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Covering Based Soft Rough Fuzzy Set and its Application in Soil Chemical Analysis for Soybean Crop

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Abstract: In the agricultural field several studies were done using mathematical and statistical tools. But these methods are incapable of dealing with the incompleteness and vagueness of data. Hence to deal with such data nowadays non-classical set theories are proving their worth. The study incorporates concepts of covering based rough set with soft set and fuzzy set. Various literature is available in which soft, rough, and fuzzy sets are applied but none of them are based on covering features. To analyze soil chemical treatments for the soybean crop an attempt is made through Covering based Soft Rough Fuzzy set (CSRFS). Initially, soft rough subspaces are defined. Then these subspaces are mapped with membership and non-membership functions along with appropriate regions generated through the boundary of soft rough subspaces to define soft rough fuzzy set. Lastly, the ranking of treatments is defined with set-valued mapping, and a comparison of the proposed method is done with the other existing methods. The proposed study namely CSRFS is an extension of the covering based rough set, soft set, and fuzzy set to generate a decision system for soil chemical analysis of Soybean crop.
Keywords: Rough Set, Soft Set, Covering Based Rough Set, Soft Rough Fuzzy Set, Soil Chemical Analysis, and Soil Fertility.

1. Introduction

With the use of mathematical and statistical approaches, Data Mining is emerging as a vital tool for industrial/organizational sectors of all sizes. Interpretation of real-world data with the help of data mining methodologies provides an insight into the existing aspects in various situations. Non-classical set theory, one of the Data Mining tools, is grabbing the attraction of researchers. Due to its characteristic of dealing with imperfect, incomplete, and vague data, it is being widely used in sectors of pattern recognition, image processing, signal processing, banking, agriculture, the medical industry, and many other fields.

Agriculture is an important sector for developing countries. One of the major factors of the field is soil fertility. The available nutritional values of soil are needed to be timely analyzed for maintaining the appropriate nutritional values required for sown crops. The implication of such a tracking-based system can aid in the better yield of crops. The proposed method is an attempt towards extracting the hidden knowledge in soil chemical analysis.

The non-classical set theories viz. fuzzy set by Zadeh (Zadeh, 1965), rough set by Pawlak (Pawlak, 1982), vague set by Gau and Buhrer (Gao & Danied, 1993) and soft set by Molodtsov (Molodtsov, 1999) are being used for knowledge extraction. Pawlak's rough set theory (RST) is based on the concept of approximation lying under the vagueness of data. It characterizes the universe of discourse in subsets based on equivalence relations. But the classical rough set (RS) does not satisfy many practical situations; therefore investigators have extended rough set to covering-based rough set, tolerance-based rough set, binary relation-based rough set, dominance-based rough set, variable precision rough set, and clustering-based rough set. Zhu has studied generalized rough sets based on covering and also established their relationship with binary relation-based generalized rough sets (Zhu, 2009). In the paper "A Comparison of Two Types of Rough Sets Induced by Coverings", the relation among two different covering-based rough sets and binary relation-based rough sets are depicted (Liu & Sai, 2009). In 2012, a study was proposed for covering based rough set, the authors formulated three different scenarios namely the equivalence relation with element based definition, the partition with granule based definition, and σ-algebra based formulation with subsystem based definition (Yao & Yao, 2012). Huang et. al., presented various concepts in their paper (Huang, Li, & Guofu, 2020). The concepts mentioned in aforementioned paper are intuitionistic fuzzy (IF) β–covering minimal description along with four order relations on IF β approximation space, four IF β–covering based rough sets and their reducts, lastly four optimistic and pessimistic multi-granulation IF β– covering based rough set and their discernibility function based reduction methods.

