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Research article

Regression coefficient measure of intuitionistic fuzzy graphs with application to soil selection for the best paddy crop

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Abstract: According to United Nations forecasts, India is now expected to pass China as the most populous country in the world in 2023. This is due to the fact that in 2022, China saw its first population decline in over 60 years. In order to keep pace with the rapid rise in its population, India will need to significantly raise food production in the future. Specific soil selection can help in achieving expected food production. In this article, we use Laplacian energy and regression coefficient measurements to face decision-making issues based on intuitionistic fuzzy preference relations (IFPRs). We present a novel statistical measure for evaluating the appropriate position weights of authority by computing the fuzzy evidence of IFPRs and the specific similarity grade among one distinct intuitionistic preference connection to the others. This new way of thinking bases decisions on evidence from both external and internal authorities. We evolved a statistical (regression coefficient measure) approach to determine the importance of alternatives and the best of the alternatives after integrating the weights of authority into IFPRs. This statistical analysis can be put to good use to choose the best soil for different crops to provide food for India's rapidly growing population in the future. To show how useful and realistic the suggested statistical measure is, a good example from real life is given. Additionally, we discovered how correlation and regression coefficient measurements are related to one another in intuitionistic fuzzy graphs.

Keywords: regression coefficient (RC); Laplacian energy (LE); group decision-making problem (GDMP); intuitionistic fuzzy preference relation (IFPR); intuitionistic fuzzy graph (IFG)
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1. Introduction

The application of decision-making strategies is necessary for every aspect of life when there is ambiguity and difficulty. When someone is given vague numbers instead of exact numbers, it could cause a number of problems. Many people use the guidelines to choose between different options based on a clear set of factors. In simple terms, Zadeh [1] suggested fuzzy sets (FS), which give the truth grade for a constrained value from a group of features bound to the unit interval [0, 1]. Many thinkers kept them in the natural environs of distinct zones after their successful usage. A promising area of study had emerged around the fuzzy set theory [2], and the fuzzy graph theory had lately become more well-known. The idea of a fuzzy relation was implemented by Tamura et al. [3] and it had been used to evaluate cluster patterns. In order to build the architecture of fuzzy graphs (FGs), Rosenfeld [4] studied fuzzy relations on fuzzy sets and combined numerous graph-theoretical subjects. Moderson and Peng [5] presented the combination of FGs and their various functions. Sunitha and Vijayakumar [6] looked at a number of FG operations and came up with a new way to define the fuzzy graph's complement. Yeh and Bang [7] also provided several connection concepts in FGs. Several key fuzzy graph-based ideas and implementations were introduced in 1975 as a result of the creative research of Yeh, Banh and Rosenfeld. IFGs were invented as a consequence, and they were well used. Parvathi and Karunambigai [8] made the first presentation on IFGs and their linkages. Gutman [9] invented the concept of energy and the Laplacian energy of a graph. Karthik and Basha [10] developed the notion of fuzzy graph LE into the LE of IFGs. Wang et al. [11] described integrating intuitionistic preferences into the graph model, just like IFPRs. Initially, in addition to the IFS in decision-making, Rajgopal and Basha [12], Xu [13], Chen and Tan [14], Hong and Choi [15], Liu and Wang [16], Ye [17] and Pei [18] proposed many similarity measures. Later on, IFG-based decision-making approaches were developed by Mou et al. [19], Malik and Akram [20, 21], Saho et al. [22], Ramesh et al. [23, 24] and Talebi et al. [25]. Furthermore, Wu et al. [26–28] presented some graph models for composite decision-making and their applications. Likewise, several feedback mechanisms had been established by Wu et al. [29–31] in social network group decision-making situations.

Recently, a number of statistical strategies for addressing decision-making situations have been made available, including those used by Naveen and Basha [32], Rajgopal and Basha [33], Garg and Rani [34], Huang and Guo [35], Zulqarnain et al. [36], Ejegwa [37], Augustine [38], Jenifer and Helen [39], Yong et al. [40] and Mohseni et al. [41] among others. The intuitionistic fuzzy set (IFS) and intuitionistic fuzzy graphs (IFG) are very helpful because they offer a flexible way to describe the uncertainty and vagueness that come up when making decisions. Research using intuitionistic fuzzy sets shows that the use of statistics has grown significantly in the last few years. This prompts us to think about its extensions, like IFGs, and their possible applications in decision making problems. As a result, we incorporate statistical measures from IFS into IFGs and the applications that go with them. In this study, intuitionistic fuzzy graphs were used to show how effective the replacements worked when the weight of each criterion was shown as a fuzzy value. We show how the regression coefficient and Laplacian energy can be used to make decisions based on IFGs. First, the Laplacian energy is used to figure out the criterion weights if the information about the weights is unclear and their values are expressed in terms of fuzzy digits. To achieve the whole weighting vector, we meld each LE weight that was found. From the given criteria weights, authorities' "internal" weights are calculated. Then, the regression coefficient measure that is connected to each criterion is used to rank the options so that the best one can be selected.

The rest of this article is divided into the following sections: In Section 2, we described how the Laplacian energy, correlation and regression coefficient metrics of the IFG were formulated. In fuzzy situations, this section also shows how regression and correlation coefficient measurements are related. Section 3 explains how to calculate expert weights using membership and non-membership significances. In order to determine the ranking order of the alternatives in this part, we also estimate the independent weights of authority using Laplacian energy and regression coefficient measures. A prime illustration is provided in Section 4 to demonstrate the applicability of the recommended strategy. The relation between correlation and regression coefficient measures is also proved in this section, and the article's conclusion is provided in Section 5.

2. Preliminaries

Definition 2.1. *An IFG $G_i = (V, E, \mu, v)$ is a "fuzzy graph" that has both a vertex set 'V' and an edge set 'E' with a fuzzy membership function (FMF) 'μ' defined on VXV and a fuzzy non-membership function (FNMF) 'ϑ', such that*

(a) $0 \le \mu_{ij} + \vartheta_{ij} \le 1$,

(b) $0 \le \mu_{ij}, \vartheta_{ij}, \pi_{ij} \le 1$, *where* $\pi_{ij} = 1 - \mu_{ij} - \vartheta_{ij}$.

