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Fuzzy set approach–A tool to cluster Holy samples of groundwater quality parameters at Rameswaram, South India

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Abstract: A fuzzy set theoretic approach has been developed to study the potable nature of the holy groundwater samples in summer and winter by clustering method using equivalence relation. The physico-chemical parameters *viz*., pH, Salinity, TDS, CH, MH, TH, Chloride and Fluoride are considered as attributes to develop the clusters. Based on the WHO recommendations, the linguistic approach has been developed for the water quality parameters of 22 holy groundwater samples in this study. Normalized eucilidean distance chosen for this study, measures the deviation of the determined quality parameters for any two holy groundwater samples. In the present paper, the seasonal changes in the quality of the water samples among the clusters at various rational alpha cuts are derived. The fluctuation in the water quality parameters was apparent such that the clusters contract from summer to winter with an exception of one sample with remarkable quality called Sethumadhava.

Keywords: Fuzzy Set, Potable Nature, Groundwater, Fuzzy Cluster, Alpha Cuts

1. Introduction

The physico-chemical quality of drinking water becomes as important as its availability. The water quality parameters with desirable, acceptable and not acceptable values, recommended by World Health Organisation (WHO) create awareness among the public, which enroute them towards the removal techniques [1, 2]. From the WHO guideline values, the groundwater samples are categorized for quality with respect to each water quality parameter. This may lead to a decision but with ambiguity, because it is derived out of only one parameter. So far, numerous research works have been carried out in the determination of water quality using fuzzy synthetic evaluation [3 – 5], fuzzy process capability [6], fuzzy clustering and pattern recognition method [7, 8], fuzzy logic approach [9], fuzzy logical rule [10],fuzzy simulink model [11], fuzzy logic drastic vulnerability map [12], fuzzy GNDCI-CNR method [13] and fuzzy set theory [14]. In the present work, a new focus has been attempted using fuzzy equivalence relation to arrive at non-overlapping clusters of 22 groundwater samples by considering various agreement levels (alpha cuts).

2. Study Objectives and Methods

The objective of the present study is to obtain non-overlapping clusters of twenty two holy groundwater samples (Table 1) of Rameswaram temple in the summer and winter seasons based on the water quality parameters *viz.,* pH, Salinity, Total Dissolved Solids (TDS), Calcium Hardness(CH), Magnesium Hardness(MH), Total Hardness(TH), Chloride(Cl) and Fluoride(F).

2.1. Study Area

Rameswaram is located around an intersection of the

9º28'North Latitude and 79º3'East Longitude with an average elevation of 10 meters above the MSL, covering an area of 61.8 sq.kms and bearing a population of about 38,000, as on September 2007. This Indian Island having connection with main land assumes a shape of conch, is a Taluk with 1 Firka, 2 Revenue villages and 31 Hamlets. Climate prevails with a minimum temperature of 25ºC in winter and a maximum of 36ºC in summer. The average rainfall is 813mm [15, 16].

Table 1. *Name of the holy groundwater samples*

Sample No.	Name of the holy groundwater
1	Mahalakshmi
2	Savithri
3	Gayathri
4	Saraswathi
5	Sangu
6	Sarkarai
7	Sethumadhava
8	Nala
9	Neela
10	Kavaya
11	Kavacha
12	Kandhamadhana
13	Bramahathi
14	Ganga
15	Yamuna
16	Gaya
17	Sarwa
18	Siva
19	Sathyamrudham
20	Surya
21	Chandra
22	Kodi

2.2. Clustering of Groundwater Samples

Let S_1, S_2 ......S_{22} were the twenty two groundwater samples of Rameswaram temple are considered for clustering based on the criteria C_1, C_2..........C_8 *viz.,* pH, Salinity, TDS, CH, MH, TH, Cl and F.

Linguistic terms such as Excellent, Fairly Excellent, Good, Fairly Good and Poor were assigned to the chosen water samples with respect to the recommendations of the World Health Organisation [17].

2.3. Membership Functions and Fuzzy Relations

Membership function (μ) is a critical measure which represents numerically the degrees of elements belonging to a set. Distance measure is a term that describes a difference between fuzzy sets and can be considered as a dual concept of similarity measure.

The linguistic terms (Table 2) were converted into fuzzy numbers (membership functions) using probability technique. Using the fuzzy numbers, the Normalised euclidean distance (eqn.1)

$$\sqrt{\frac{1}{n}\sum_{1}^{n}\left[(\mu_A(x_i)-\mu_B(x_i))^2+(\nu_A(x_i)-\nu_B(x_i))^2\ \right]} \quad (1)$$

was used to obtain similarity measures, which was found by subtracting the distance measure from 1 using MATLAB (version 7). The obtained similarity measure possesses tolerance relation (R) between the undertaken groundwater samples (Tables 3 and 4). A fuzzy relation (R) is said to be fuzzy tolerance relation if R is reflexive [if $\mu_R(x,x)=1$, for every x Є X] and symmetric [if $\mu_R[x,y)=\mu_R(y,x)$ for every x,y Є X].