In soft set, the concept of parameterization is used to describe the universe of discourse (Maji, Biswas, & Roy, 2003). The fusion of rough and soft sets either as a rough soft set or as a soft rough set is flourishing rapidly. In decision making, the duo of these is being proved very beneficial. The authors of the paper "Soft Sets and Soft Rough Sets" (Feng, Liu, Fotea, & Jun, 2011) generalized Pawlak's rough set to soft rough approximation spaces as well introduced new types of soft sets such as full soft sets, intersection complete soft sets, and partition soft sets. In 2011, Ali proposed an approximation space based on soft set for each parameter (Ali, 2011). Meng et. al. in their paper combined fuzzy set, rough set, and soft sets to introduce the soft fuzzy rough set model (Meng, Zhang, & Keyun, 2011). Karaaslan introduced the concept of soft class and soft rough class along with their properties (Karaaslan, 2016). In a paper published by "Annals of Pure and Applied Mathematics", a multi-granular rough soft set and its properties are proposed (Rani, Rajeshwari, & Seronmani, 2017).

The present study describes an extension of Covering-based Rough Set to Covering based Soft Rough Fuzzy Set. The basic notations along with an algorithm are mentioned and the developed theory is then applied to the soil chemical analysis to obtain the optimum treatment for better yield of the soybean crop.

2. Material and Method

2.1 Preliminaries

This section contains fundamental facts about Rough Set (RS) (Pawlak, 1982), Covering Based Rough Set (CRS), and Soft Set (Molodtsov, 1999). RS provides a probable region grounded on the lower and upper approximations (Walczak & Massart, 1999). Soft set is the concept based on parameterization (Molodtsov, 1999).

Let *U* be the universal set.

Definition 2.1.1: An information system IS (or rough approximation space) is defined as a pair IS = (*U, T*) where *U* = non-empty finite set called the universe, *T* = non-empty finite set of attributes. Each attribute of *T* i.e. $a \in T$ defines an information function $f_a : U \to V_a$, where V_a called as domain the set of values of *a*.

Definition 2.1.2: Let $\hat{C}$ be a family of non-empty subsets of *U*. If $\cup\hat{C} = U$, then $\hat{C}$ is called covering of *U* and if $\hat{C}$ is a family of disjoint subsets of *U* then it is called the partition of *U*.

Definition 2.1.3: The minimal description of I is defined as:

$$Md(y) = \left\{ A \in \hat{C} \mid y \in A \wedge \left(\forall B \in \hat{C} \wedge y \in B \wedge B \subseteq A \Rightarrow A = B \right) \right\}.$$

Definition 2.1.4: The neighborhood of y is defined as: $Neighbor(y) = \cap\left\{ A \mid y \in A \in \hat{C} \right\}$.

Definition 2.1.5: The covering lower and covering upper approximations:

$$CL(Y) = \left\{ y \mid Neighbor(y) \subseteq Y \right\} \text{ and } CH(Y) = \left\{ y \mid Neighbor(y) \cap Y \neq \phi \right\}$$

Definition 2.1.6: The boundary of a region:

$$Bn(Y) = CH(Y) - CH(L)$$

Definition 2.1.7: Let *D* be the set of parameters, *P(U)* denote the power set of *U* and $E \subseteq D$. The pair $\delta = (F, E)$ is called a soft set over *U* with the mapping $F : E \rightarrow P(U)$.

Definition 2.1.8: Let U be the universal set and $\xi \subseteq U \times U$ be a crisp relation. The mapping $\xi^* : U \rightarrow P(U)$ defined by $\xi^*(\alpha) = \{ y \in U \mid (\alpha, y) \in \xi \}, \alpha \in U$ is known to be the set-valued mapping (SVM).

2.2 Method and Application

This section provides the proposed methodology and its application from the preprocessing of soil chemical analysis data into an information table, membership function, and non-membership function to determine the ranking of soil chemical treatments. The proposed method then provides a layout of the decision system based on available soil nutritional values. The given chart shows the proposed methodology (figure 1).