Definition 2.2. *An intuitionistic fuzzy adjacency matrix (IFAM) is $A(G_i) = \left(\mu_{ii}, \vartheta_{ij}\right)$, where $G_i = (V, E, \mu, \vartheta)$ is an IFG and μ_{ij}, ϑ_{ij} represents the membership and non-membership bond between ϑ_i and ϑ_j respectively.*

Definition 2.3. *An intuitionistic fuzzy laplacian matrix (IFLM) '$L(G_i)$' is defined as the difference of $A(G_i)$ from $D(G_i)$, while and $D(G_i)$ acts as the degree matrix and* $\mathrm{A(G_i)}$ *acts as an IFAM of an IFG, i.e.,*

$$L(G_i) = D(G_i) - A(G_i).$$

Definition 2.4. *Assuming an IFG $G_i = (V, E, \mu, \vartheta)$, in which λ_i, α_i are the eigen roots of the intuitionistic fuzzy adjacency matrix $A(G_i)$, then the LE of the IFG is as follows:*

$$LE(G_i) = \left(LE\left(A_\mu(G_i)\right), LE\left(A_\vartheta(G_i)\right)\right), \forall i = 1, 2, 3.$$

Here, $A_\mu(G_i)$ and $A_\vartheta(G_i)$ represent the membership and non-membership matrices of an IFG's $A(G_i)$, respectively, while λ_i, α_i represent the eigen roots of $A_\mu(G_i), A_v(G_i)$. The Laplacian energies of the IFG's membership matrix $A_\mu(G_i)$ and non-membership matrix $A_v(G_i)$ are given by the equations

$$\begin{aligned} \mathrm{LE}\left(A_\mu(G_i)\right) &= \sum_{i=1}^{n} \left| \lambda_i - \frac{2\sum_{1 \le i \le j \le n} \mu\left(u_i, u_j\right)}{n} \right|, \\ \mathrm{LE}\left(A_\vartheta(G_i)\right) &= \sum_{i=1}^{n} \left| \theta_i - \frac{2\sum_{1 \le i \le j \le n} \vartheta\left(u_i, u_j\right)}{n} \right|. \end{aligned} \tag{2.1}$$

Definition 2.5. *(Correlation coefficient of IFGs) The intuitionistic energies of two intuitionistic fuzzy graphs (IFG_S) G_l and G_m are defined as*

$$E_{IFG}(G_l) = \textstyle\sum_{i=1}^{n} \left[u_{G_l}^2(x_i) + \vartheta_{G_l}^2(x_i)\right] = \sum_{j=1}^{n} \lambda_j^2(G_l)$$

and

$$E_{IFG}(G_m) = \sum_{i=1}^{n}\left[u_{G_m}^2(x_i) + \vartheta_{G_m}^2(x_i)\right] = \sum_{j=1}^{n}\lambda_j^2(G_m).$$

The covarience (Cov) of the IFG_S G_l and G_m is defined as

$$Cov(G_l, G_m) = \sum_{i=1}^{n}\left[u_{G_l}(x_i)\,u_{G_m}(x_i) + \vartheta_{G_l}(x_i)\,\vartheta_{G_m}(x_i)\right].$$

The correlation coefficient of the G_l and G_m is defined as

$$\begin{aligned} K(G_l, G_m) &= \frac{\mathrm{Cov}(G_l, G_m)}{\sqrt{E_{IFG}(G_l)\,E_{IFG}(G_m)}} = \frac{\mathrm{Cov}(G_l, G_m)}{\sqrt{\sigma_{G_l}^2}\sqrt{\sigma_{G_m}^2}} \\ &= \frac{\sum_{i=1}^{n}\left[u_{G_1}(x_i)\,u_{G_2}(x_i) + \vartheta_{G_1}(x_i)\,\vartheta_{G_2}(x_i)\right]}{\sqrt{\sum_{i=1}^{n}\left[u_{G_1}^2(x_i) + \vartheta_{G_1}^2(x_i)\right]}\sqrt{\sum_{i=1}^{n}\left[u_{G_2}^2(x_i) + \vartheta_{G_2}^2(x_i)\right]}} \\ &= \frac{\mathrm{Cov}(x, y)}{\sqrt{\mathrm{Var}(x)}\sqrt{\mathrm{Var}(y)}} = \frac{\mathrm{Cov}(x, y)}{\sigma_x\sigma_y} = \frac{S_{xy}}{S_x S_y}, \end{aligned} \tag{2.2}$$

where $\mathrm{Cov} = \frac{\sigma}{\mu}$.

On the other hand, Xu et al., suggested an alternative form of the correlation coefficient of IFG_S A *and* B*, so the same form can be converted on IFG_S G_l and G_m as follows:*

$$K(G_l, G_m) = \frac{\sum_{i=1}^{n}\left[u_{G_l}(x_i)\,u_{G_m}(x_i) + \vartheta_{G_l}(x_i)\,\vartheta_{G_m}(x_i)\right]}{\max\left\{\left[\sum_{i=1}^{n}\left[u_{G_l}^2(x_i) + \vartheta_{G_l}^2(x_i)\right]\right]^{\frac{1}{2}}, \left[\sum_{i=1}^{n}\left[u_{G_m}^2(x_i) + \vartheta_{G_m}^2(x_i)\right]\right]^{\frac{1}{2}}\right\}},$$

$$K(G_l, G_m) = \frac{\sum_{i=1}^{n}\left[u_{G_l}(x_i)\,u_{G_m}(x_i) + \vartheta_{G_l}(x_i)\,\vartheta_{G_m}(x_i) + \pi_{G_l}(x_i)\,\pi_{G_m}(x_i)\right]}{\max\left\{\left[\sum_{i=1}^{n}\left[u_{G_l}^2(x_i) + \vartheta_{G_l}^2(x_i) + \pi_{G_l}^2(x_i)\right]\right]^{\frac{1}{2}}, \left[\sum_{i=1}^{n}\left[u_{G_m}^2(x_i) + \vartheta_{G_m}^2(x_i) + \pi_{G_m}^2(x_i)\right]\right]^{\frac{1}{2}}\right\}}$$

and

$$K(G_l, G_m) = \frac{\sum_{i=1}^{n}\left[u_{G_l}(x_i)\,u_{G_m}(x_i) + \vartheta_{G_l}(x_i)\,\vartheta_{G_m}(x_i) + \pi_{G_l}(x_i)\,\pi_{G_m}(x_i)\right]}{\mathrm{Max}\left\{\sqrt{\sum_{i=1}^{n}\left[u_{G_l}^2(x_i) + \vartheta_{G_l}^2(x_i) + \pi_{G_l}^2(x_i)\right]}, \sqrt{\sum_{i=1}^{n}\left[u_{G_m}^2(x_i) + \vartheta_{G_m}^2(x_i) + \pi_{G_m}^2(x_i)\right]}\right.}.$$

The function $K(G_l, G_m)$ satisfies the following conditions:

(P_1) $0 \le K(G_l, G_m) \le 1$,
(P_2) $K(G_l, G_m) = K(G_m, G_l)$,
(P_3) $K(G_l, G_m) = 1$, *if* $G_l = G_m$.

