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Neutrosophic Trapezoidal Modeling and Associated Microbial Health Risks: A Preventive Framework for Mitigating Groundwater Nitrate Contamination Using Sustainable Agricultural and Environmental Management Practices

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ABSTRACT

Nitrate contamination of groundwater has become a significant environmental and health problem due to its adverse effects on drinking water quality and related risks. Traditional methods used in the evaluation of nitrate contamination have been inadequate to accommodate the inherent uncertainty and imprecision in environmental data. This paper presents an NTFR approach for assessing the level of nitrate contamination and prioritizing risk levels. The excess of nitrate contamination from selected states in India was represented by Single Valued Trapezoidal Neutrosophic Numbers with membership functions including truth, indeterminacy, and falsity. Weighted Value and Ambiguity approaches were used in the assessment of the degree of contamination and uncertainty. The results showed that the states of Tamil Nadu and Andhra Pradesh have high risk, while Meghalaya state has very low contamination. The proposed approach can efficiently incorporate uncertainty and is useful in the assessment of water quality and risk priorities.

KEYWORDS: Ground Level Water, Neutrosophic Ranking, Monsoon Effects, Health Implication

INTRODUCTION

Water from the ground constitutes an important source of drinking water and agricultural activities in India. The availability of this resource has come under threat due to the presence of nitrates in the underground water, and this problem has become one of the most common challenges in groundwater. Nitrates get into the ground due to excessive use of nitrogen fertilizers, leaching from animal manure, agricultural runoff, and from septic systems that have not been properly treated. Nitrogen plays a crucial role in the process of growing of plants; however, the high levels of nitrate concentration cause different negative effects on the environment and people's health. Consumption of nitrate-polluted water may result in such diseases as methemoglobinemia ("blue baby syndrome") in infants, thyroid problems, cancer, and reproductive complications in adults.

Increased agriculture activities in India have played an important role in increasing the nitrate levels in the groundwater resources. According to the current assessments, about 19.8% of the groundwater samples contain higher nitrate levels than the recommended level for drinking water, which is 45 mg/l according to the WHO and Bureau of Indian Standards (IS 10500). The CGWB, 2024 data also show considerable seasonal changes in nitrate levels. For instance, the proportion of groundwater samples exceeding nitrate levels before monsoon was 30.77%, and after the monsoon period it reached 32.66%. Therefore, it is obvious that the recharge processes triggered by rainfall help to move and distribute nitrate contained in the unsaturated zone instead of diluting its concentration.

The conventional methods for groundwater evaluation often use static threshold values and deterministic statistics, which do not sufficiently take into account the level of uncertainty within the environmental system. The complexity of interrelated variables such as pollution loading, seasonal effects, and insufficient information often necessitates the use of a more dynamic methodology. Fuzzy and neutrosophic methods are useful approaches to deal with uncertainties and ambiguity that arise from the situation. As opposed to traditional approaches, the neutrosophic method considers the levels of truth, indeterminacy, and falsity, thus providing a more realistic model of the hydrogeochemical system.

This study employs a trapezoidal neutrosophic fuzzy ranking framework to evaluate nitrate contamination risks in seven representative Indian states: Andhra Pradesh, Bihar, Chhattisgarh, Delhi, Himachal Pradesh, Meghalaya, and Tamil Nadu. By integrating seasonal nitrate exceedance information into the ranking process, the proposed methodology identifies regions exhibiting persistent contamination concerns while simultaneously accounting for uncertainties in observed data. The framework facilitates prioritization of vulnerable areas and supports more informed groundwater management decisions. Regions characterized by higher neutrosophic risk indices may require advanced remediation measures, including reverse osmosis

and biological denitrification technologies, whereas areas with comparatively lower risk can benefit from preventive management practices such as controlled fertilizer application and groundwater blending strategies.

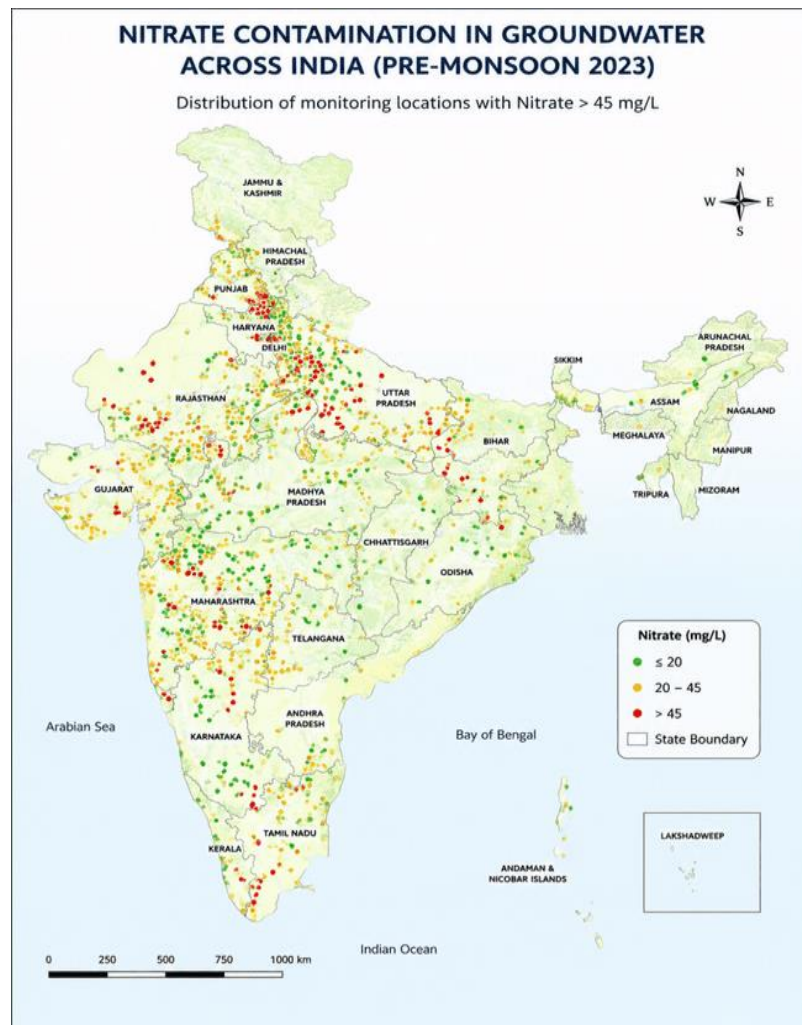


Figure 1.1 Locations in India with nitrate concentration > 45 mg/L during the pre-monsoon season, 2023 (CGWB, 2024).