The Table 1 gives preprocessed information system for soil chemical analysis of soybean crop having treatments $U = \{T_1, T_2, T_3, T_4, T_5\}$ as objects and the set $L = \{A, B, C, D\}$ of attributes where *A* = nitrogen, *B* = phosphorous oxide, *C* = potassium oxide, and *D* = sulphur. The domain V_z = {a, b, c}, where a, b, c represents the concentration of nutrients as low, medium, and high respectively, categories the attributes of the set *L*. Table 2 and Table 3 provide preprocessed membership function λ and non-membership function γ respectively for different soil chemical treatments and their corresponding attribute values.

Table 1: Information System

$U\downarrow / L\rightarrow$	*A*	*B*	*C*	*D*
T_1	a	b	a	b
T_2	b	b	a	b
T_3	b	c	a	b
T_4	c	c	c	c
T_5	b	c	b	c

Table 2: Membership Function

$U\downarrow / L\rightarrow$	*A*	*B*	*C*	*D*
T_1	0.23	0.51	0.18	0.31
T_2	0.37	0.54	0.20	0.35
T_3	0.48	0.74	0.28	0.28
T_4	0.72	0.78	0.86	0.83
T_5	0.70	0.73	0.60	0.79

Table 3: Non-Membership Function

$U\downarrow / L\rightarrow$	*A*	*B*	*C*	*D*
T_1	0.96	0.74	0.97	0.90
T_2	0.86	0.71	0.96	0.88
T_3	0.77	0.45	0.92	0.92
T_4	0.48	0.39	0.26	0.31
T_5	0.51	0.47	0.64	0.38