A fuzzy relation, R is said to be fuzzy equivalence relation R_E, if R is fuzzy tolerance relation and transitive closure [if μ_R satisfies $\mu_R(x,z)\geq \min\{\mu_R(x,y), \mu_R(y,z)\}$for every x,y,z Є X.

An equivalence relation (R_E) in Tables 5 and 6 was determined from the computed tolerance relation by the following algorithm using Visual C $^{++}$ on windows platform.

Step 1: R' =R o (R∪R)

Step 2: If R' ≠R, make R=R' and go to step 1.

Step 3: Stop: R' = RE

In the above o is the max-main composition of fuzzy relations and ∪ is the standard fuzzy union. By the consideration of reasonable alpha cuts ({x/μ(x) > α, for some x ЄX}), the groundwater samples were clustered in the non-overlapping nature.

3. Results and Discussion

For grouping the 22 groundwater samples with respect to nine water quality parameters according to the WHO recommendations, the present work was initiated with a consideration of two suitable agreement levels (alpha cut), α = 0.85 and 0.90 from four reasonable agreement levels, from α = 0.80, 0.85, 0.9 and 0.95. The remaining two alpha cuts (α = 0.8 and 0.95) generated a minimum number (two) of clusters, which does not reveal any significant impact in grouping the groundwater samples in accordance with the chosen water quality parameters. The non-overlapping clusters (grouped water samples) for the above two suitable alpha cuts in summer and winter seasons are depicted in Fig.1.

From the Fig 1, it can be accounted that the samples 7, 8, 11 and 20 & 21 remain as separate clusters both at 85% and 90% Agreement Level (AL). Thus the above said samples did not have any quality parametric changes at both the agreement levels. The samples 4 and 10 from a similar cluster at 85% AL were found to stay as independent clusters at 90% AL. Similarly, the samples 14, 15, 16 and 17 of same cluster at 85% AL got separated into an individual cluster at 90% AL. From these results, it is observed that, even at 0.05% difference in AL reveal some changes in the water quality characteristics.

The seasonal influence can also be witnessed from the merging of different clusters at 90% AL. Obviously, in summer, the samples 14, 15, 16 and 17 of a single cluster and the samples 20 & 21 of another single cluster, got merged with the cluster containing the samples 1-6, 8 and 17-21 in winter. Also it was observed that the samples 10 and 12 from two different clusters in summer grouped into a particular cluster in winter.

In summer, at 0.9 AL, there were nine clusters which get converged into five clusters in winter. Similarly, six clusters in summer at 0.85 AL get grouped and formed three separate clusters in winter.

A cluster with the samples 1,2,3,4,5,6,9,13,18,,19 & 22 in summer breaks into a separate cluster with the samples 9 & 22 and another cluster with the sample designated as 13 in winter. The above cluster separation from summer to winter indicates the change in the water quality parameters with respect to dilution influenced by seasons.

The samples 7 and 11, identified as separate clusters in summer were found to retain the same identity in winter at both agreement levels (0.9 and 0.85). This shows that the water quality parameters of both the samples falls within the standards fixed in this study as per WHO even after the seasonal influence.

In winter, the number of clusters at 0.9 AL and 0.85 AL were computed to be 6 and 3 respectively and this highlights the reduction of clusters indicates the role of dilution which causes recharging of groundwater and setting the water quality parameters with respect to the fixed standards as per WHO. In winter, at 0.9 and 0.85, there were two separate clusters formed with 7 and 10 & 12 as samples. The remaining samples have formed as a separate cluster by indicating their suitability within a particular water quality standard. The agreement level of 0.85 in both summer and winter was found with 6 and 3 clusters respectively.

In this case a separate cluster having the sample no.7 in both summer and winter was observed. Samples 12 and 10 from two separate clusters in summer were found to form a particular cluster in winter. This reflects that these two samples possess the quality characteristics within a particular limit, fixed in the study in accordance with WHO recommendations.

The identity of a single membered cluster containing a groundwater sample No. 7 (Sethumadhava) at both the agreement levels in two different seasons, ascertains the distinct quality of the water sample. Evidently, the present observation was in agreement with our earlier work [18].