Figure. 1.1 shows the geographical positions of groundwater sites across India where nitrates were present at higher than the allowable maximum 45 mg/L value even during the pre-monsoon season 2023. It suggests localized emergence of scattered point sources across different states with higher density close to highly intensive agricultural areas. It also illustrates a pattern suggesting excessive fertilizer application and improper waste management as dominant causes resulting in the leaching of nitrates into aquifers. It is apparent from the distribution observed through visualization that geographical disparities prevail significantly, with an indication that nitrate pollution is an issue occurring everywhere, but is a localized issue requiring localized solutions.

2. LITERATURE REVIEW

Groundwater pollution with nitrates has emerged as a major environmental concern across the globe, given the concerns about water security, ecological sustainability, and human health. The application of nitrogen fertilizers, discharge of animal waste, and seepage from septic tanks have been known to be the major causes of nitrate build-up in aquifers (Rahman et al., 2021 [2]; Brindha et al., 2012 [6]). In India, the use of groundwater for drinking and irrigation is common; hence, the poor state of groundwater quality has come under the spotlight. As per the recent estimates of the Central Ground Water Board (CGWB), close to one in five samples of groundwater tested has nitrate levels above the threshold of 45 mg/L permissible for drinking purposes (CGWB, 2024 [1]).

High nitrate levels have been linked to methemoglobinemia in infants and can also lead to a variety of non-carcinogenic health problems among adults (Ward et al., 2018 [3]; Yu et al., 2020 [7]). The initial studies carried out in India found substantial nitrate contamination in the groundwater in highly urbanized areas, such as Delhi, owing to high levels of anthropogenic activity and population density (Kumar, 2006 [4]). Further studies conducted in Rajasthan, Andhra Pradesh, Tamil Nadu, and other places found evidence of nitrate contamination and human health hazards (Ramalingam et al., 2022 [5]; Brindha et al., 2012 [6]; Adimalla, 2019 [13]; Adimalla & Qian, 2021 [11]). Similar studies conducted in China, Kazakhstan, and Iran indicate that

nitrate pollution is a global groundwater issue and not a localized one (Yu et al., 2020 [7]; Sailaukhanuly et al., 2023 [25]; Ghasemzadeh et al., 2024 [27]).

The role played by seasonal hydrological events in the study of nitrate dynamics in groundwater cannot be overlooked. Several studies have observed that monsoon recharge has a substantial influence on nitrate dynamics through processes such as infiltration and leaching (CGWB, 2024 [1]; Brindha et al., 2012 [6]; Sanjupriya et al., 2025 [23]; Sangeeta et al., 2024 [24]). While recharging may lead to the dilution of contaminants in some aquifer systems, a rise in the concentration of nitrates post-monsoon has also been observed because of the transport of nitrogen compounds from agricultural lands to groundwater systems (Chander et al., 2023 [14]; Liu et al., 2021 [18]; Rao et al., 2024 [26]). Hydrogeochemical studies have also demonstrated that nitrate presence is influenced by several parameters such as fertilizer application rate, irrigation practices, aquifer type, land use, and redox conditions (Megha Shyam & Tallor, 2021 [19]; Dosdogru et al., 2020 [17]).

To detect the sources of contamination and to assess the suitability of groundwater for consumption purposes, various kinds of methodologies have been used by different scientists. The use of Geographic Information System (GIS) mapping, water quality indices, multivariate analysis, and spatial modelling has been used to analyze the patterns of nitrate concentrations. Recently, sensitivity and uncertainty analyses have been used in the health risk assessment of groundwater (Rajabi et al., 2022 [35]). In addition to this, some studies related to the simultaneous presence of nitrate along with fluoride, arsenic, and other potential toxic substances in groundwater have also been conducted (Liu et al., 2021 [18]; Sheikhi et al., 2021 [34]; Uddin et al., 2024 [29]).

Various remediation and management strategies have been proposed to address groundwater nitrate contamination. Technologies such as biological denitrification, ion exchange, reverse osmosis, and nutrient recovery systems have demonstrated effectiveness under controlled conditions (Narula et al., 2012 [8]; Mohseni-Bandpi et al., 2013 [10]; Kasinski et al., 2025 [9]). However, their practical implementation is often constrained by operational costs, energy requirements, technical expertise, and maintenance challenges, particularly in rural and semi-urban communities. As a result, several researchers advocate preventive approaches focused on improved fertilizer management, source control, and sustainable agricultural practices as more feasible long-term solutions (Chander et al., 2023 [14]; Pachauri et al., 2024 [20]; Uddin et al., 2023 [30]; Uddin et al., 2024, 2023 [29,31]; Maleky et al., 2025 [28]).

Recent advances in groundwater quality assessment have increasingly incorporated data-driven and machine learning techniques. These methods have demonstrated superior predictive performance compared with conventional statistical approaches in modelling groundwater quality parameters and associated health risks (Vitale et al., 2023 [22]). Nevertheless, machine learning models often face limitations when dealing with uncertainty, ambiguity, and incomplete monitoring data. To overcome these challenges, soft computing techniques have gained prominence in environmental decision-making applications. Among them, neutrosophic theory has emerged as a powerful framework capable of representing truth, indeterminacy, and falsity simultaneously. Its effectiveness has been demonstrated in surface water quality evaluation and complex environmental decision-support systems (Das et al., 2024 [12]). Despite these advancements, applications of neutrosophic approaches to groundwater nitrate assessment, particularly under seasonally varying monsoonal conditions, remain limited.