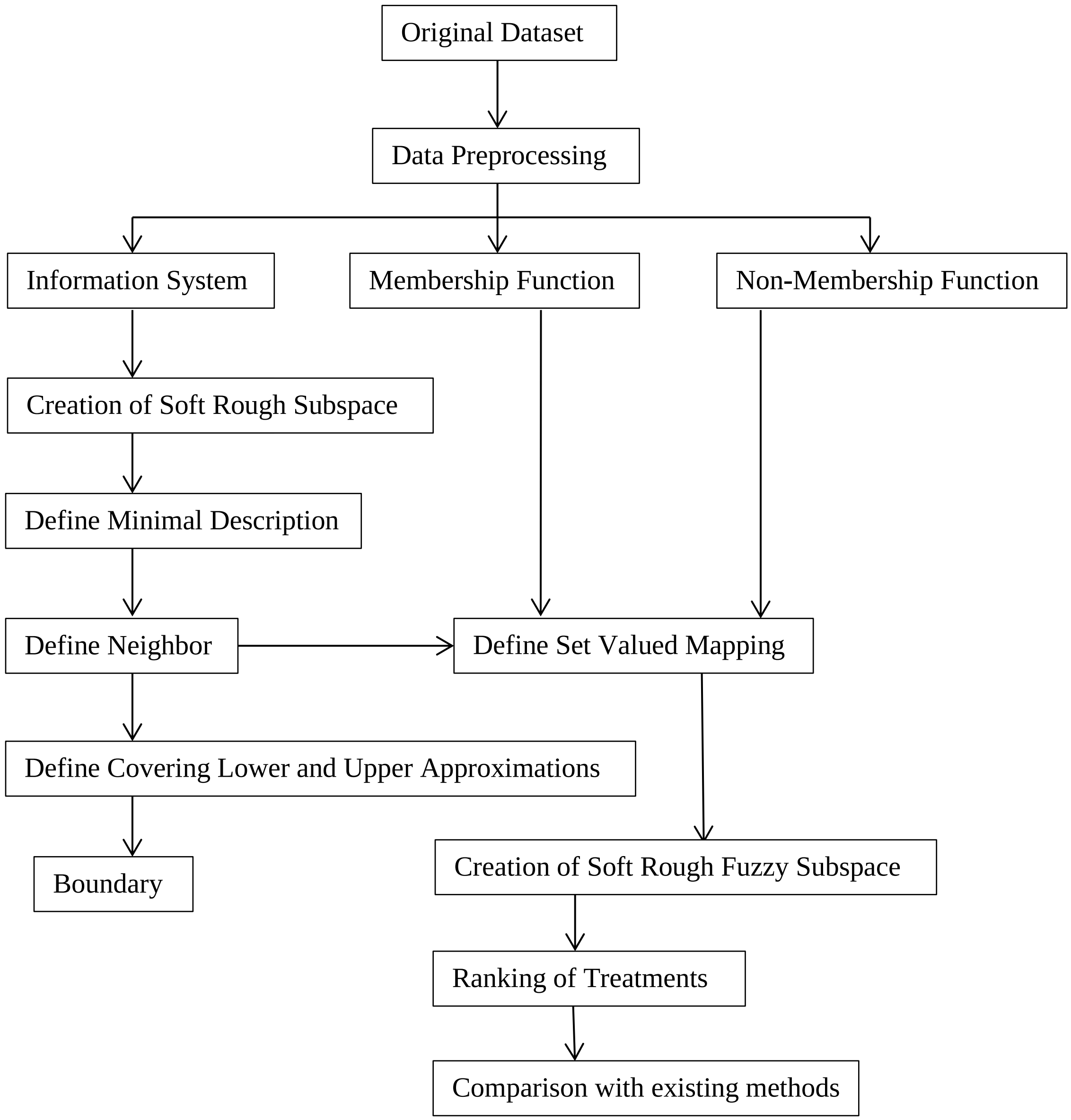

Figure 1: Proposed Framework for Covering Soft Rough Fuzzy set

2.2.1 Soft Rough Subspace: The Soft Rough Subspace (SRS) is defined as the subset of the universe of discourse having the same values for corresponding attributes. SRS for a, b and c are defined by

$$f(L): T \to P(U), \text{ where } T: U \to V_c$$

$$g(L): T \to P(U), \text{ where } T: U \to V_b$$

$$h(L): T \to P(U), \text{ where } T: U \to V_a.$$

The given information system is divided into three SRS as follows:

$f(A) = \{T_4\}$, $f(B) = \{T_4, T_5\}$, $f(C) = \{T_4\}$, $f(D) = \{T_4, T_5\}$;

$g(A) = \{T_2, T_3, T_5\}\{T_3\}$, $g(B) = \{T_1, T_2\}$, $g(C) = \{T_5\}$, $g(D) = \{T_1, T_2, T_3\}$;

$h(A) = \{T_1\}$, $h(B) = \phi$, $h(C) = \{T_1, T_2, T_3\}$, $h(D) = \phi$.

These subspaces are called as covering of *U*.

2.2.2 Minimal description of Soft Rough Subspace: Let $\hat{H}$ be the covering of *U* and let *t* ∈ *U* then the minimal description of t is defined as:

$$E(t)=\left\{K\in\hat{H}\mid t\in K\wedge\left(\forall M\in\hat{H}\wedge t\in M\wedge M\in K\Rightarrow K=M\right)\right\}$$

where $K=f(L)\vee g(L)\vee h(L)$.

The minimal description of soft rough subspace is:
$E(T_1)=\{g(B), h(A)\}$, $E(T_2)=\{g(B), h(C)\}$, $E(T_3)=\{g(A), g(D), h(C)\}$, $E(T_4)=\{f(A), f(C)\}$, $E(T_5)=\{f(A), f(C), g(C)\}$.

2.2.3 Neighbor of Soft Rough Subspace: The neighbor is defined as: $N(t)=\bigcap\left\{K\mid t\in K\in\hat{H}\right\}$.

The neighbor of soft rough subspace is:
$N(T_1)=\{T_1, T_2\}$, $N(T_2)=\{T_1, T_2, T_3\}$, $N(T_3)=\{T_1, T_2, T_3, T_5\}$, $N(T_4)=\{T_4\}$, $N(T_5)=\{T_4, T_5\}$.

