# ORDERED INTUITIONISTIC FUZZY SOFT MODEL OF FLOOD ALARM

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ABSTRACT. A flood warning system is a non-structural measure for flood mitigation. Several parameters are responsible for flood related disasters. This work illustrates an ordered intuitionistic fuzzy analysis that has the capability to simulate the unknown relations between a set of meteorological and hydrological parameters. In this paper, we first define ordered intuitionistic fuzzy soft sets and establish some results on them. Then, we define similarity measures between ordered intuitionistic fuzzy soft (OIFS) sets and apply these similarity measures to five selected sites of Kerala, India to predict potential flood.

#### 1. Introduction

An efficient flood alarm system may significantly improve public safety and mitigate damages caused by inundation. Flood forecasting is undoubtedly a challenging field of operational hydrology, and over the years lots of analytical works have accumulated in related areas. Although conceptual models allow a deep understanding of the hydrological processes, their calibration requires the collection of a great amount of information regarding the physical properties of the watershed under study, which may be expensive and very time consuming. Since flood warning systems do not aim at providing an explicit knowledge of the rainfall process, black box models are largely used besides the traditional physically-based ones. Over the last decade, fuzzy technology (FT) has been increasingly used in hydrological forecasting. Furthermore, its computational speed in simulating and forecasting is welcomed in real time operations.

A flood warning system is a non-structural measure for flood mitigation. Several parameters are responsible for flood related disasters. A quick-responding flood warning system is required for effective flood mitigation measures. Atmospheric parameters affecting floods are rainfall, wind speed, wind direction, relative humidity and surface pressure. River and topography are two other local parameters.

In our daily life, we frequently deal with vague or imprecise information. Information available is sometimes vague, sometimes inexact or sometimes inefficient. Out of the several higher order fuzzy sets, intuitionistic fuzzy sets (IFS) by Atanassov [1] has been found to be highly useful in dealing with vagueness. IFS is described by two functions: a membership function and a non-membership function. The

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U	Wind speed	Wind direction	Relative humidity	Surface pressure
$L_1$	1	0	1	0
$L_2$	1	0	1	1
$L_3$	0	1	1	1
$L_4$	1	0	0	0
$L_5$	0	1	0	1

Table 1. Tabular Representation of a Soft Set

importance of membership degree varies in different situations. The importance of wind speed may be different for different locations, i.e. one parameter is important for one location and it may be unimportant for another location. So we need a generalization of intuitionistic fuzzy sets, which is called "ordered intuitionistic fuzzy sets". The location important parameters are termed as weighted indices. If the weighted indices are unity, then ordered intuitionistic fuzzy sets coincide with intuitionistic fuzzy sets. Many researchers have applied the fuzzy approach to various fuzzy models [15, 2, 3] and rainfall runoff models [14, 4, 6, 7, 8, 9, 10, 16]. In this paper we define ordered intuitionistic fuzzy soft sets and establish some results on them.

## 2. Preliminaries

We present brief preliminaries on the theory of soft sets, fuzzy soft sets, intuitionistic fuzzy sets and intuitionistic fuzzy soft sets mainly from [13, 12, 1, 11].

**Definition 2.1.** [13] Let U be an initial universe set and E be a set of parameters (real-valued variables). Let P(U) denote the power set of U and  $A \subset E$ . A pair (F, A) is called a soft set over U, where F is a mapping given by  $F: A \to P(U)$ .

**Example 2.2.** Let the initial universe  $U = \{L_1, L_2, L_3, L_4, L_5\}$  be the five selected locations in Kerala, viz., Trivandrum, Alappuzha, Cochin AP (Airport), Palakkad and Kozhikode and  $E = \{P_1, P_2, P_3, P_4\}$  be the atmospheric parameters, where  $P_1, P_2, P_3, P_4$  are wind speed, wind direction, relative humidity and surface pressure respectively. Suppose that

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F(P_1) = \{L_1, L_2, L_4\},\
F(P_2) = \{L_3, L_5\},\
F(P_3) = \{L_1, L_2, L_3\},\
F(P_4) = \{L_2, L_3, L_5\}.
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Each approximation has two parts

- (i) a predicate p
- (ii) an approximate value set.

Consider  $F(P_1)$ , here predicate name is wind speed and value set is  $\{L_1, L_2, L_4\}$ .