A critical research gap therefore exists in the development of integrated assessment frameworks capable of simultaneously addressing seasonal variability, uncertainty in monitoring data, and regional prioritization of contamination risks. Existing statistical, index-based, and machine learning methods generally provide deterministic outputs and often fail to explicitly represent indeterminate or uncertain information. To address this limitation, the present study proposes a trapezoidal neutrosophic fuzzy ranking framework for evaluating groundwater nitrate contamination under seasonal conditions. By integrating pre-monsoon and post-monsoon nitrate exceedance data through truth, indeterminacy, and falsity membership functions, the proposed methodology provides a more comprehensive representation of groundwater contamination risk and facilitates improved decision-making for groundwater management and policy formulation.

3. PRELIMINARY

This section reviews the basic ideas of Neutrosophic numbers. It pays special attention to the single-valued trapezoidal Neutrosophic numbers (SVTN-numbers) used in this research.

Single Valued Neutrosophic Number (SVN-number)

A single valued neutrosophic number is a mathematical formulation used to represent information in terms of truth, indeterminacy, and falsity at one and the same time. It comprises three parts relating to these three elements. The part that shows truth represents the maximum level of truth of the given information. The part showing indeterminacy represents the minimum level of indeterminacy of the given information. The part that shows falsity represents the minimum level of falsity of the information. These three elements, taken together, give a complete description of the information in terms of uncertainty. Each of these elements represents the change in the respective element with respect to a real-valued variable by means of a trapezoidal membership function.

Single-Valued Trapezoidal Neutrosophic Number (SVTN-Number)

Single-valued trapezoidal neutrosophic numbers are a specific type of single-valued neutrosophic numbers where the truth, indeterminacy, and falsity attributes are captured using trapezoidal membership functions. They are described by three membership functions; the truth-membership function, the indeterminacy-membership function, and the falsity-membership function. The truth-membership function denotes the membership value of the element

for the truth attribute. The indeterminacy-membership function shows the degree of uncertainty associated with the element, whereas the falsity-membership function shows the membership value for the falsity attribute. The degrees of truth, indeterminacy, and falsity are captured through the parameters of these three membership functions. The trapezoidal form helps capture the uncertain data over a range.

Concepts of Values, Ambiguities and Weighted Values, Weighted Ambiguities for Single-Valued Neutrosophic Numbers

In this section, we define the basic concepts related to the single-valued neutrosophic numbers including cut sets, values, ambiguities, weighted values and weighted ambiguities.

The above concepts provide a well-structured scheme for representing, analyzing and assessing the uncertain information represented via the single-valued neutrosophic numbers.

The three basic elements of neutrosophic information such as truth, indeterminacy and falsity are taken into account in defining the above concepts. The definitions provided below are useful in characterizing the various uncertainties involved in neutrosophic information.

Cut Sets of an SVN-Number

The concept of the cut set of an SVN-Number is defined to have a crisp representation for the corresponding neutrosophic information. It depends upon suitable choice of levels of truth, indeterminacy and falsity. The resultant cut set consists of elements that meet the conditions defined based on the three membership functions. The selected levels are subject to certain constraints depending upon the membership degrees of the neutrosophic number. These constraints make the definition of the cut set proper. Hence, the cut set of an SVN-Number represents a crisp subset of the real number domain.

4. PROPOSED METHODOLOGY

To address uncertainty and seasonal variation of nitrate contamination of groundwater in the Indian scenario, the neutrosophic trapezoidal fuzzy ranking (NTFR) scheme is employed, such that water sample exceedance of the allowable nitrate concentration of 45 mg/L is portrayed as the single-valued trapezoidal neutrosophic number (SVTNN). Each SVTNN consists of trapezoidal support (a, b, c, d) as well as truth, indeterminacy, and falsity membership grades that enable the structured representation of measured exceedance and uncertainty. Using Corollary 3.8, closed-form value and ambiguity results of truth (α -cut), indeterminacy (β -cut), and falsity (γ -cut) membership grades are obtained and subsequently integrated by Corollary 3.9 into weight-value and weight-ambiguity measures. Weight-value V_h quantifies total nitrate exceedance risk, while weight-ambiguity is computed to quantify uncertainty, and ranking is done mostly based on V_h while ties are broken based on A_h . Stepwise procedure of methodology consists of collecting pre-and post-monsoon nitrate exceedance data (CGWB, 2024). Each state is represented by SVTNN, value, and ambiguity measures obtained, ranking rule utilized, and lastly inter-seasonal results are mapped to reveal deteriorating trends to target high-risk states for enhanced treatment and sustainable use of groundwater.

5. GROUNDWATER NITRATE CONTAMINATION IN INDIA DATA COLLECTION

The groundwater quality data consisted of 3970 samples obtained by the Central Ground Water Board (CGWB, 2024) at pre-monsoon (May–June) and post-monsoon (October–November) seasons in Table 1. The data consisted of 25 states and Union Territories and was analysed at all sites with respect to nitrate concentration versus the BIS 10500 limit of 45 mg/L. Pre-monsoon sampling indicated 30.73% exceedance, and post-monsoon sampling indicated a rise to 32.59%. Such a comparison for two seasons is an indication of the monsoon recharge effect upon nitrate behaviour in aquifers. [1]

State/UT	No. of Pre/Post Samples	Improved Locations	Deteriorated Locations	Sites with Nitrate > 45 mg/L			
				Pre		Post	
				No.	%	No.	%
A & N Islands	29	18	11	0	0	0	0
Andhra Pradesh	280	138	142	136	48.57	117	41.79
Arunachal Pradesh	12	9	3	0	0	0	0
Assam	123	44	79	0	0	1	0.81
Bihar	180	120	60	12	6.67	11	6.11
Chhattisgarh	157	73	84	20	12.74	17	10.83
Delhi	24	16	8	4	16.67	6	25