2.2.4 Covering Lower and Upper Approximation of Soft Rough Subspace: The lower and upper approximations are defined by:

$$X_*=\{t\mid N(t)\subseteq F\} \text{ and } X^*=\{t\mid N(t)\cap F\neq\phi\}$$

where $F\subseteq P(U)$.

2.2.5 Boundary of Soft Rough Subspace: The boundary is defined by:

$$\mathrm{Bn(X)}=\mathrm{X}^*-\mathrm{X}_*$$

Let $X_1=\{T_2\}$, $X_2=\{T_2, T_3, T_4\}$, $X_3=\{T_1, T_2\}$, $X_4=\{T_1, T_3, T_4, T_5\}$, $X_5=\{T_1, T_2, T_3, T_4, T_5\}$ be the subsets of universal set.
The lower approximation based on soft rough subspace for given sets:
$(X_1)_*=\phi$, $(X_2)_*=\{T_4\}$, $(X_3)_*=\{T_1, T_2\}$, $(X_4)_*=\{T_4, T_5\}$, $(X_5)_*=\{T_1, T_2, T_3, T_4, T_5\}$.
The upper approximation based on soft rough subspace for given sets:
$(X_1)^*=\{T_1, T_2\}$, $(X_2)^*=\{T_1, T_2, T_3, T_4, T_5\}$, $(X_3)^*=\{T_1, T_2, T_3, T_4, T_5\}$, $(X_4)^*=\{T_1, T_2, T_3, T_4, T_5\}$, $(X_5)^*=\{T_1, T_2, T_3, T_4, T_5\}$.
The boundary based on soft rough subspace for given sets:
$\mathrm{Bn}(X_1)=\{T_1, T_2\}$, $\mathrm{Bn}(X_2)=\{T_1, T_2, T_3, T_5\}$, $\mathrm{Bn}(X_3)=\{T_3, T_4, T_5\}$, $\mathrm{Bn}(X_4)=\{T_1, T_2, T_3\}$, $\mathrm{Bn}(X_5)=\phi$.

2.2.6 Set-Valued Mapping of Soft Rough Fuzzy Subspace: Let U be the universal set and $\xi\subseteq U\times U$ be a rough set relation with the probable region. The set-valued mapping of Soft Rough Fuzzy Subspace is defined by $\xi^*(\alpha_i)=\{(N(t)\in U,\lambda(N(t)),\gamma(N(t)))\mid(\alpha_i,N(t))\in\xi\}$ is known to be the set-valued mapping (SVM) where $\lambda(N(t))=\max\limits_{t_i\in N(t)}(\lambda(t_i))$ and $\gamma(N(t))=\min\limits_{t_i\in N(t)}(\gamma(t_i))$.

The set-valued mapping is defined by:

$\xi^*(T_1)=\{(T_1,0.23,0.96),(T_2,0.54,0.71)\}$,

$\xi^*(T_2)=\{(T_1,0.51,0.74),(T_2,0.54,0.71),(T_3,0.74,0.45)\}$,

$\xi^*(T_3)=\{(T_1,0.31,0.90),(T_2,0.37,0.86),(T_3,0.48,0.77),(T_5,0.79,0.38)\}$,

$\xi^*(T_4)=\{(T_4,0.86,0.26)\}$,

$\xi^*(T_5)=\{(T_4,0.86,0.26),(T_5,0.79,0.38)\}$

2.3 Algorithm

Input:

Information System; L: attributes and U: objects

Membership Function λ and Non-membership Function γ

X_k: Subsets of $P(U)$ to define boundary regions

Begin

Create Soft Rough subspaces: f(X), g(X), h(X).

for j = 1 to m

Begin

E(Tj) $\leftarrow$ *Minimal Description for subspaces*

Calculate N(Tj), $\forall j$ *//Neighbor for subspaces*

End

$(X_k)_*$ *//Lower approximation*

$(X_k)^*$ *// Upper approximation*

$Bn(X_k)$ *// Boundary Region*

Create soft rough fuzzy subspace

for i = 1 to n

Begin

$\xi^*(\alpha_i) \leftarrow$ *The set-valued mapping associated with every element of U*

//Set-valued mapping is defined for objects of the approximated region with the maximum value of membership function and minimum value of non-membership function.