4. Conclusions

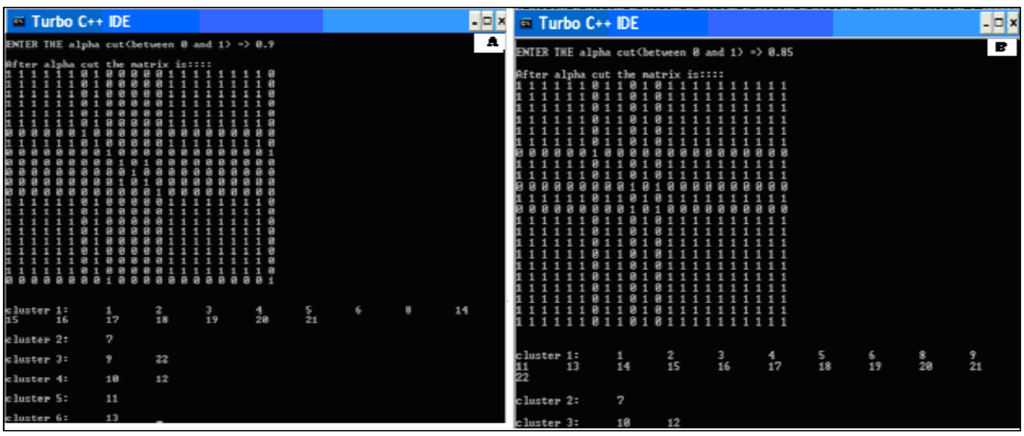
Based on the above discussions, the following conclusions are drawn.

1. Among the four agreement levels (alpha cuts), the suitability was found for those at $\alpha = 0.85$ and 0.9, where appreciable number of clusters were generated.
2. From each appreciable cluster containing a group of water samples, the similarity of ground water quality among the samples with respect to the chosen parameters, was identified.
3. A cluster consisting of only one groundwater sample i.e. sample no.7 (Sethumadhava) at the suitable agreement levels in both summer and winter, was found to exhibit a distinct water quality by itself.
4. The contraction of clusters from summer to winter signifies the fluctuations in the water quality parameters at both the agreement levels.

Table 2. *Membership values assigned for the water quality parameters*

Parameters	Membership values (Linguistic forms) 1.0 (Excellent)	0.8 (Fairly Excellent)	0.6 (Good)	0.4 (Fairly Good)	0.2(Poor)
pH	6.5 – 7.5	7.5 – 8.0	8.0 – 8.5	8.5 – 9.0	>9.0
TDS	<500	500 – 650	650 – 800	800 – 1000	>1000
CH	<75	75 – 100	100 – 150	150 – 200	>200
MH	<30	30 – 75	75 – 115	115 – 150	>150
TH	<100	100 – 250	250 – 350	350 – 500	>500
F	<0.5	0.50 – 0.75	0.75 – 1.0	1.0 – 1.5	>1.5
SAL	<200	200 – 350	350 – 500	500 – 600	>600
Cl	<250	250 - 350	350 - 450	450 - 600	>600

TDS-Total Dissolved Solids; CH-Calcium Hardness; MH-Magnesium Hardness; TH-Total Hardness; F-Fluoride; SAL-Salinity; Cl-Chloride



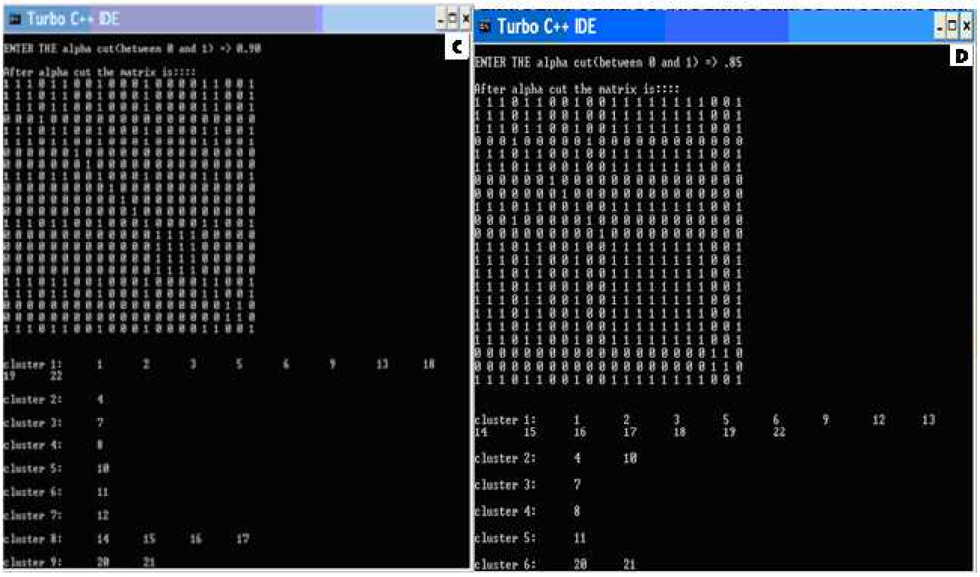


Figure 1. *Clustered (non-overlapping) groundwater samples by MAT LAB program for A) summer, α = 0.9 B) summer, α = 0.85 C) winter, α = 0.9 D) winter, α = 0.85*