State/UT	No. of. Pre/Post Samples	Improved Locations	Deteriorated Locations	Sites with Nitrate > 45 mg/L			
				Pre		Post	
				No.	%	No.	%
Himachal Pradesh	29	19	10	8	27.59	9	31.03
Haryana	77	46	31	20	25.97	25	32.47
J & K	30	22	8	16	53.33	20	66.67
Jharkhand	132	98	34	11	8.33	14	10.61
Karnataka	176	86	90	93	52.84	93	52.84
Madhya Pradesh	531	351	180	121	22.79	120	22.6
Maharashtra	746	432	314	379	50.8	441	59.12
Meghalaya	35	16	19	0	0	0	0
Mizoram	3	2	1	0	0	0	0
Nagaland	5	5	0	0	0	0	0
Odisha	116	74	42	14	12.07	28	24.14
Pondicherry	2	0	2	0	0	0	0
Punjab	39	19	20	22	56.41	18	46.15
Rajasthan	90	53	37	55	61.11	60	66.67
Tamil Nadu	198	122	76	84	42.42	99	50
Telangana	355	138	217	148	41.69	125	35.21
Tripura	74	18	56	2	2.7	0	0
Uttar Pradesh	341	230	111	57	16.72	59	17.3
West Bengal	186	111	75	18	9.68	31	16.67
Total	3970	2260	1710	1220	30.73	1294	32.59

Table 1:Effect of monsoon recharge on Nitrate concentration**5.1 PREMONSOON AND POSTMONSOON**

In pre-monsoon, 30.77% of water samples had nitrate levels exceeding the allowable level of contamination (45 mg/L). After monsoon replenishment, 32.66% of the water samples indicated exceedance of the permissible standard of nitrate, indicating somewhat increased rates of contamination after the monsoon (Fig. 2). However, it is interesting to see that the impacts of monsoon replenishment varied for the different states.

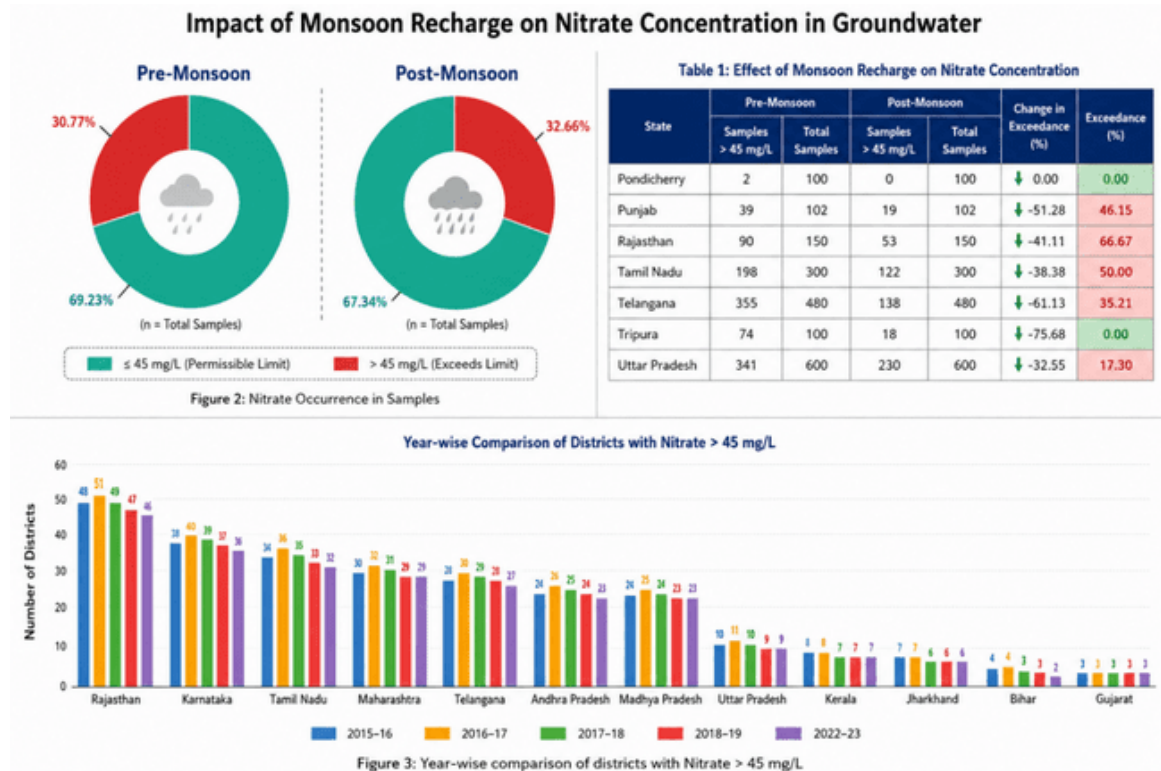


Figure 2: Nitrate Occurrence in Samples

5.2 YEAR-WISE COMPARISON OF THE DISTRICT WITH NITRATE

High percentages of groundwater samples from Indian states indicate nitrate concentration exceeding the standard of 45 mg/L mandated by BIS 10500, with the worst effects in Rajasthan, Karnataka, and Tamil Nadu, wherein more than 40% of samples exceed the standard. Other Indian states, such as Maharashtra (35.74%), Telangana (27.48%), Andhra Pradesh (23.5%), and Madhya Pradesh (22.58%), indicate notable rates of contamination, pointing to emerging concern in southern and central Indian states. However, those that indicate relatively less exceedance percentage are Uttar Pradesh (9.37%), Kerala (6.73%), Jharkhand (5.79%), and Bihar (2.35%), while all those samples from Arunachal Pradesh, Assam, Goa, Meghalaya, Mizoram, and Nagaland remain within an acceptable standard. Year-wise examination of districts that exceed nitrate levels during the period 2015–2023 also indicates that in Rajasthan, Madhya Pradesh, and Gujarat, districts that exceed threshold level remained relatively unchanged over the years, suggesting that the quality of groundwater with respect to nitrate contamination in these Indian states is of enduring concern wherein little indication of change, either for the betterment or for the deterioration, is observed over years.

