hydrological (0.17), Sociological (0.15), Humanitarian Relief (0.15), Infrastructure (0.15). Significance weights of the model parameters are explained in Sect. 3.2. In the IVN-AHP model, topographic is calculated as the most important main criterion among the risk parameters. When the experts' opinions were taken, it was found that 2 of 4 experts had a high weight for topographic [Table 6]. Taking into account the topographic data, it should be noted that the region is geographically inclined position to flood. For post-flood evacuation, shelter, and rescue activities, the accessibility criterion has also been found to be of great importance. Additionally, the humanitarian relief criterion, which has not been included as the main criterion in other studies before, is considered as important by experts. After determining the weight of each main criterion, the weights of the sub-criteria are calculated. As a result of the model, the first three sub-criteria of high importance among a total of 24 sub-criteria resulted in proximity to flood risk area (0.076), flow accumulation (0.060), and drainage density (0.058).

Twelve different candidate post-flood assembly points are evaluated in the IVN-CODAS model. As a result of the evaluation, each alternative assembly point is ranked according to risk factors [Table 14]. The order from the lowest risk to the highest is as follows: A-9, A-5, A-11, A-8, A-3, A-10, A-1, A-4, A-7, A-6, A-12, A-2. In other words, in case of any flood, the most suitable area to gather the victims is A-9. In terms of the most important sub-criteria, the fact that the A-9 region is far from flood risk areas and the flow accumulation and drainage density are low indicates that the area is durable and permeable. In addition to these, being close to the center and in a sloping area has also been effective in choosing the most suitable assembly point. The fact that A-2 is very close to the river, with high population density, flow accumulation, and drainage density supports the high-risk rate of this region.

An effective disaster management process is necessary to establish in order to minimize all material and moral losses arising from disasters. Evaluation of the flood risk of assembly points is one of these important processes. At this point, researchers and aid organizations should work to develop a successful disaster management policy with the support from experts in the field. For this reason, the risks of candidate assembly points should be evaluated in case of any flood. The theoretical contribution of this study is the use of the IVN-CODAS technique for the first time in a flood study. In addition, we use IVN-AHP and IVN-CODAS techniques together to evaluate the assembly points. In terms of practical applications, this study provides a comprehensive set of criteria for assessing flood risk for the assembly point. Unlike other studies, it is seen that the flood risk at the assembly point is affected not only by topological criteria, but also by different criteria such as human and infrastructure. In terms of administrative practices, this study provides local administrators with strategically important information about flood criteria that affect assembly points. In addition, this study offers academic researchers an area where they can study disasters other than floods and earthquakes.

## 5 Conclusions

In this paper, the problem of assessing the flood risk of assembly points is discussed. First, four expert opinions are taken to determine the most important risk parameters that affect flood and assembly points. Then a new two-level IVN-AHP integrated IVN-CODAS methodology is structured and performed. With IVN-AHP, the importance weights of each criterion are determined, and then with IVN-CODAS, twelve alternative assembly points are ranked according to their risks.

The numerical results obtained with both IVN-AHP and IVN-CODAS show that the most important sub-criteria is "Proximity to flood risk area" (C42) with a final weight of 0.076, while the assembly point with the lowest risk score (13.831) is A-9. Although ‘Topographic’ is the most relevant factor in this context, considering that there is no significant difference between this criterion and the others, it is suggested that each criterion should be considered in similar proportions for selecting the location of an assembly point. Except for the importance of the topographic, it is seen that the priority ranking of the hydrological criteria is a higher ranking for the sub-criteria.

When it comes to issues that have an impact on human loss of life and property, such as the risk assessment of post-flood assembly points, it is crucial to look into the factors that can lead to disasters. The relative importance of these criteria is one of the topics that has drawn the interest of numerous researchers over time. The local community and regional organizations are informed about the criteria that should be given priority to recovery before and after the disaster by determining the weights of the criteria. Furthermore, research into the effectiveness of various risk assessment techniques is beneficial for guiding researchers, as well as providing insight to government and humanitarian aid organizations.

This paper presents expert opinions on the 5 main criteria and 24 sub-criteria that are useful in assessing flood and assembly point risk. The "Topographic" criterion is determined to be the most significant of the main criteria at the conclusion of the risk assessment process, while the "Social" and "Infrastructure" criteria are found to be less significant. However, there are only 2% to 5% differences in the relative importance of each of the main criteria. In terms of sub-criteria, hydrological criteria like "Flow accumulation," "Drainage density," and "Surface runoff" have the highest importance weights, with the exception of the criterion of "Proximity to flood risk area.

The contributions of this study to the literature and applications can be listed as follows: (1) Two well-known MCDM methods, AHP and CODAS, are adapted to the assembly point flood risk assessment problem under neutrosophic environment, (2) the important risk criteria for flood and assembly points are defined and classified, (3) the main criteria and sub-criteria determined are evaluated with the proposed methodology and the importance weights of each criterion are determined, (4) twelve assembly points in Merkez district of Bartın province are ranked according to flood risk, (5) the validity and reliability of the proposed flood risk assessment method is demonstrated in a real-life disaster problem, (6) the proposed flood risk assessment method is considered to be a useful approach for future flood risk studies, (7) to the best of our knowledge, this study is the first to assess assembly point flood risk using a neutrosophic MCDM method, (8) it enables decision makers to make an effective assessment to address assembly point flood risks, (9) comparisons are made with similar studies in the literature, (10) unlike other studies, the criterion of humanitarian relief in flood disasters is considered the main criterion, (11) provides local administrators strategically important information on flood criteria affecting assembly points. In addition, it provides a broader perspective by comprehensively considering the criteria compared to studies on similar subjects.

As future directions, this study can be extended to rank different cities in Turkey for the risks of flooding at the assembly point. Furthermore, the flood risk criteria considered in the proposed method can be increased for large-scale regions or a different fuzzy MCDM can be used to make a more comprehensive evaluation. In future studies, thanks to developments in neutrosophic theory, similar problems can be solved with other distance-based MCDM methods and all results obtained from the methods can be compared. In this way, a more detailed risk assessment is in the future using the proposed methods.

**Funding** The authors have not disclosed any funding.

## Declarations

**Conflict of interest** The authors have not disclosed any competing interests.

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