Definition 2.6. *(Regression coefficient of IFGs) In genereal, the regression coefficient of* y *on* x *is defined as*

$$R_{yx} = K\frac{\sigma_y}{\sigma_x} = \frac{\mathrm{Cov}(x, y)}{\sigma_x\sigma_y}\frac{\sigma_y}{\sigma_x} = \frac{\mathrm{Cov}(x, y)}{\sigma_x^2}.$$

The regression coefficient of x *on* y *is defined as*

$$R_{xy} = K\frac{\sigma_x}{\sigma_y} = \frac{\mathrm{Cov}(x, y)}{\sigma_x\sigma_y}\frac{\sigma_x}{\sigma_y} = \frac{\mathrm{Cov}(x, y)}{\sigma_y^2}.$$

Also, the relation between correlation coefficient and regression coefficient can be written as

$$K = \sqrt{R_{yx} \times R_{xy}}.$$

Therefore, in fuzzy situations, the regression coefficient measure of G_m on G_l can be defined as

$$R\left(G_l, G_m\right) = \frac{\sum_{i=1}^{n}\left[u_{G_l}\left(x_i\right)u_{G_m}\left(x_i\right) + \vartheta_{G_l}\left(x_i\right)\vartheta_{G_m}\left(x_i\right)\right]}{\sum_{i=1}^{n}\left[u_{G_l}^2\left(x_i\right) + \vartheta_{G_l}^2\left(x_i\right)\right]}, \tag{2.3}$$

and the regression coefficient measure of G_l on G_m can be defined as

$$R\left(G_m, G_l\right) = \frac{\sum_{i=1}^{n}\left[u_{G_l}\left(x_i\right)u_{G_m}\left(x_i\right) + \vartheta_{G_l}\left(x_i\right)\vartheta_{G_m}\left(x_i\right)\right]}{\sum_{i=1}^{n}\left[u_{G_m}^2\left(x_i\right) + \vartheta_{G_m}^2\left(x_i\right)\right]}. \tag{2.4}$$

Relationship between correlation and regression coefficients: using the above statistical relations, we have

$$K\left(G_m, G_l\right) = \sqrt{R\left(G_l, G_m\right) \times R\left(G_m, G_l\right)}, \tag{2.5}$$

this equation depicts the relationship between the CC *and* RC *measures.*

3. Group decision making based on intuitionistic fuzzy graph's Laplacian energy and regression coefficient

3.1. Algorithm 1

For the purpose of finding group decision making problem based on IFPR, let $w = (w_1, w_2, \ldots, w_m)$ be a subjective weighting vector of authorities, where $w_k > 0$, k=1,2, …, m., and $\sum_{k=1}^{m} w_k = 1$.
Step-(i). Calculate the Laplacian Energy LE of G_i, using the following formulae

$$LE\left(G_{\mu(i)}\right) = \left|\lambda_i - \frac{2\sum\limits_{1\le i\le j\le n}\mu(v_i, v_j)}{n}\right| \text{ and } LE\left(G_{\vartheta(i)}\right) = \left|\lambda_i - \frac{2\sum\limits_{1\le i\le j\le n}\vartheta(v_i, v_j)}{n}\right|. \tag{3.1}$$

Step-(ii). Calculate the weight w_k^a by using Laplacian energy of the authorities e_k using the equation

$$w_k^a = \left((w_u)_k, (w_\vartheta)_k\right) = \left[\frac{LE\left((G_u)_k\right)}{\sum_{i=1}^{m} LE\left((G_u)_i\right)}, \frac{LE\left((G_\vartheta)_k\right)}{\sum_{i=1}^{m} LE\left((G_\vartheta)_i\right)}\right], \forall k = 1, 2, ..., m. \tag{3.2}$$

Step-(iii). Calculate the regression coefficient $R\left(G_m, G_l\right)$ between G_m and G_l for $m \neq l$ using the equation

$$R\left(G_m, G_l\right) = \frac{\sum_{i=1}^{n}\left[u_{G_m}\left(x_i\right)u_{G_l}\left(x_i\right) + \vartheta_{G_m}\left(x_i\right)\vartheta_{G_l}\left(x_i\right)\right]}{\sum_{i=1}^{n}\left[u_{G_m}^2\left(x_i\right) + \vartheta_{G_m}^2\left(x_i\right)\right]}. \tag{3.3}$$

Compute the average regression coefficient degree $R\left(G_k\right)$ of G_k to the others using the equation

$$R\left(G_k\right) = \frac{1}{m-1}\sum_{l=1, m\neq l}^{n} R\left(G_m, G_l\right), k = 1, 2, \ldots, m. \tag{3.4}$$

Step-(iv). Compute the weight w_k^b determined by $R(G_k)$ of the authority e_k using the equation

$$w_k^b = \frac{R(G_k)}{\sum_{i=1}^{m} R(G_i)}, \forall k = 1, 2, \ldots, m. \tag{3.5}$$

Step-(v). Calculate the authirity e_k's objective weight ${w_k}^2$ using the equation

$$w_k^2 = \eta w_k^a + (1-\eta) w_k^b, \eta \in [0,1], \forall k = 1, 2, \ldots, m. \tag{3.6}$$

Step-(vi). Incorporate the subjective weight w_k^a and objective weight w_k^2 into the weight w_k of the authority e_k using the equation

$$w_k = \gamma w_k^a + (1-\gamma) w_k^2, \gamma \in [0,1], \forall k = 1, 2, \ldots, m. \tag{3.7}$$

Step-(vii). Find $r_i^{(k)}$ using the formula

$$r_i^{(k)} = \frac{1}{n} \sum_{j=1}^{n} r_{ij}^{(k)}, \forall i = 1, 2, ..., n \; and \; k = 1, 2, \ldots, m. \tag{3.8}$$

Step-(viii). Use the equation

$$r_i = \sum_{k=1}^{m} w_k r_i^{(k)}, \forall i = 1, 2, \ldots, n \tag{3.9}$$

to make a total intuitionistic fuzzy value of the alternative $r_i, (\forall i = 1, 2, ..., n)$ over other choices by summing all $r_i^{(k)}, (\forall i = 1, 2, \ldots, n \; and \; k = 1, 2, ..., m)$ corresponding to n-authorities.
Step-(ix). Calculate the score function using the equation

$$R(v_i) = u_i - \vartheta_i, \forall i = 1, 2, \ldots, n \tag{3.10}$$

of r_i and alternative with the larger value of $R(v_i)$ is the better alternative, so the group ranking of the alternates is obtained accordingly.