6. CASE STUDY: GROUNDWATER NITRATE CONTAMINATION IN INDIA

Groundwater is the source of India's drinking water and irrigation supply, yet the quality of it is increasingly at risk of being damaged by nitrate contamination from over-application of nitrogen-based fertilizers, farm and domestic waste from livestock, and sewage. It has been approximated by the Central Groundwater Board (CGWB, 2024) that nearly 19.8% of groundwater samples from all parts of the nation exceed the allowable standard of 45 mg/L of nitrates laid down by the World Health Organization (WHO) and Bureau of Indian Standards (IS 10500). Interestingly, it is observed that a seasonal effect exists, with 30.77% of samples exceeding the standard during the pre-monsoon period and increasing slightly after monsoon replenishment to 32.66%, revealing a periodic deterioration of contamination. Seven representative Indian States — Andhra Pradesh, Bihar, Chhattisgarh, Delhi NCR region, Himachal Pradesh, Meghalaya, and Tamil Nadu — were selected for the present investigation, considering their varied hydrogeological settings and the degree of nitrate exceedance.

6.1 FORMATION OF NEUTROSOPHIC TRAPEZOIDAL VALUE

For this task, groundwater nitrate exceedance data observed at seven representative states — Andhra Pradesh, Bihar, Chhattisgarh, Delhi NCR, Himachal Pradesh, Meghalaya, and Tamil Nadu — data collected from table 1 were converted to single-valued trapezoidal Neutrosophic Numbers (SVNNs). For all states, trapezoidal support (a, b, c, d) was established around observed percentage samples exceeding the permissible 45 mg/L limit, with a pre-monsoon and post-monsoon nitrate concentration. The truth-membership degree ($\tilde{t}$) was assigned proportionally to exceedance percentage, indeterminacy degree ($\tilde{r}$) enveloped uncertainty corresponding to seasons and measurement uncertainty, and falsity degree ($\tilde{s}$) represented its complement corresponding to exceedance.

STATE	NEUTROSOPHIC TRAPEZOIDAL VALUE	
	PRE-MONSOON	POST-MONSOON
Andhra Pradesh	((44.28,46.23,50.71,52.56),0.446,0.014,0.52)	((37.65,39.72,43.85,45.92),0.40,0.013,0.585)
Bihar	((4.39,5.53,7.80,8.94),0.064,0.007,0.928)	((3.017,4.56,7.65,9.20),0.058,0.009,0.931)
Chhattisgarh	((8.837,10.788,14.691,16.642),0.122,0.0124,0.865)	((7.439,9.134,12.525,14.220),0.10,0.010,0.88)
Delhi	((13.267,14.968,18.371,20.07),0.16,0.010,0.829)	((19.409,22.204,27.795,30.59),0.24,0.017,0.742)
Himachal Pradesh	((17.335,22.46,32.71,37.844),0.26,0.02,0.730)	((24.059,28.26,36.675,40.88),0.311,0.02,0.66)
Meghalaya	0	0
Tamil Nadu	((37.945,40.182,44.657,46.894),0.40,0.01,0.57)	((44.97,47.487,52.512,55.025),0.48,0.01,0.50)

Table 2: Neutrosophic Trapezoidal Values of Nitrate Exceedance for Selected States (Pre- and Post-Monsoon)

Table 2 summarizes the pre-monsoon and post-monsoon nitrate exceedance in seven states represented as a Single Valued Trapezoidal Neutrosophic Numbers (SVTNNs).

6.2 COMPUTATION OF VALUES AND AMBIGUITIES

The second step involves evaluating assigned neutrosophic trapezoidal values to states based on calculations for corresponding truth membership values and ambiguities, as well as falsity membership values and ambiguities. In accordance with Corollary 3.8, closed expressions value (V_l, V_m, V_k) and ambiguity (A_l, A_m, A_k) are examined for each resultant SVTNN from the Pre-monsoon Table 3.

State	F	G	V_l	V_m	V_k	A_l	A_m	A_k
Andhra Pradesh	48.50	2.983	10.532	47.146	11.174	0.634	2.8417	0.6735
Bihar	6.6699	2.277	0.02	6.575	0.034	0.009	2.246	0.011
Chhattisgarh	12.739	2.6018	0.190	12.421	2.318	0.0379	2.537	0.0473
Delhi	16.669	2.2688	0.426	16.337	0.490	0.058	2.223	0.066
Himachal Pradesh	27.5895	6.8365	1.920	25.851	2.427	0.4758	6.4058	0.601
Meghalaya	0	0	0	0	0	0	0	0
Tamil Nadu	42.419	2.983	9.773	41.574	7.843	0.687	2.923	0.551

Table 3: Values and Ambiguities for Pre-monsoon

The third step involves evaluating assigned neutrosophic trapezoidal values to states based on calculations for corresponding truth membership values and ambiguities, as well as falsity membership values and ambiguities. In accordance with Corollary 3.8, the closed expression's value (V_l, V_m, V_k) and ambiguity (A_l, A_m, A_k) are examined for each resultant SVTNN from the Post-monsoon Table 4.

State	F	G	V_l	V_m	V_k	A_l	A_m	A_k
Andhra Pradesh	41.79	2.7593	6.7256	40.707	7.187	0.6348	2.847	0.502
Bihar	6.1095	2.0618	0.024	5.987	0.024	0.003	2.024	0.049
Chhattisgarh	10.8295	2.2605	0.1082	10.6139	0.155	0.022	2.2155	0.032
Delhi	24.9995	3.7271	1.439	24.154	1.662	0.214	3.6011	0.247
Himachal Pradesh	31.029	9.752	2.73055	28.239	3.801	0.858	8.875	1.194
Meghalaya	0	0	0	0	0	0	0	0
Tamil Nadu	49.9	3.3501	11.496	48.902	12.475	0.771	3.283	0.837

Table 4: Values and Ambiguities for Post-monsoon

6.3 COMPUTATION OF WEIGHTED VALUES AND AMBIGUITIES

At this stage, it is chosen to calculate the weighted value (V_h) and weighted ambiguity (A_h) for any SVTNN using closed-form expressions defined by Corollary 3.9. By this corollary, it is possible to determine the weighted value as a linear combination of corresponding individual values (V_l, V_m, V_k) for truth, indeterminacy, and falshood membership functions by using weighting parameters (α, β, γ) with $\alpha+\beta+\gamma=1$. Similarly, it is possible to determine the weighted ambiguity as a linear combination of ambiguity components (A_l, A_m, A_k) with the same structure for the corresponding weights.