**Definition 2.3.** [12] Let U be an initial universe set and E be a set of parameters (real-valued variables). Let P(U) denote the set of all fuzzy sets of U and  $A \subset E$ .

A pair (F,A) is called a fuzzy soft set over U, where F is a mapping given by  $F:A\to P(U)$ .

**Example 2.4.** Consider the Example 2.2, Suppose that

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\begin{split} F(P_1) &= \{L_1/0.7, L_2/0.6, L_3/0.6, L_4/0.9, L_5/0.5\}, \\ F(P_2) &= \{L_1/0.7, L_2/0.8, L_3/0.9, L_4/0.6, L_5/0.9\}, \\ F(P_3) &= \{L_1/0.8, L_2/0.8, L_3/1.0, L_4/0.7, L_5/0.8\}, \\ F(P_4) &= \{L_1/0.9, L_2/0.9, L_3/1.0, L_4/0.8, L_5/0.9\}. \end{split}
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**Definition 2.5.** [1] Let E be a fixed set and  $A \subset E$ . Intuitionistic fuzzy set or IFS in E is an object having the form  $A = \{\langle x, \mu_A(x), \nu_A(x) \rangle | x \in E\}$ , where the function  $\mu_A : E \to [0,1]$  and  $\nu_A : E \to [0,1]$  define the degree of membership and non-membership respectively of the element x to the set A. Also  $0 \le \mu_A(x) + \nu_A(x) \le 1$ ,  $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$  is called the indeterministic part for x. Clearly  $0 \le \pi_A(x) \le 1$ .

**Definition 2.6.** [11] Let U be an initial universe set and E be a set of parameters. Let P(U) denote the set of all intuitionistic fuzzy sets of U and  $A \subset E$ . A pair (F, A) is called an intuitionistic fuzzy soft set over U, where F is a mapping given by  $F: A \to P(U)$ .

**Example 2.7.** Let the universe set  $U = \{L_1, L_2, L_3, L_4, L_5\}$  be a set of tropical river systems in Kerala. Let E be the set of parameters. Each parameter is a fuzzy word or a sentence involving fuzzy words.  $E = \{P_1, P_2, P_3, P_4\}$ , where  $P_1 = wind \ speed \$ ,  $P_2 = wind \ direction, P_3 = relative \ humidity, P_4 = surface \ pressure.$  The intuitionistic fuzzy soft set (F, E) is defined as  $(F, E) = \{ \{ wind \ speed \}, \{ wind \ direction \}, \{ relative \ humidity \}, \{ surface \ pressure \} \} = \{L_1/(0.7, 0.2), L_2/(0.6, 0.3), L_3/(0.6, 0.2), L_4/(0.9, 0), L_5/(0.5, 0.3)\}, \{L_1/(0.7, 0.3), L_2/(0.8, 0.1), L_3/(0.9, 0), L_4/(0.6, 0.3), L_5/(0.9, 0)\}, \{L_1/(0.8, 0.1), L_2/(0.8, 0.1), L_3/(1.0, 0), L_4/(0.7, 0.2), L_5/(0.8, 0.1)\}, \{L_1/(0.9, 0), L_2/(0.9, 0), L_3/(1.0, 0), L_4/(0.8, 0.1), L_5/(0.9, 0)\}.$ 

#### 3. Model Formulation

The application of fuzzy modeling normally includes three procedures, i.e. fuzzification, logic decision and defuzzification. Fuzzification involves the identification of the input variables and the control variables (outputs), the division of both input and the control variables into different domains, and choosing a membership and non-membership function. Logic decision involves process design (formulas and algorithms), and the determination of output which may retain a fuzzy or crisp nature. If the output produced is of a fuzzy nature it will require defuzzification which will produce a crisp output. Interpretation of real world situations may be based on either the output of the logic decision or the defuzzified crisp output.