3.2. TOPSIS method for finding intuitionistic fuzzy preference relation (IFPR)

It is a method of compensatory grouping that examines a fixed set of alternatives by identifying weights for every criterion, standardizing assessments for every instruction (rule) and calculating the geometric separation between one alternative and the precise other alternatives. This method stands for acceptable rankings in every aspect.

3.3. Computational procedure for TOPSIS method problem

We consider the r choices $Y_1, Y_2, ..., Y_r$, each choice of Y_i is involved with s rules $b_1, b_2, ..., b_s$ which are communicated through positive numbers b_{ij}. Measure $b_1, b_2, ..., b_k$ are an advantage (monotonically increasing incline), while rules $b_{k+1}, b_{k+2}, ..., b_s$ is a disadvantage (monotonically decreasing incline). Weights ω_t are assigned to the measurements y_t so that $\sum_{t=1}^{n} \omega_t = 1$.

3.4. Initial table and decision matrix

Other alternatives, rules and their weights are listed in Table 1 for better comprehension.

Table 1. Initial table for TOPSIS method.

$Criteria$	b_1	b_2	b_3	...	b_s
	$Cr.1$	$Cr.2$	$Cr.3$	...	$Cr.s$
Weights	ω_1	ω_2	ω_3	...	ω_s
Y_1	b_{11}	b_{12}	b_{13}	...	b_{1s}
Y_2	b_{21}	b_{22}	b_{23}	...	b_{2s}
...	...	...	...	...	...
Y_r	b_{r1}	b_{r2}	b_{r3}	...	b_{rs}

For IFGs, the cumulative grid may be obtained by intuitionistic fuzzy weighted averaging (IFWA) is found by the equation

$$IFWA\left(Z_{ij}^{(1)}, Z_{ij}^{(2)}, ..., Z_{ij}^{(n)}\right) = \left(1 - \Pi_{i=1}^{m}\left((1-\mu_{jk}^{(i)})^{\omega_i}\right),\ \Pi_{i=1}^{m}(\vartheta_{jk}^{(i)})^{\omega_i}\right), \tag{3.11}$$

where ω_i be the weight function, $Z_{ij}^{(1)}, Z_{ij}^{(2)}, ..., Z_{ij}^{(n)}$ be an individual IFPR, μ_{jk} be the membership element, and ϑ_{jk} be the nonmembership element. then the weight function ω_i for m number of laplacian energies are calculating by using the equation (which is similar to the Bayesian formula)

$$\omega_i = \left((\omega_\mu)_i, (\omega_\vartheta)_i\right) = \left[\frac{LE\left(\left(G_\mu\right)_i\right)}{\sum_{i=1}^{m} LE\left(\left(G_\mu\right)_i\right)}, \frac{LE\left((G_\vartheta)_i\right)}{\sum_{i=1}^{m} LE\left((G_\vartheta)_i\right)}\right], \forall i = 1, 2, ..., m. \tag{3.12}$$

3.5. Agorithm 2

The steps to take in order to choose the most acceptable soil for the best paddy harvest are as follows:

Input. Let $S = S_1, S_2, S_3, ..., S_n$ is the set of soil types and, $e = e_1, e_2, e_3..., e_n$ is the decision expert (soil scientist) set and build IFPR for every expert $S_k = \left(z_{ij}^{(k)}\right)_{nxn}$.

Output. To select the most acceptable soil for the best paddy crop.

Step-(i). Start.

Step-(ii). Compute the LE for every IFG $G_i, \forall i = 1, 2, ..., n.$ by using the equation

$$LE\left(G_{(i)}\right) = \sum_{i=1}^{n}\left|\lambda_i - \frac{2\sum_{1\leq i\leq j\leq n}\mu(v_i, v_j)}{n}\right|.$$

Step-(iii). Compute the weight for experts on the basis of Laplacian energy of IFGs using (3.12).

Step-(iv). Compute the IFWA by using (3.11).

Step-(v). Using the IFWA operator, calculate a collective intuitionistic fuzzy elements $r_i, \forall i = 1, 2, .., n$ based on the proposed criteria, over all ther soil types $S_k = \left(z_{ij}^{(k)}\right)_{nxn}$.

Step-(vi). Calculate their out-degrees by using the equation $out - d(v_k), \forall k = 1, 2..., n$, where $d(v_k)$ is the degree of membership element of $\left(z_{ij}^{(k)}\right)$.
Step-(vii). Compute the ranking of the factors of $V_k, \forall k = 1, 2, ..., n$, on the basis of membership degrees of $out - d(v_k)$.
Step-(viii). Identify the most acceptable soil for best paddy crop in the ranking of the vectors V_k.
Step-(ix). Stop.

4. Real-life illustration: choosing the most acceptable soil for best paddy crop

4.1. Decision-making implementation for soil selection

In this section, we apply the idea of the regression coefficient measure of IFGs to decision-making issues. To demonstrate the application of the suggested concept of IFGs in a concrete situation based on IFPRs, the decision-making issue regarding "the most acceptable soil selection for the best crop" was considered. For instance, the algorithm for choosing the soil selection for a paddy crop under the IFPR framework is described.