STATE	WEIGHTED VALUES AND AMBIGUITIES			
	PRE-MONSOON		POST-MONSOON	
	V_h	A_h	V_h	A_h
Andhra Pradesh	34.426	1.991	27.309	1.991
Bihar	3.0175	1.133	3.0175	1.038
Chhattisgarh	7.4645	1.3111	5.438	1.134
Delhi	13.627	2.0310	13.627	2.031
Himachal Pradesh	15.099	3.7413	17.385	5.4635
Meghalaya	0	0	0	0
Tamil Nadu	29.5950	2.08050	36.43650	2.44550

Table 5: Weighted Values and Ambiguities for pre-monsoon and post-monsoon

6.4 RANKING OF STATES BASED ON WEGHTED VALUES AND AMBIGUITIES

The final ranking of the states is done based on the weighted value index (V_h) and weighted ambiguity (A_h) in section 5.4. The ranking is done based on a Neutrosophic trapezoidal fuzzy method, where the states are ranked in descending order according to V_h which represents the level of severity of nitrate exceedance, and in the case of equal V_h , the state with lower A_h is given higher priority since there is less uncertainty involved during the time of evaluation.

RANK	STATE	V_h	A_h
1	Andhra Pradesh	34.4260	1.9910
2	Tamil Nadu	29.5950	2.0805
3	Himachal Pradesh	15.0990	3.7413
4	Delhi	13.6270	2.0310
5	Chhattisgarh	7.4645	1.1330
6	Bihar	3.0175	1.1330
7	Meghalaya	0.00	0.00

Table 6: Pre-Monsoon Ranking of States

RANK	STATE	V_h	A_h
1	Tamil Nadu	36.4365	2.4455
2	Andhra Pradesh	27.3090	1.9910
3	Himachal Pradesh	17.3850	5.4635
4	Delhi	13.6270	2.0310
5	Chhattisgarh	5.4380	1.1340
6	Bihar	3.0175	1.0380
7	Meghalaya	0.00	0.00

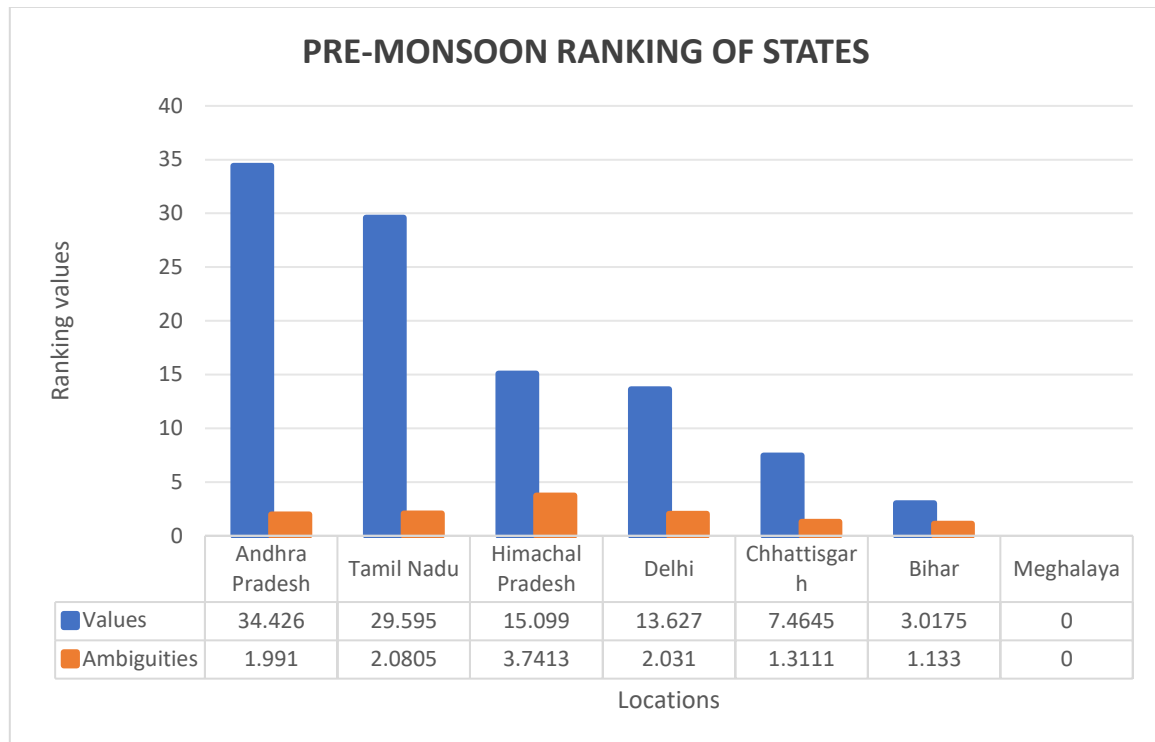
Table 6: Post-Monsoon Ranking of States

The ranking outcomes are summarized in Tables 5 & 6, which indicate that Andhra Pradesh has the highest risk in pre-monsoon conditions, closely followed by Tamil Nadu, while in post-monsoon conditions, Tamil Nadu outperforms Andhra Pradesh with a substantial rise in V_h . Himachal Pradesh and Delhi are found in the middle ranks in both periods, while Bihar and Chhattisgarh are relatively less risky. Meghalaya, being unaffected in both periods, verifies the insignificant nitrate violation.