End

Output: *The ranking of soil chemical treatment in descending order of membership function from set-valued mapping*

End

The above algorithm describes the proposed methodology step by step.

(i) It takes the information system, membership function, and non-membership function as input.

(ii) The first step involves the creation of soft rough subspaces based on categorical attribute values as defined in Section III.

(iii) Then the minimal description of all objects is defined in terms of soft rough subspaces.

(iv) Afterward, the neighbor of soft rough subspaces is created based on the minimal descriptions.

(v) Covering-based lower and upper approximations along with boundary regions for different subsets are then defined.

(vi) The soft rough fuzzy subspace is created through set-valued mapping by utilizing the neighbor of the soft rough set, membership function, and non-membership function.

(vii) The desired output of the algorithm is the ranking of soil chemical treatments in descending order of membership function from set-valued mapping.

3. Result

In section 2, the procedure of Covering based Soft Rough Fuzzy Set is derived and explained with the dataset of soil chemical treatments for the Soybean crop. The Covering based Soft Rough Fuzzy Set for the information system is

$$\xi^*(U) = \{(T_1, 0.51, 0.74), (T_2, 0.54, 0.71), (T_3, 0.74, 0.45), (T_4, 0.86, 0.26), (T_5, 0.79, 0.38)\}$$

From the set-valued mapping of the universal set, it is concluded that T_4 is the optimum chemical treatment among others. The order of treatments is: $T_4 > T_5 > T_3 > T_2 > T_1$.

4. Comparison and Discussion

Rough Set is proving its effectiveness for agricultural data. Few of the soil fertility-related works are summarized here.

Chen and Ma evaluated the soil fertility levels based on clustering, rough set, and decision tree (Chen & Ma, 2011).

(i) The clustering method is used to reduce sample space;
(ii) Removal of redundant attributes using rough set which also results in reduced size of decision tree;
(iii) Lastly, a combination of rough set and decision tree is used to define decision-making rules and improving decision-making accuracy.

A decision support system for nutrition management of rice under the consideration of various physical aspects was proposed in the paper *Rough Set Model for Nutrition Management in Site-Specific Rice Growing Areas* (Lavanya & Iyengar, 2014).

(i) Attribute values are preprocessed and mapped with numerical code values;
(ii) Computation of lower and upper approximations of elementary sets;
(iii) Generation of decision rules with the proposed algorithm in the aforementioned study;
(iv) Lastly, a decision system is developed for nutrition management with the validated decision rules.

A study of 2015 (Lavanya, Durai, & Iyengar, 2015), establishes the connection between the concepts of similarity and dissimilarity for ranking soil fertility with the use of the Fuzzy Rough Set and Fuzzy Bayesian model.

(i) The study comprises two phases;
(ii) Phase I is to generate soil ranking to determine soil fertility based on intuitionistic fuzzy rough set;
(iii) Phase II is to decide the crop selection parameters for paddy cultivation based on the combination of fuzzy and Bayesian methodology.

A study of 2018 (Bagherzadeh, Gholizadeh, & Keshavarzi, 2018) depicted a soil fertility zonation map for potato production based on soil nutrient elements by integrating Fuzzy and AHP approaches.

To suggest a sustainable cultivation plan based on patterns of soil fertility classes of various crops based on Fuzzy – Analytical Hierarchy Process and parametric analysis are developed through a study of 2020 (Kesharvazi, Tuffor, Bagherzadeh, Tattrah, Amin, & Rodrigo-Comino, 2020).

The various pieces of literature provided in section I (Introduction) give a conceptual insight into features utilized in different studies. The summary is given in table 4.