4.2. Application background

Cultivated crops are crucial for human survival on Earth. For the majority of crops, seeds and cultivated fields are very essential. In general, a farmer's careful attention is paid to selecting both the seed and the soil for a good harvest. By selecting healthy, top-notch seeds, a healthy harvest can be created. Therefore, selecting your seeds wisely is crucial. Mostly using high-quality seeds and the planting techniques advised by the National Food Corporation will result in the crop yield that is sought. The first stage in seed germination and the growth of new seedlings is the selection of the correct growth medium or substrate. Even though a substrate has to have physical properties such as being able to contain air and water, organic manures are also important to consider. It is essential to have the optimum starting pH, ionic properties and nutrient content for favourable early plant growth. Therefore, soil that is acceptable and rich in nutrients is required for a suitable crop.

4.3. Soil types and characteristics

Generally, the word "soil" refers to the loose layer of earth that covers the surface of the world. Disintegrated rock, humus, organic compounds and inorganic elements are all found in the soil, which is a region of the earth's surface. It takes at least 500 years for soil to develop from rocks. Typically, the breakdown of rocks into their component elements creates soil. The soil is created when the rocks fracture into smaller pieces as a result of a variety of pressures acting on them. Some of these factors included the effects of air, rainfall and salty reactions. Different soil types are subjected to various environmental forces. The primary characteristics of soil are its texture, ratios and various mineral and organic contents. Based on this, the basic characteristics of soil are silt, clay and loam. One popular approach to describing soil is based on the amount of sand, clay and silt present. We refer to this as texture, and these varieties are classified below.

Sandy soil: Sandy soils (particle size > 63 micrometers) have a coarse texture until they are about 50 cm deep. As a result, they don't hold many nutrients and have a low water-holding capacity and are light, warm, dry, acidic in nature and poor in nutrients. It is the soil type most commonly associated with sandy areas. As a result of their low clay content and high sand content, these soils are often referred to as “light soils”.

Silt soil: Silt is known to include significantly smaller particles than sandy soil and is made up of rock and other mineral particles (particle size > 2 micrometers) that are bigger than clay but smaller than sand. Because it is smooth and fine, the soil holds water better than sandy soil. Silt is easily transported by flowing currents. Hence, it is often found next to rivers, lakes and other bodies of water. In order to increase soil fertility, it is also employed in agricultural practices.

Clay soil: Clay soil (particle size 2 micrometers) is made up of very fine mineral particles. The soil is quite sticky since there is not much space between the mineral particles. This soil has an excellent capacity to hold water. When wet, it feels quite sticky to the touch, but when dry, it feels silky. The thickest and most heavy form of soil is clay, which does not drain effectively or provide space for plant roots to spread out.

Loamy soil: The primary constituents of loamy soil are sand, silt and clay. Its mineral composition is roughly 40-40-20 percent sand, silt and clay concentrations by weight. For instance, it can hold onto nutrients and moisture, making it ideal for cultivation. Due to the balance of all soil types (sandy, clay and silt) and the presence of humus, this soil is also known as agricultural soil. Due to its inorganic origins, it also has nutrients and pH levels in addition to these.

Peat soil: Peat is the partly decomposed organic matter that has formed on the top of a soil’s organic layer as a result of waterlogging, oxygen scarcity, excessive acidity and nutrient shortage. This material is mostly produced from plant matter. It is a kind of soil created over thousands of years from decayed organic components. Organic material from plant matter, such as decomposing sphagnum peat moss, makes up a large portion of peat soil’s composition. Wetland environments known as peatlands or peat bogs collect peat soil.

Rice is the most significant food crop in India, producing around one-fourth of all cultivated land and supplying almost half of the country’s population. Rice is grown in India under a variety of conditions, ranging from $8°C$ to $25°C$N latitude and sea level to approximately 2,500 meters altitude. It is a tropical plant that needs both high temperatures and high humidity levels to flourish. Also, the temperature should be fairly high, with a mean monthly temperature of $24°C$. It should be $20°–22°C$ at the time of sowing, $23°–25°C$ during growth and $25°–30°C$ at harvest time. Rice needs 150 cm of rainfall each year on average. Silts, loams, gravels and other types of soil may all be used to cultivate rice, which can also thrive in both acidic and alkaline soils. However, deep rich clayey or loamy soils are said to be best for growing this crop since they are readily puddled into the mud and create cracks as they dry up. It has evolved as a major crop on coastal plains, floodplains, deltas and river valleys due to its soil needs. High-level loams and lighter soils can be used for quick-maturing varieties of rice. Black lava soil is also useful for rice cultivation.

In order to keep up with its rapidly expanding population, India will need to significantly enhance its rice output in the future. It is feasible only when the desired crop production for future needs can be achieved. In this instance, soil selection is one of the most important factors that should be considered. For this, the following criteria help in selecting the most acceptable soil for the best paddy crops:

(1) High water retention capacity.
(2) Availability of nutrients and minerals.
(3) Weather conditions.

A soil scientist is someone who has the training and experience to evaluate soils and data about soils in order to understand how soil resources affect agricultural productivity and environmental quality, as well as how they should be managed in the future to protect human welfare. These scientists will inspect which types of soil are best for farming based on the criteria, and their guidance may help the farmers produce the best crops. For the best paddy production, a group of decision experts (soil scientists) who followed this suggested procedure would consider the 5 vertices of an IFG as 5 soil types: V_1 (loamy soil), V_2 (silt soil), V_3 (peat soil), V_4 (clay soil) and V_5 (sandy soil). Also, using IFPRs, they can only pick one soil based on these three criteria: e_1 (high water retention capacity), e_2 (availability of nutrients and minerals) and e_3 (weather conditions). Experts in decision-making examine each alternative and reach individual conclusions based on their experiences as follows.