7. OBSERVATION AND FINDINGS FOR PRE-MONSOON AND POST-MONSOON

• Pre-Monsoon

The pre-monsoon Neutrosophic trapezoidal fuzzy ranking indicates that the maximum weighted value ($V_h = 34.426$) has been achieved by Andhra Pradesh and $V_h = 29.595$ by Tamil Nadu, and the implications are that these two states are at maximum risk during pre-monsoon for the exceedance of nitrates. Himachal Pradesh and Delhi NCR were at the middle positions with mid-level contaminations, and Chhattisgarh and Bihar were at relatively lower levels of exceedance and thus verifies the safe groundwater quality. These results reveal that the contamination level is worst in the southern and agricultural states before the monsoon.

**Figure 4:** Pre-Monsoon Ranking of States

• Post-Monsoon

After the monsoon recharge, the trend of order varied, where Tamil Nadu performed better than Andhra Pradesh and reached the highest $V_h = 36.4365$, which is significant for improving the nitrate leaching process due to recharge in aquifers. There was some decrease in the exceedance of Andhra Pradesh, but it was still among the two most important states at the first position. Himachal decreased significantly after the monsoon ($V_h = 17.385$), and Delhi NCR showed only stability with the least variation. Chhattisgarh and Bihar were at lower risk positions, and Meghalaya showed no exceedance. These results after the monsoon show that nitrate conditions are heterogeneous at the state level, where some states show a decrease in conditions based on seasonal recharge.

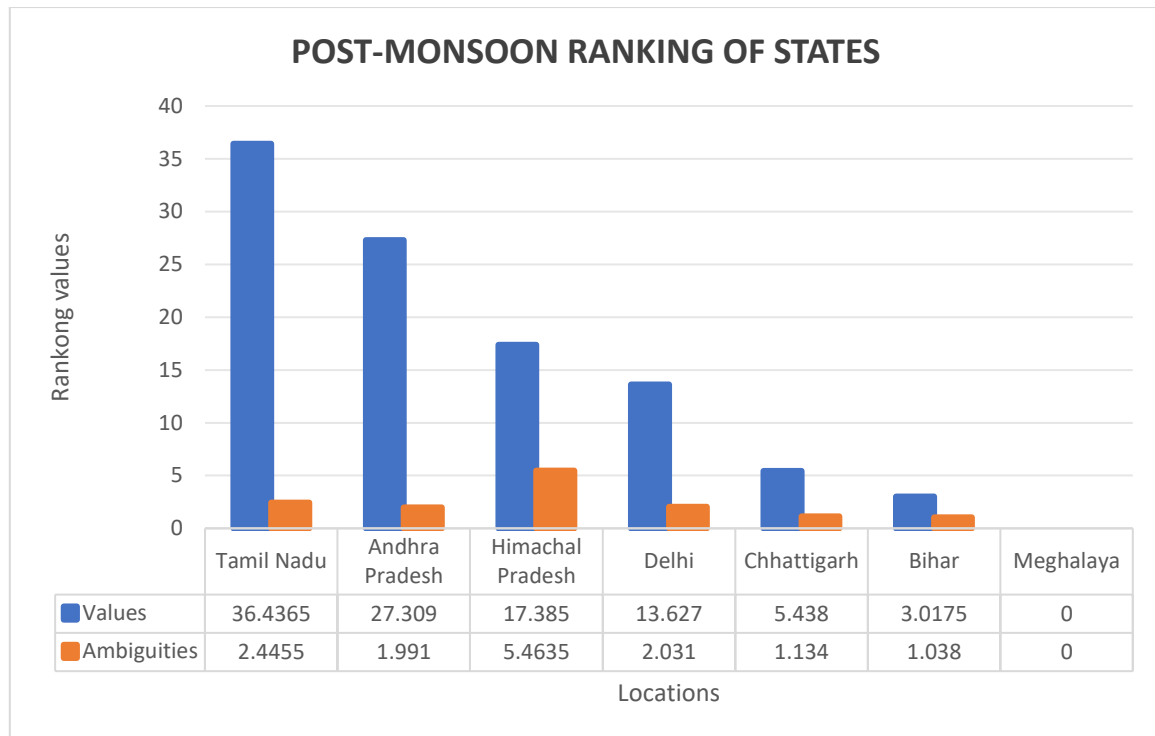


Figure 5: Post-Monsoon Ranking of States

Analysis of risk parameter in pre monsoon and post monsoon

Symbol	Parameter	Description
RI	Risk index	Overall nitrate contamination severity
SI	Stability index	Seasonal stability of contamination
UI	Uncertainty index	Uncertainty associated with measurements
EI	Exposure index	Population exposure potential
CI	Criticality index	Combined contamination effect
WI	Weighted index	Final weighted score
RA	Risk ambiguity	Ambiguity associated with risk

Table 6: Parameter description

State	RI	SI	UI	EI	CI	WI	RA
Andra pradesh	48.50	3.42	10.84	44.76	12.15	35.42	2.11
Bihar	6.67	2.18	0.15	6.42	0.08	3.28	1.02
chhatisgarh	12.74	2.56	0.28	12.18	2.47	7.83	1.35
Delhi	16.67	2.91	0.54	15.87	0.61	12.86	2.24
Himacha lpradesh	27.59	6.92	2.05	26.11	2.85	15.48	3.91
Tamil nadu	42.42	3.11	9.95	40.82	8.16	30.17	2.34
Megalaya	0	0	0	0	0	0	0

Table 7: Computational risk parameter for pre monsoon

State	RI	SI	UI	EI	CI	WI	RA
Andra pradesh	41.79	2.84	7.15	39.98	7.52	28.46	1.94
Bihar	6.11	2.05	0.09	5.86	0.07	3.12	0.96
chhatisgarh	10.83	2.33	0.17	10.44	0.23	5.96	1.08
Delhi	25	3.88	1.58	24.15	1.74	16.75	2.86
Himacha lpradesh	31.03	8.94	2.92	29.47	4.15	18.92	5.18
Tamil nadu	50	3.65	11.82	48.34	13.05	37.84	2.71