**Definition 3.1.** Let E be a fixed set and  $A \subset E$ . For  $p, q \in N$ , an ordered intuitionistic fuzzy (OIF) set in E is an object having the form  $A_{p,q} = \{\langle x, (\mu_A(x))^p, (\nu_A(x))^q \rangle | x \in E\}$  where, the functions  $\mu_A^p : E \to [0,1]$  and  $\nu_A^q : E \to [0,1]$  define the degree of

membership and non-membership respectively of the element x to the set A. p. and q are called weighted indices of the set A. Also  $0 \le (\mu_A(x))^p + (\nu_A(x))^q \le$  $1, \pi_{A_{p,q}}(x) = 1 - (\mu_A(x))^p - (\nu_A(x))^q$  is called the ordered indeterministic part for x. Clearly  $0 \le \pi_{A_{p,q}}(x) \le 1$ . If p = q = 1, then  $A_{1,1} = \{\langle x, (\mu_A(x))^1, (\nu_A(x))^1 \rangle | x \in P \}$  is called intuitionistic fuzzy set.

**Definition 3.2.** If  $A_{p,q}$  and  $B_{r,s}$  are two ordered intuitionistic fuzzy sets of the set

- 1.  $A_{p,q} \subset B_{r,s}$  iff  $\forall x \in E, [(\mu_A(x))^p \le (\mu_B(x))^r$  and  $(\nu_A(x))^q \ge (\nu_B(x))^s]$ .  $A_{p,q} \subset B_{r,s} \text{ iff } B_{r,s} \supset A_{p,q}$ .
- 2.  $A_{p,q} = B_{r,s}$  iff  $\forall x \in E, [(\mu_A(x))^p = (\mu_B(x))^r \text{ and } (\nu_A(x))^q = (\nu_B(x))^s].$
- 3.  $\overline{A}_{p,q} = \{ \langle x, (\nu_A(x))^q, (\mu_A(x))^p \rangle | x \in E \}.$

- 4.  $A_{p,q} \cap B_{r,s} = \{\langle x, \min((\mu_A(x))^p, (\mu_B(x))^r), \max((\nu_A(x))^q, (\nu_B(x))^s)\rangle | x \in E\}.$ 5.  $A_{p,q} \cup B_{r,s} = \{\langle x, \max((\mu_A(x))^p, (\mu_B(x))^r), \min((\nu_A(x))^q, (\nu_B(x))^s)\rangle | x \in E\}.$ 6.  $A_{p,q} + B_{r,s} = \{\langle x, (\mu_A(x))^p + (\mu_B(x))^r (\mu_A(x))^p, (\mu_B(x))^r, (\nu_A(x))^q, (\nu_B(x))^s\rangle | x \in E\}.$
- 7.  $A_{p,q}.B_{r,s} = \{\langle x, (\mu_A(x))^p.(\mu_B(x))^r, (\nu_A(x))^q + (\nu_B(x))^s (\nu_A(x))^q.(\nu_B(x))^s \rangle | x \rangle$

**Definition 3.3.** Let U be an initial universe set and E be a set of parameters. Let  $P_{p,q}(U)$  denote the set of all ordered intuitionistic fuzzy sets of U and  $A \subset E$ . A pair  $(F_{p,q}, A)$  is called an ordered intuitionistic fuzzy soft set over U, where  $F_{p,q}$  is a mapping given by  $F_{p,q}: A \to P_{p,q}(U)$ .

**Definition 3.4.** Ordered intuitionistic fuzzy soft set  $S_{t,u}$  of E is said to be the ordered super intuitionistic fuzzy set of E if  $(\mu_s(x))^t = 1, (\nu_s(x))^u = 0$  and  $\pi_{S_{t,u}}(x) = 0$  $0, \forall x \in E$ . This is possible only if t = u = 1. Therefore the weighted indices of an ordered super intuitionistic fuzzy soft set are unity.

**Definition 3.5.** For two ordered intuitionistic fuzzy soft sets  $A_{p,q}$  and  $B_{r,s}$ ,  $A_{p,q}$  is said to dominate  $B_{r,s}$  if  $T_{dk}^{t,u,p,q}(S_{t,u},A_{p,q}) \geq T_{dk}^{t,u,r,s}(S_{t,u},B_{r,s})$ . The ordered super intuitionistic fuzzy soft set  $S_{t,u}$  clearly dominates all over the ordered intuitionistic fuzzy soft sets of E.