The IFAM of $IFG\,(G_1)$ is

$$A\,(G_1) = \begin{bmatrix} (0,0) & (0.6,0.2) & (0.2,0.5) & (0.4,0.3) & (0.3,0.6) \\ (0.6,0.2) & (0,0) & (0.1,0.5) & (0.3,0.5) & (0.1,0.7) \\ (0.2,0.5) & (0.1,0.5) & (0,0) & (0.2,0.6) & (0.1,0.6) \\ (0.4,0.3) & (0.3,0.5) & (0.2,0.6) & (0,0) & (0.3,0.4) \\ (0.3,0.6) & (0.1,0.7) & (0.1,0.6) & (0.3,0.4) & (0,0) \end{bmatrix}.$$

The IFAM of $IFG\,(G_2)$ is

$$A\,(G_2) = \begin{bmatrix} (0,0) & (0.3,0.6) & (0.7,0.2) & (0.2,0.5) & (0.1,0.6) \\ (0.3,0.6) & (0,0) & (0.2,0.5) & (0.1,0.6) & (0.3,0.5) \\ (0.7,0.2) & (0.2,0.5) & (0,0) & (0.1,0.7) & (0.1,0.8) \\ (0.2,0.5) & (0.1,0.6) & (0.1,0.7) & (0,0) & (0.2,0.5) \\ (0.1,0.6) & (0.3,0.5) & (0.1,0.8) & (0.2,0.5) & (0,0) \end{bmatrix}.$$

The IFAM of $IFG\,(G_3)$ is

$$A\,(G_3) = \begin{bmatrix} (0,0) & (0.6,0.1) & (0.6,0.3) & (0.5,0.4) & (0.3,0.5) \\ (0.6,0.1) & (0,0) & (0.5,0.4) & (0.1,0.6) & (0.2,0.5) \\ (0.6,0.3) & (0.5,0.4) & (0,0) & (0.3,0.6) & (0.1,0.6) \\ (0.5,0.4) & (0.1,0.6) & (0.3,0.6) & (0,0) & (0.7,0.2) \\ (0.3,0.5) & (0.2,0.5) & (0.1,0.6) & (0.7,0.2) & (0,0) \end{bmatrix}.$$

4.3.1. Algorithm 1

Step-(i). Using Eq (3.1), we calculate the Laplacian energies of $G_i, \forall i = 1, 2, 3$ as follows.

From Figure 1 and A (G_1) we get

$$LE\,(G_1) = (2.8184, 4.1481).$$

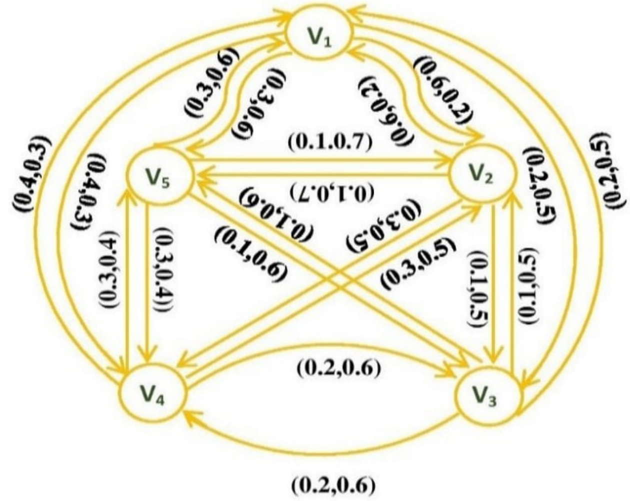

Figure 1. $IFG(G_3)$: IFPR for high water retention capacity.

From Figure 2 and A (G_2) we get

$$LE\,(G_2) = (2.5409, 4.4483).$$

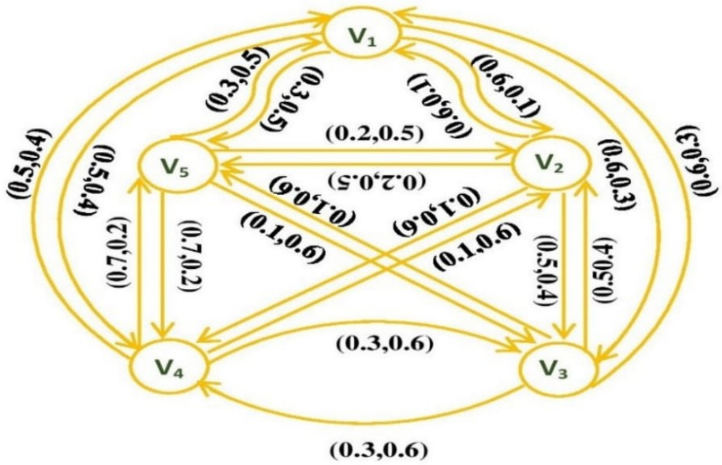

Figure 2. $IFG(G_3)$: IFPR for weather conditions.

From Figure 3 and A (G_3) we get

$$LE\,(G_3) = (3.9744, 3.7671).$$

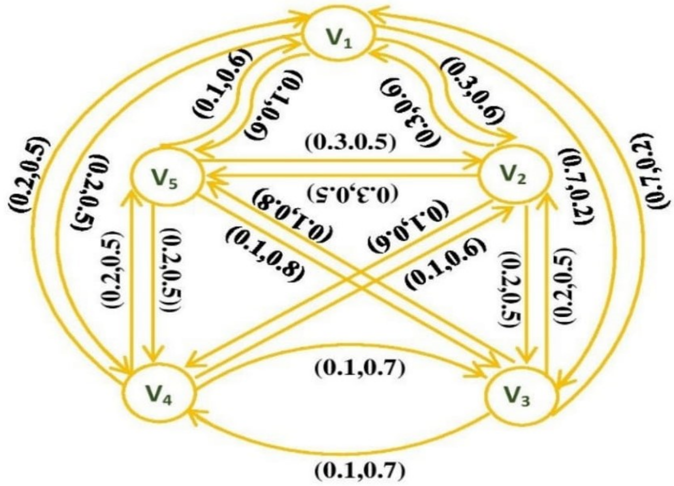

Figure 3. $IFG(G_3)$: IFPR for availability of nutrients and minerals.