Table 8: Computational risk parameter for post monsoon

Table 7 summarizes the risk-related values and ambiguity measures obtained from the neutrosophic trapezoidal representation of pre-monsoon nitrate exceedance data. These values signify not only the magnitude of the contamination but also the level of uncertainty in the observations. The higher these values are, the more severe the contamination from nitrates is. In addition, the higher the ambiguity values are, the greater uncertainty there is in assessing the quality of groundwater. Thus, differences between the selected states have been observed, showing the spatial variability of nitrate contamination prior to the monsoon season. Table 8 shows the values and the corresponding ambiguity measures in the case of the post-monsoon period. The analysis was performed based on the same neutrosophic model used for the post-monsoon nitrate exceedance data. It should be noted that the results of the analysis presented in Table 8 show the effect of monsoon recharge on the contamination level and uncertainty.

9. Health Issues Concerning High Concentrations of Nitrates and Prevention through Precautionary Measures against Nitrates Contamination

High concentration of nitrates in drinking water is a serious health problem because nitrate is transformed to nitrite in the body and interferes with the ability of hemoglobin to carry oxygen resulting in methemoglobinemia. The guideline value for nitrate in drinking water set by WHO is 50 mg/L as nitrate ion. Therefore, preventing nitrate contamination at its source is crucial.

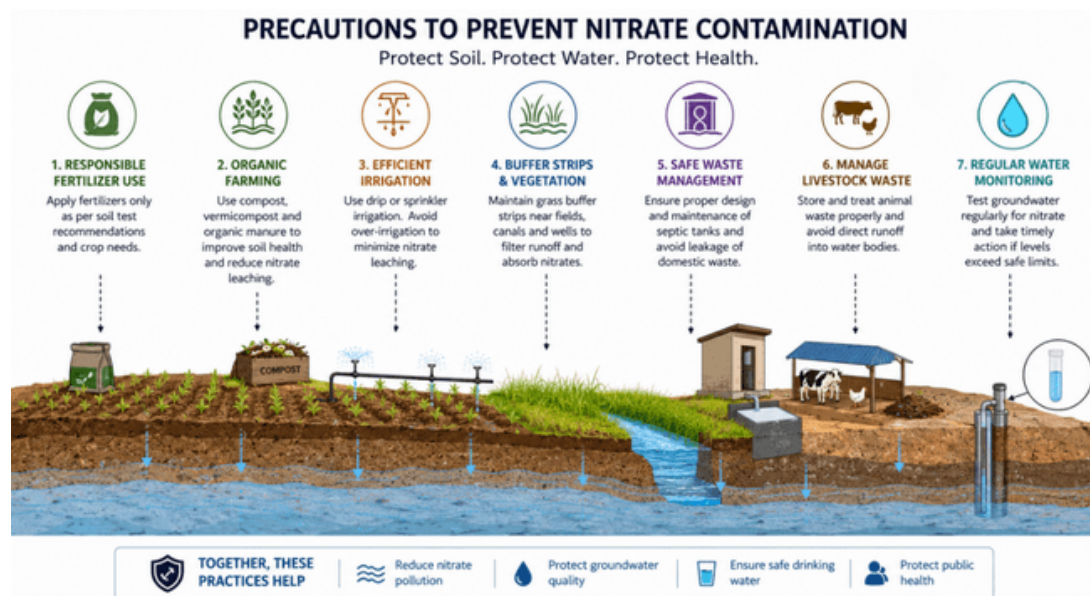


Figure 6: Precautions to prevent nitrate contamination

9.1 Moderate- and Low-Nitrate Level States

While critical nitrate levels are noted for certain states, such as Tamil Nadu and Andhra Pradesh, others fall in the category of being in the middle range or range of low contamination. Regarding Neutrosophic fuzzy ranking, Himachal Pradesh and Delhi NCR always remained in the middle range and had a moderate risk level with weighted values from 13–17 during the seasons. The two are an indication of local contamination that is associated with urban garbage and fertilizer misuse but not an indicator of any serious groundwater problem.

In the case of less severe levels of contamination, the states with the lowest exceedance of pre-monsoon and post-monsoon season are Bihar, Chhattisgarh, and Meghalaya, out of which Meghalaya shows no contamination at all. Such states can be served with non-techniques such as blending of good quality water with contaminated water and controlled fertilizer.

10. Conclusion

The Neutrosophic Trapezoidal Fuzzy Ranking method has been used for the seasonal nitrate contamination of groundwater in selected Indian states. It was a very effective means to incorporate complex uncertainties in the environmental data and provided efficient decision support. This methodology resulted in identification of two states of India namely, Tamil Nadu and Andhra Pradesh as the major hot spots, whereas Tamil Nadu showed the degradation post monsoon season. On the other hand, rest of the selected Indian states like Himachal Pradesh, Delhi, Bihar, Chhattisgarh, and Meghalaya remained relatively safer. In fuzzy ranking methodology, both truth, indeterminacy and falsity memberships are incorporated together for ranking purposes. Not only the level of severity was calculated through this method, but also the seasonal trend noticed through classical analysis. With respect to public health consideration, the study emphasizes the need for certain standards as established by WHO and BIS for safe drinking water since these factors may be dangerous in causing certain chronic diseases and methemoglobinemia. For the states where the impacts were quite strong, the high nitrate content in the drinking water posed a great environmental threat especially for the children. For avoiding such hazards, the combination of preventive measures and proper monitoring techniques should include proper use of fertilizer, agricultural practices, irrigation efficiency, buffer vegetation, waste disposal from households and animals as well as regular water quality testing. Such methods will decrease the level of nitrate leaching and run-off. In addition, when the levels go beyond their acceptable limits then suitable treatment techniques such as reverse osmosis, ion exchange, biological denitrification and electro dialysis should be adopted. Thus the combination of both preventative methods along with proper monitoring techniques should prove beneficial.

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