3.1. Similarity Measures Between OIFSs. In this paper, we extend the work done by Chen et al., [5] and Zeshui Xu [18]. Chen examined the similarity measures of fuzzy sets. This work was extended by Zeshui Xu to similarity measures between IFSs. An overview of distance and similarity measures of IFSs was done by Xu et al.,[17]. Here, we introduce the similarity measures of ordered intuitionistic fuzzy soft (OIFS) sets. Let P(U) be the set of all OIFSs of X. Let  $A_{p,q} \in P(U)$  and  $B_{r,s} \in P(U)$  be two ordered intuitionistic fuzzy soft sets, where

$$A_{p,q} = \{ \langle x_i, (\mu_A(x))^p, (\nu_A(x))^q \rangle | x_i \in E \},$$
 (1)

$$B_{r,s} = \{ \langle x_i, (\mu_B(x))^r, (\nu_B(x))^s \rangle | x_i \in E \}.$$
 (2)

Let  $T_{d_k}$  be a mapping such that  $T_{d_k}: (P(U))^2 \to [0,1]$ , for k = 1, 2.

**Definition 3.6.** The similarity measure between two OIFSs is defined as  $T_{d_1}^{p,q,r,s}(A_{p,q},B_{r,s}) =$ 

$$1 - \frac{1}{2n} \sum_{i=1}^{n} \left[ |M^{(p,r)}(i)|^{\frac{(p+r)}{2}} + |N^{(q,s)}(i)|^{\frac{(q+s)}{2}} + |I^{(p,q,r,s)}(i)|^{\frac{w}{4}} \right]$$
(3)

where

$$M^{(p,r)}(i) = (\mu_A(x_i))^p - (\mu_B(x_i))^r,$$
  

$$N^{(q,s)}(i) = (\nu_A(x_i))^q - (\nu_B(x_i))^s,$$
  

$$I^{(p,q,r,s)}(i) = \pi_{A_{p,q}}(x_i) - \pi_{B_{r,s}}(x_i).$$

and n is the number of attributes (parameters) of the system and w = p + q + r + s. If r = p and s = q, then the above formula becomes  $T_{d_1}^{p,q}(A_{p,q}, B_{p,q})$ 

$$=1-\frac{1}{2n}\sum_{i=1}^{n}[|M^{p}(i)|^{p}+|N^{q}(i)|^{q}+|I^{(p,q)}(i)|^{\frac{p+q}{2}}]$$
(4)

where

$$M^{p}(i) = (\mu_{A}(x_{i}))^{p} - (\mu_{B}(x_{i}))^{p},$$
  

$$N^{q}(i) = (\nu_{A}(x_{i}))^{q} - (\nu_{B}(x_{i}))^{q},$$
  

$$I^{(p,q)}(i) = \pi_{A_{p,q}}(x_{i}) - \pi_{B_{p,q}}(x_{i}).$$

**Definition 3.7.** Another form of similarity measure between two OIFSs is defined as  $T_{d_2}^{p,q,r,s}(A_{p,q},B_{r,s})$ 

$$=1-\sqrt{\frac{\sum_{i=1}^{n}[\mid M^{(p,r)}(i)\mid \frac{(p+r)}{2}+\mid N^{(q,s)}(i)\mid \frac{(q+s)}{2}+\mid I^{(p,q,r,s)}(i)\mid \frac{w}{4}]}{\sum_{i=1}^{n}[\mid E^{(p,r)}(i)\mid \frac{(p+r)}{2}+\mid F^{(q,s)}(i)\mid \frac{(q+s)}{2}+\mid G^{(p,q,r,s)}(i)\mid \frac{w}{4}]}}}$$
(5)

where

$$E^{(p,r)}(i) = (\mu_A(x_i))^p + (\mu_B(x_i))^r,$$
  

$$F^{(q,s)}(i) = (\nu_A(x_i))^q + (\nu_B(x_i))^s,$$
  

$$G^{(p,q,r,s)}(i) = \pi_{A_{p,q}}(x_i) + \pi_{B_{r,s}}(x_i).$$

If r = p and s = q, then the above formula becomes  $T_{d_2}^{p,q}(A_{p,q}, B_{p,q})$ 

$$=1-\sqrt{\frac{\sum_{i=1}^{n}[\mid M^{p}(i)\mid^{p}+\mid N^{q}(i)\mid^{q}+\mid I^{(p,q)}(i)\mid^{\frac{(p+q)}{2}}]}{\sum_{i=1}^{n}[\mid E^{p}(i)\mid^{p}+\mid F^{q}(i)\mid^{q}+\mid G^{(p,q)}(i)\mid^{\frac{(p+q)}{2}}]}}$$
(6)