In this paper, the combination of Rough Set, Soft Set, and Fuzzy Set is studied. The categorical partition as Soft Rough Subspaces of information system helps to classify the treatments based on nutrient values. In addition to the analysis of chemical treatments for soil fertility under the general or combined circumstances, it facilitates the n-tier analysis too as per the need of producers. Then the ranking of different treatments is based on Covering based Soft Rough Fuzzy set (CSRFS). None of the aforementioned studies depicted the derived method in this paper via an algorithm.

The proposed method (CSRFS) is the most suitable as it provides solutions on various parameters of vague data. The parameters it incorporates are upper and lower approximation with boundary region, covering space, parameterization, fuzzy membership, and fuzzy non-membership. The result is compared with the two different existing methods: Pythagorean Fuzzy Soft Rough Set (PFSRS) and Soft Rough Pythagorean Fuzzy Set (SRPFS) (Hussain, Ali, & Mahmood, 2020). It is found that the order of chemical treatments derived from the proposed method is more accurate and in synchronization to the yield based on different treatments considered.

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Table 5: Comparison of ranking with existing methods

Methods	Ranking
CSRFS	$T_4 > T_5 > T_3 > T_2 > T_1$
SRPFS	$T_3 > T_5 > T_4 > T_2 > T_1$
PFSRS	$T_3 > T_5 > T_4 > T_2 > T_1$

Lower and upper approximation	Boundary region	Parameterization	Fuzzy membership	Fuzzy membership	non-Covering Space
N	N	N	Y	N	N
Y	Y	N	N	N	N
N	N	Y	N	N	N
Y	Y	Y	N	N	Y
Y	Y	Y	N	N	N
Y	Y	Y	Y	N	N
Y	Y	N	N	N	N
Y	Y	N	Y	Y	N
N	N	N	Y	N	N
N	N	N	Y	N	N
Y	Y	N	Y	Y	Y
Y	Y	Y	Y	Y	Y

Method	Fuzzy Set (Zadeh, 1965)	Rough Set (Pawlak, 1982)	Soft Set (Molodtsov, 1999)	Rough Sets induced by Covering (Liu & Sai, 2009)	Soft Set and Soft Rough Sets (Feng, Liu, Fotea, & Jun, 2011)Y	Soft Fuzzy Rough Set and Soft Rough Fuzzy Set Model (Meng, Zhang, & Keyun, 2011)	Rough Set Model for Nutrition Management (Lavanya & Iyengar, 2014)	Intuitionistic Fuzzy Rough Set and Fuzzy Bayesian based Decision Model (Lavanya, Durai, & Iyengar, 2015)	Fuzzy and AHP Approach based Soil Fertility Zonation Map (Bagherzadeh, Gholizadeh, & Keshavarzi, 2018)	Cultivation plan for Soil Fertility based on Fuzzy- AHP process and parametric analysis (Kesharvazi, Tuffor, Bagherzadeh, Tattrah, Amin, & Rodrigo-Comino, 2020)	Intuitionistic Fuzzy beta–Covering-based Rough Sets (Huang, Li, & Guofu, 2020)	Covering based Soft Rough Fuzzy Set (Proposed)

Table 4: Comparison of Parameters used in proposed method with existing methods

5. Conclusion

Soil fertility is a crucial factor to maintain crop well-being since through soil only crops get all the required nutrition. Non-classical set theories are emerging as a solution concept for discrete and vague data; the data criterion exists in Soil fertility analysis. The study incorporates a decision system for the nutrient assessment based on the available nutrient in the soil. It is an extended version of Covering based Rough set to Covering based Soft Rough Fuzzy set wherein the ranking of different chemical treatments is obtained to strengthen the decision making criteria. The information system is partitioned into three Soft Rough Subspaces then with the minimal description and neighbor of Soft Rough Subspaces chemical treatments are classified. Lastly, the set-valued mapping is used to transform the system into Covering based Soft Rough Fuzzy set and based on which the ranking of different treatments are defined. The ranking is then compared with different methods and it is concluded that the proposed theory gives a more accurate solution and when compared with the yields obtained after applying different treatments.

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