Step-(ii). The Eq (3.2) is used to calculate the weights of G_i determined by LE.

$$w_1^a = (0.3020, 0.3357), \qquad w_2^a = (0.2722, 0.3600), \qquad w_3^a = (0.4258, 0.3044).$$

Step-(iii). Using (3.3) formula, we have

$$R(G_1, G_2) = 0.9487, \qquad R(G_1, G_3) = 0.9658, \qquad R(G_2, G_3) = 0.8603.$$

Therefore from the Eq (3.4), we get

$$R(G_1) = 0.9573, \qquad R(G_2) = 0.9045, \qquad R(G_3) = 0.9131.$$

Step-(iv). From Eq (3.5), we get

$$w_1^b = 0.3450, \qquad w_2^b = 0.3260, \qquad w_3^b = 0.3291.$$

Step-(v). Let $\eta = 0.5$, where $\eta\epsilon[0, 1]$ in Eq (3.6), we get

$$w_{1,\mu}^2 = 0.3235, \qquad w_{1,\nu}^2 = 0.3404,$$
$$w_{2,\mu}^2 = 0.2991, \qquad w_{2,\nu}^2 = 0.3430,$$
$$w_{3,\mu}^2 = 0.3775, \qquad w_{3,\nu}^2 = 0.3168.$$

So, the weights of authorities are

$$w_1^2 = (0.3235, 0.3404), \qquad w_2^2 = (0.2991, 0.3430), \qquad w_3^2 = (0.3775, 0.3168).$$

Step-(vi). Let $\gamma = 0.5$, where $\gamma\epsilon[0, 1]$ in Eq (3.7), we get

$$w_{1,\mu} = 0.3128, w_{1,\nu} = 0.3381,$$

$$w_{2,\mu} = 0.2857, w_{2,v} = 0.3515,$$

$$w_{3,\mu} = 0.4017, w_{3,v} = 0.3106.$$

So, the impartial weights are

$$w_1 = (0.3128, 0.3381), \qquad w_2 = (0.2857, 0.3515), \qquad w_3 = (0.4017, 0.3106).$$

Step-(vii). From Eq (3.8), we have $r_i^{(k)} = \frac{1}{n}\sum_{j=1}^{n} r_{ij}^{(k)}, i = 1, 2, \ldots, n \; and \; k = 1, 2, ..., m.$ Then from Figure 1 and $A(G_1)$ we get

$$r_1^{(1)} = (0.3750, 0.4000), \qquad r_2^{(1)} = (0.2750, 0.4750),$$
$$r_3^{(1)} = (0.1500, 0.5500), \qquad r_4^{(1)} = (0.3000, 0.4500),$$
$$r_5^{(1)} = (0.2000, 0.5750).$$

From Figure 2 and A (G_2) we get

$$r_1^{(2)} = (0.3250, 0.4750), \qquad r_2^{(2)} = (0.2250, 0.5500),$$
$$r_3^{(2)} = (0.2750, 0.5500), \qquad r_4^{(2)} = (0.1500, 0.5750),$$
$$r_5^{(2)} = (0.1750, 0.6000).$$

From Figure 3 and $A(G_3)$ we get

$$r_1^{(3)} = (0.5000, 0.3250), \qquad r_2^{(3)} = (0.3500, 0.4000),$$
$$r_3^{(3)} = (0.3750, 0.4750), \qquad r_4^{(3)} = (0.4000, 0.4500),$$
$$r_5^{(3)} = (0.3250, 0.4500).$$

Step-(viii). From Eq (3.9), we get

$$r_{1,u} = 0.4110, \qquad r_{1,v} = 0.4031,$$
$$r_{2,u} = 0.2909, \qquad r_{2,v} = 0.4782,$$
$$r_{3,u} = 0.2761, \qquad r_{3,v} = 0.5268,$$
$$r_{4,u} = 0.2974, \qquad r_{4,v} = 0.4940,$$
$$r_{5,u} = 0.2431, \qquad r_{5,v} = 0.5451.$$

Therefore

$$r_1 = (0.4110, 0.4031), \qquad r_2 = (0.2909, 0.4782),$$
$$r_3 = (0.2761, 0.5268), \qquad r_4 = (0.2974, 0.4940),$$
$$r_5 = (0.2431, 0.5451).$$

Step-(ix). From Eq (3.10), we get

$$R(v_1) = 0.0079, \qquad R(v_2) = -0.1873, \qquad R(v_3) = -0.2507,$$

$$R(v_4) = -0.1966, \qquad R(v_5) = -0.3020.$$

Therefore $R(v_1) > R(v_2) > R(v_4) > R(v_3) > R(v_5)$ and hence $v_1 > v_2 > v_4 > v_3 > v_5$.

As a result, loamy soil is considered the most significant alternative for the best paddy crop based on the three criteria. According to rank, loamy soil comes in first, silty soil comes in second, clay soil comes in third, peat soil comes in fourth and sandy soil comes in last. In the same way, we find the aggregate intuitionistic fuzzy values and position outcomes for different η and γ values (where $\eta, \gamma \epsilon [0, 1]$), which are shown in Tables 2 and 3 below:

Table 2. The weight function and the aggregate intuitionistic fuzzy values for different values of η and γ.

η	w_k^2 $(k = 1, 2, 3)$	γ	w_k $(k = 1, 2, 3)$	r_i $(i = 1, 2, 3, 4, 5)$
	(0.1258,0.1326)		(0.0856,0.0937)	(0.1156,0.1136)
0.2	(0.1211,0.1386)	0.2	(0.0787,0.0997)	(0.0818,0.1348)
	(0.1531,0.1288)		(0.1158,0.0866)	(0.0779,0.1485)
				(0.0838,0.1394)
				(0.0685,0.1536)
	(0.3235,0.3404)		(0.3128,0.3381)	(0.4110,0.4031)
0.5	(0.2991,0.3404)	0.5	(0.2857,0.3515)	(0.2909,0.4782)
	(0.3775,0.3168)		(0.4017,0.3106)	(0.2761,0.5268)
				(0.2974,0.4940)
				(0.2431,0.5451)
	(0.5034,0.5303)		(0.6443,0.6928)	(0.8536,0.8378)
0.8	(0.4842,0.5545)	0.8	(0.6051,0.7316)	(0.6040,0.9938)
	(0.6124,0.5153)		(0.8306,0.6558)	(0.5745,1.0949)
				(0.6163,1.0275)
				(0.5047,1.1324)

Table 3. The ranking order of the alternatives by using $Xu's$ model algorithm.

γ	$R(v_1)$	$R(v_2)$	$R(v_3)$	$R(v_4)$	$R(v_5)$	*Ranking*
0.2	0.0020	−0.0530	−0.0706	−0.0556	−0.0851	$v_1 > v_2 > v_4 > v_3 > v_5$
0.5	0.0079	−0.1873	−0.2507	−0.1966	−0.3020	$v_1 > v_2 > v_4 > v_3 > v_5$
0.8	0.0158	−0.3898	−0.5204	−0.4112	−0.6277	$v_1 > v_2 > v_4 > v_3 > v_5$

From the above table, we can see that the positions are the same for η and γ values. Finally, the relationship between CC and RC measures $K(G_m, G_l) = \sqrt{R(G_l, G_m) \times R(G_m, G_l)}$ in fuzzy graph situations is proved in Table 4.