where

$$E^{p}(i) = (\mu_{A}(x_{i}))^{p} + (\mu_{B}(x_{i}))^{p},$$
  

$$F^{q}(i) = (\nu_{A}(x_{i}))^{q} + (\nu_{B}(x_{i}))^{q},$$
  

$$G^{(p,q)}(i) = \pi_{A_{p,q}}(x_{i}) + \pi_{B_{p,q}}(x_{i}).$$

**Remark 3.8.**  $0 \le T_{d_k}^{p,q,r,s}(A_{p,q},B_{r,s}) \le 1.$ 

Remark 3.9.  $T_{d_k}^{p,q,r,s}(A_{p,q},B_{r,s}) = T_{d_k}^{r,s,p,q}(B_{r,s},A_{p,q}).$ 

**Remark 3.10.**  $T_{d_k}^{p,q,r,s}(A_{p,q},B_{r,s})=1$  if and only if  $A_{p,q}=B_{r,s}$ , i.e.  $(\mu_A(x))^p=(\mu_B(x))^r$  and  $(\nu_A(x))^q=(\nu_B(x))^s$  for any  $x_i\in E$ .

**Remark 3.11.** If  $T_{d_k}^{p,q,r,s}(A_{p,q},B_{r,s})=0$  and  $T_{d_k}^{p,q,t,u}(A_{p,q},C_{t,u})=0, C_{t,u}\in P(U)$ , then  $T_{d_k}^{r,s,t,u}(B_{r,s},C_{t,u})=0$ , for k=1,2.

- 3.2. Similarity Measure Algorithm. Reliable flood prediction cannot be done by subjecting available data to conventional methods of analysis. We therefore turn to ordered intuitionistic fuzzy soft sets and develop a simple but effective model (algorithm) which has been designed in such a way as to produce reliable output in the prediction of flood possibility. The inputs are basic parameters (real-valued variables) related to flood occurrence and fuzzy membership and non-membership degrees were assigned to each parameter. The model processes the ordered intuitionistic fuzzy soft set constructed from collected data and identifies the most flood prone location (the location which shows maximum discrimination factor).
  - (1) Selection of a desired number of parameters  $(P_i)$ .
  - (2) Selection of a desired number of locations  $(L^i)$ .
  - (3) Constructing ordered intuitionistic fuzzy set

$$L_{p,q}^{i} = \{ \langle P_{j}, (\mu_{L_{p,q}^{i}}(P_{j}))^{p}, (\nu_{L_{p,q}^{i}}(P_{j}))^{q} \rangle | P_{j} \in E \}.$$
 (7)

- (4) Calculating  $\pi_{L_{p,q}^i}(P_j)$ .
- (5) Calculating  $T_{d_k}^{t,u,p,q}(S_{t,u},L_{p,q}^i)$  for k=1,2.
- (6) Find  $L^i$  for which

$$T_{d_k}^{t,u,p,q}(S_{t,u}, L_{p,q}^i) = \max_i T_{d_k}^{t,u,p,q}(S_{t,u}, L_{p,q}^i). \tag{8}$$

- (7) If  $L^i$  is not unique, choose that one corresponding to which  $\pi_{L^i_{p,q}}(P_j) = \sum_{i=1}^m \pi_{L^i_{p,q}}(P_j)$  is the greatest.
- (8) The optimal solution is  $L^i$ .

# 4. Experiment and Results

4.1. **Study Area.** The area selected for the study is Kerala, a narrow segment in the south western part of Peninsular India, extending over a distance of 560Km along the west coast with width varying from 15 to 420Km within a limited area of  $38,863Km^2$  and presents very wide variation in its physical features. Physiographically, Kerala is subdivided into highland (elev.= > 75m), midland (7.5-75m) and lowland (< 7.5m) regions. The lowland (coastal land) is unique in many ways, viz., high density of population, fragile nature of shoreline, presence of many rivers, estuaries, backwaters, bays etc. Natural calamities like flood and coastal erosion are common events in many regions in the lowlands of Kerala during the monsoon season.

Towards monitoring and assessing the flood system in the coastal lands of Kerala, five locations viz., Trivandrum (N. Lat. 08:31:00 and E. Long. 76:50:00), Alappuzha (N.Lat.09:30:00 and E.Long.76:50:00), Cochin AP (N.Lat.09:54:00 and E.Long.76:16:00), Kozhikode (N.Lat.11:17:01 and E.Long 75:50:00) and Palakkad (N.Lat:10:45:00 and E.Long.76:45:00) have been selected (Figure 1). The first four locations are in the low to mid-coastal region especially vulnerable to flood and have a relatively higher density of population. Palakkad, the "Rice Bowl of Kerala", a

Label	Location	Geographical desc.	Topography	Rivers/Backwaters
$L_1$	Trivandrum	Coastal Mid land	Moderate	River=1,Backwater=1
$\parallel L_2$	Alappuzha	Coastal Low land	Low	Backwater=1
$\parallel L_3$	Cochin AP	Coastal Low land	Low	River=1,Backwater=1
$\parallel L_4$	Palakkad	Inland (Mid land)	Moderate	River=1
$L_5$	Kozhikode	Coastal Mid land	Moderate	River=1

Table 2. Catchments Descriptions

plateau devoid of a shore face, is located in the midland. The selected locations are natural laboratories in the tropical river systems of Kerala offering representative geographical regions enabling flood related studies based on the model discussed.

4.2. **The Result.** The study intends to predict the possibility and severity of floods in five selected stations in Kerala. We define ordered intuitionistic fuzzy soft set properties to establish an algorithm for a reliable prediction. Simulations are done using Java Server Pages. The five selected locations in Kerala, Trivandrum, Alappuzha, Cochin AP, Plaakkad and Kozhikode are denoted by  $L^1, L^2, L^3, L^4$ , and  $L^5$ . The parameter set  $E = P_1, P_2, P_3, P_4, P_5, P_6, P_7$  respectively denotes wind speed, wind direction, relative humidity, surface pressure, river contribution, topography, and rainfall amount.

$$L_{p,q}^i = \{\langle P_j, (\mu_{L_{p,q}^i}(P_j))^p, (\nu_{L_{p,q}^i}(P_j))^q \rangle | P_j \in E\}, \ i = 1, 2, 3, 4, 5 \text{ and } j = 1, 2, ..., 7, 1, 2, \dots, 7, 1, 2, \dots,$$

where  $(\mu_{L_{p,q}^i}(P_j))^p$  indicates the degree that the location  $L^i$  satisfies the parameter  $P_j$ ,  $(\nu_{L_{p,q}^i}(P_j))^q$  indicates the degree to which the location  $L^i$  does not satisfy the parameter  $P_j$  and  $(\mu_{L_{p,q}^i}(P_j))^p \in [0,1], (\nu_{L_{p,q}^i}(P_j))^q \in [0,1], (\mu_{L_{p,q}^i}(P_j))^p + (\nu_{L_{p,q}^i}(P_j))^q \leq 1$ . Let  $\pi_{L_{p,q}^i}(P_j) = 1 - (\mu_{L_{p,q}^i}(P_j))^p - (\nu_{L_{p,q}^i}(P_j))^q$ , for all  $P_j \in E$ . Since  $(\mu_{S_{t,u}}(x))^t = 1$ ,  $(\nu_{S_{t,u}}(x))^q = 0$ ,  $\pi_{S_{t,u}}(x) = 0$  and t = u = 1.