Table 4. Relationship between correlation and regression coefficient measures of IFGs.

$K(G_l, G_m)$	$R(G_l, G_m)$	$R(G_m, G_l)$	$\sqrt{(R(G_l, G_m) \times R(G_m, G_l))}$
$K(G_1, G_2) = 0.8800$	$R(G_1, G_2) = 0.9487$	$R(G_2, G_1) = 0.8162$	0.8800
$K(G_1, G_2) = 0.9059$	$R(G_1, G_3) = 0.9658$	$R(G_3, G_1) = 0.8496$	0.9059
$K(G_1, G_2) = 0.8699$	$R(G_2, G_3) = 0.8603$	$R(G_3, G_2) = 0.8797$	0.8699

4.4. Algorithm 2 (TOPSIS method)

In the aforementioned example given above (see Section 4.1), the THOPSIS method is used after the eigenvalues for the intuitionistic fuzzy adjacent matrices $A(G_1)$–$A(G_3)$ have been found. Find the Laplacian energies of IFGs by using equation

$$LE\left(G_{(i)}\right) = \sum_{i=1}^{n} \left| \lambda_i - \frac{2 \sum_{1 \le i \le j \le n} \mu(v_i, v_j)}{n} \right|,$$

we have

$$\begin{aligned} LE\left(G_1\right) &= (2.8184, 4.1481), \\ LE\left(G_2\right) &= (2.5409, 4.4483), \\ LE\left(G_3\right) &= (3.9744, 3.7671). \end{aligned}$$

The calculation of every expert's weight by using (3.12), we get

$$\begin{aligned} w_1 &= (0.3128, 0.3381), \\ w_2 &= (0.2857, 0.3515), \\ w_3 &= (0.4017, 0.3106). \end{aligned}$$

Using the IFWA operator (3.11) , the collective intuitionistic fuzzy elements $r_i, \forall i = 1, 2, .., n$ based on the proposed criteria, over all ther soil types $S_k = (z_{ij}^{(k)})_{nxn}$, we have

$$z = \begin{bmatrix} (0,0) & (0.5307, 0.2372) & (0.5424, 0.3091) & (0.3947, 0.3925) & (0.2479, 0.5667) \\ (0.5307, 0.2372) & (0,0) & (0.3128, 0.4665) & (0.1681, 0.5641) & (0.2011, 0.5602) \\ (0.5424, 0.3091) & (0.3128, 0.4665) & (0,0) & (0.2158, 0.6333) & (0.1, 0.6638) \\ (0.3946, 0.3925) & (0.1680, 0.5641) & (0.2159, 0.6333) & (0,0) & (0.4826, 0.3488) \\ (0.2479, 0.5669) & (0.2011, 0.5602) & (0.1, 0.6638) & (0.4826, 0.3488) & (0,0) \end{bmatrix}.$$

Figure 4 shows a directed network related to a collective IFPR.

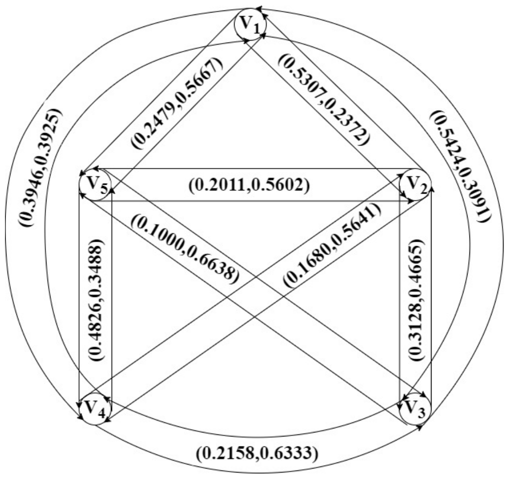

Figure 4. Ituitionistic fuzzy graph.

Calculate the out-degrees by using the equation $out - d(v_k), \forall k = 1, 2..., n$, we get

$$out - d(v_1) = (1.7126, 1.5055),$$

$$out - d(v_2) = (1.2625, 1.8280),$$

$$out - d(v_3) = (1.1710, 2.0727),$$

$$out - d(v_4) = (1.2610, 1.9387),$$

$$out - d(v_5) = (1.0316, 2.1397).$$

The ranking of the factors of $V_k, \forall k = 1, 2, ..., n$, on the basis of membership degrees of $out - d(v_k)$, we get $v_1 > v_2 > v_4 > v_3 > v_5$. Hence, v_1 (loamy soil) is the most acceptable soil for paddy forming.

The two working techniques produced the same ranking order after a generic comparison. Even if the ranking order remains the same when comparing the different similarity measures, one parameter called "time consumption" identifies the suggested algorithm as the best one. Thus, in comparison to TOPSIS algorithms (see [22]), our approach produces results a bit quicker. Hence, the suggested statistical approach is best suited for GDM issues in an intuitionistic fuzzy environment.

The advantage of the suggested approach is that it might help you make better decisions as a group now and in the future when the information is given in fuzzy numbers. The functional connection between variables (the relationship between CC and RC measures) is also measured using this method. Furthermore, this kind of statistical idea (correlation coefficient, association coefficient, variation coefficient measures, etc.) may be used for other kinds of fuzzy graphs (hesitancy fuzzy graphs, polar graphs, complex fuzzy graphs, etc.).

5. Conclusions

On the basis of intuitionistic fuzzy proof, several entropy and similitude estimation schemes have recently been applied to GDM issues. In addition to these, this suggested statistical technique is well suited for decision-making processes to assign replacement ranks and aid in selecting the best alternatives. In this paper, we extended the idea of statistical measurements from IFS to IFGs and their associated applications. As a result, the regression coefficient measure and the Laplacian energy concepts were successfully used in a real-world scenario to select the optimal soil for the best paddy production. In the future, these kinds of measures (ex: correlation coefficient measure, association coefficient measure, variation coefficient measure, etc.) may also be used to provide better alternatives for many kinds of fuzzy graphs (hesitancy fuzzy graphs, complex fuzzy graphs, Pythogerian fuzzy graphs, etc.). In the end, the relationship between the correlation and regression coefficient measures was also proven.

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Conflict of interest

The authors declare that they have no conflicts of interest.

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