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The ordered intuitionistic fuzzy soft set is
E = \{\{P_1\}, \{P_2\}, \{P_3\}, \{P_4\}, \{P_5\}, \{P_6\}, \{P_7\}\}, \text{ where }
\{P_1\} = \{L^1/((0.7)^2, (0.1)^1), L^2/((0.6)^1, (0.2)^2), L^3/((.6)^2, (0.2)^2), L^4/((.9)^2, (.05)^1), L^4/((.9)^2, (.05)^2), L^4/((.9)
                                                                                                                                              L^5/((.5)^2, (.25)^1),
{P_2} = {L^1/((0.7)^1, (0.2)^2), L^2/((0.8)^1, (0.1)^3), L^3/((0.9)^3, (.05)^2), L^4/((.6)^1, (.3)^2), L^4/((.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, (.6)^3, 
                                                                                                                                              L^5/((.9)^2, (.05)^1),
{P_3} = {L^1/((0.8)^1, (0.1)^1), L^2/((0.8)^1, (0.1)^3), L^3/((1)^1, (0)^1), L^4/((0.7)^2, (0.2)^1), L^4/((0.8)^1, (0.1)^2), L^4/((0.8)^2, (0.1)^3), L^3/((0.1)^3), L^3/(
                                                                                                                                                  L^5/((0.8)^2, (0.1)^1),
{P_4} = {L^1/((0.9)^2, (.05)^1), L^2/((0.9)^1, (.05)^1), L^3/((1)^1, (0)^1), L^4/((0.8)^1, (0.1)^2),}
                                                                                                                                              L^{5}/((0.9)^{2},(.05)^{1}),
\{P_5\} = \{L^1/((1.0)^1, (0)^1), L^2/((0.5)^2, (.25)^1), L^3/((1.0)^1, (0)^1), L^4/((0.5)^2, (.25)^1), L^4/((0.5)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, L^4/((0.5)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, L^4/((0.5)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)
                                                                                                                                              L^5/((0.5)^2, (.25)^1),
{P_6} = {L^1/((0.5)^2, (.25)^1), L^2/((1)^1, (0)^1), L^3/((1.0)^1, (0)^1), L^4/((0.5)^2, (0.25)^2), L^4/((0.25)^2, (0.25)^2), L^4/((0.25)^2, (0.25)^2), L^4/((0.25)^2, (0.25)^2), L^4/((0.25)^2, (0.25)^2), L^4/((0.25)^2, 
                                                                                                                                              L^5/((0.5)^2, (0.25)^1),
\{P_7\} = \{L^1/((0.5)^2, (.25)^1), L^2/((0.6)^1, (.2)^2), L^3/((1.0)^1, (0)^1), L^4/((0.4)^2, (.45)^2), L^3/((0.5)^2, (.25)^2), L^3/((0.5)^2, (.25)^2, (.25)^2), L^3/((0.5)^2, (.25)^2, (.25)^2), L^3/((0.5)^2, (.25)^2, (.25)^2), L^3/((0.5)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.25)^2, (.
                                                                                                                                              L^5/((0.9)^2, (.05)^1).
```

U	$P_1$	$P_2$	$P_3$	$P_4$	$P_5$	$P_6$	$P_7$
$L^1_{(p,q)}$	(.49,.1)	(.7,.04)	(.8,.1)	(.81,.05)	(1,0)	(.25,.25)	(.25,.25)
$L_{(p,q)}^2$	(.6,.04)	(.8,0)	(.8,0)	(.9,.05)	(.25,.25)	(1,0)	(.6,.04)
$L_{(p,q)}^{3}$	(.36, .04)	(.73,0)	(1,0)	(1,0)	(1,0)	(1,0)	(1,0)
$L_{(p,q)}^{4}$	(.81,.05)	(.6,.09)	(.49,.2)	(.8,.01)	(.25, .25)	(.25,.06)	(.16,.2)
$L_{(p,q)}^{\overset{\leftarrow}{5}^{r,q}}$	(.25, .25)	(.81,.05)	(.64,.1)	(.81,.05)	(.25,.25)	(.25,.25)	(.81,.05)

Table 3. Ordered Intuitionistic Fuzzy Soft Set

U	$P_1$	$P_2$	$P_3$	$P_4$			$P_7$
$\pi_{L_{p,q}^1}(P_j)$	0.41	0.26	0.1	0.14	0.0	0.5	0.5
$\parallel \pi_{L^2_{-}}(P_i)$	0.36	0.199	0.199	0.05	0.5	0.0	0.36
$\parallel \pi_{L^3} (P_i)$	0.6	0.2685	0.0	0.0	0.0	0.0	0.0
$\parallel \pi_{L_{n,a}^4}(P_j)$	0.14	0.31	0.31	0.19	0.5	0.6875	0.6375
$\pi_{L^5_{p,q}}(P_j)$	0.5	0.14	0.26		0.5	0.5	0.14

Table 4. Representation of  $\pi_{L_{p,q}^i}(P_j)$ 

$L_{p,q}^i$	$T_{d_1}^{t,u,p,q}(S_{t,u},L_{p,q}^i)$	$T_{d_2}^{t,u,p,q}(S_{t,u},L_{p,q}^i)$
$L^1_{p,q}$	0.4303	0.4469
$L_{p,q}^{2^{-1}}$	0.5022	0.4517
$L_{p,q}^{3^{\prime\prime}}$	0.7048	0.7167
$L_{p,q}^{4}$	0.3458	0.3573
$L_{p,q}^{5,q}$	0.3956	0.4352

Table 5.  $T_{d_k}^{t,u,p,q}(S_{t,u}, L_{p,q}^i)$  for k = 1, 2

From all the similarity measures, we get  $L^3 > L^2 > L^1 > L^5 > L^4$ .

4.3. **Discussions.** An algorithm has been developed and implemented for the automated generation of flood alarm system. In our study we have considered five locations and seven parameters to predict the possibility of flood. The membership and non-membership degrees are designed from a prolonged study of available data. The seven parameters namely wind speed, wind direction, humidity, surface pressure, river contributions, topographical characteristics and rainfall amount are those which have a predominant role on the flood possibility.

One of the most notable difference in this fuzzy approach is that the membership degrees for each of these fuzzy variables are carefully derived from suitable relationships using standardized methods. Therefore the results of the fuzzy decisions are more reliable and dependable. In short, the statistical spatial temporal model is replaced by a more generalized fuzzy decision system. This gives us a more consistent result. Moreover, the fuzzy decision system makes use of the fuzziness in decision making which is the predominating factor in making predictions and control of a given system. **Reliability of the Formula:** The cumulated measure,  $T_{d_k}^{t,u,p,q}(S_{t,u},L_{p,q}^i)$  is analyzed on the lime light of its reliability factor. The two types of similarity measures based on the ordered super intutionistic fuzzy soft set, always gives a reliable single value. Since our parameters are chosen in such a way that they play a vital role in rainfall in some particular topographical conditions.

Basically in  $T_{d_k}^{t,u,p,q}(S_{t,u},L_{p,q}^i)$ , we choose t=u=1. Since the weighted indices of an ordered super intutionistic fuzzy set is unity, i.e. t and u are always consistent. But p and q vary in different situations. Therefore p and q are not consistent. Value of p and q are termed as assurance order of location  $L_{p,q}^i$  (compared with  $S_{t,u}$ ).  $T_{d_k}^{t,u,p,q}(S_{t,u},L_{p,q}^i)$  leads to the conclusion that for higher values of p, the membership degree is decreasing. At the same time the non-membership degree is increasing for the smaller values of q, i.e. as p increases q decreases and vice-versa. Also, the series of values may change in these different locations for different years. This helps the investigator to arrive at more important conclusions.

#### 5. Conclusion

This article, it is hoped, may go a long way in exploring the possibility of using fuzzy technology to model real time flood prediction. There are varieties of uncertainties in rainfall and flood prediction, and it is difficult to treat these uncertainties using traditional deterministic methods. In this article it has been demonstrated that OIFS (ordered intuitionistic fuzzy soft) model has its potential usage in flood prediction.

The OIFS model presented for flood warning system has furnished very promising results. This model is applied for five selected stations of Kerala, India. The five meteorological parameters collected for sixteen years (1981-1996) for each station were analyzed and a membership and non membership degrees were given to each parameter. Two local parameters (river and topography) were also considered. Simulation done through the Java Server Pages shows that the highest possibility of flood occurrence is in Cochin AP, followed by Alappuzha. A critical discussion on the results of proposed model has been conducted. It provides a new way that helps disaster management studies to cope with fatal and rapid changes in highly sensitive parameters.

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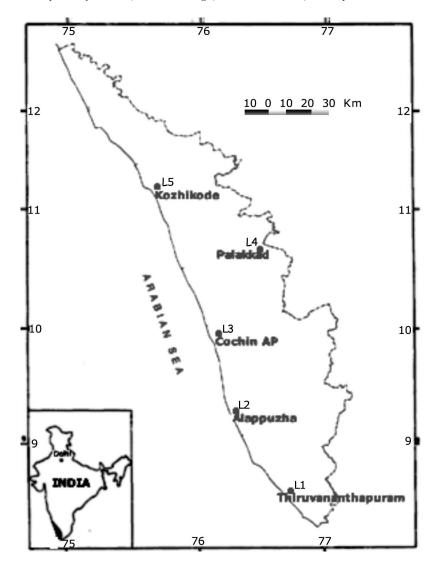


FIGURE 1. Catchment Location Map

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