Table 3. *Tolerance matrix in Summer*

1.000	0.900	0.900	0.735	0.842	0.859	0.576	0.735	0.827	0.765	0.842	0.745	0.827	0.800	0.827	0.859	0.788	0.929	0.878	0.827	0.827	0.859
0.900	**1.000**	0.900	0.735	0.842	0.900	0.588	0.700	0.859	0.788	0.842	0.745	0.827	0.735	0.776	0.776	0.708	0.929	0.929	0.800	0.800	0.900
0.900	0.900	**1.000**	0.800	0.929	0.900	0.613	0.735	0.900	0.813	0.813	0.788	0.859	0.827	0.859	0.827	0.765	0.929	0.929	0.827	0.827	0.900
0.735	0.735	0.800	**1.000**	0.842	0.776	0.613	0.735	0.827	0.878	0.765	0.745	0.800	0.776	0.755	0.700	0.661	0.745	0.788	0.776	0.776	0.735
0.842	0.842	0.929	0.842	**1.000**	0.878	0.633	0.765	0.929	0.827	0.776	0.827	0.878	0.842	0.842	0.788	0.735	0.859	0.900	0.788	0.788	0.878
0.859	0.900	0.900	0.776	0.878	**1.000**	0.613	0.735	0.900	0.813	0.813	0.788	0.859	0.755	0.776	0.755	0.692	0.878	0.929	0.776	0.776	0.900
0.576	0.588	0.613	0.613	0.633	0.613	**1.000**	0.588	0.639	0.661	0.558	0.676	0.684	0.576	0.564	0.531	0.495	0.582	0.619	0.542	0.542	0.613
0.735	0.700	0.735	0.735	0.765	0.735	0.588	**1.000**	0.776	0.726	0.708	0.813	0.827	0.735	0.668	0.668	0.619	0.692	0.745	0.639	0.639	0.735
0.827	0.859	0.900	0.827	0.929	0.900	0.639	0.776	**1.000**	0.842	0.788	0.842	0.900	0.776	0.776	0.735	0.676	0.842	0.929	0.755	0.755	0.900
0.765	0.788	0.813	0.878	0.827	0.813	0.661	0.726	0.842	**1.000**	0.827	0.755	0.842	0.726	0.726	0.692	0.639	0.776	0.827	0.788	0.788	0.765
0.842	0.842	0.813	0.765	0.776	0.813	0.558	0.708	0.788	0.827	**1.000**	0.684	0.788	0.708	0.726	0.745	0.684	0.827	0.827	0.842	0.842	0.765
0.745	0.745	0.788	0.745	0.827	0.788	0.676	0.813	0.842	0.755	0.684	**1.000**	0.878	0.745	0.708	0.676	0.626	0.735	0.800	0.646	0.646	0.813
0.827	0.827	0.859	0.800	0.878	0.859	0.684	0.827	0.900	0.842	0.788	0.878	**1.000**	0.776	0.755	0.735	0.676	0.813	0.878	0.735	0.735	0.859
0.800	0.735	0.827	0.776	0.842	0.755	0.576	0.735	0.776	0.726	0.708	0.745	0.776	**1.000**	0.900	0.859	0.842	0.788	0.765	0.776	0.776	0.755
0.827	0.776	0.859	0.755	0.842	0.776	0.564	0.668	0.776	0.726	0.726	0.708	0.755	0.900	**1.000**	0.900	0.878	0.842	0.788	0.827	0.827	0.776
0.859	0.776	0.827	0.700	0.788	0.755	0.531	0.668	0.735	0.692	0.745	0.676	0.735	0.859	0.900	**1.000**	0.929	0.842	0.765	0.827	0.827	0.755
0.788	0.708	0.765	0.661	0.735	0.692	0.495	0.619	0.676	0.639	0.684	0.626	0.676	0.842	0.878	0.929	**1.000**	0.776	0.700	0.788	0.788	0.692
0.929	0.929	0.929	0.745	0.859	0.878	0.582	0.692	0.842	0.776	0.827	0.735	0.813	0.788	0.842	0.842	0.776	**1.000**	0.900	0.842	0.842	0.878
0.878	0.929	0.929	0.788	0.900	0.929	0.619	0.745	0.929	0.827	0.827	0.800	0.878	0.765	0.788	0.765	0.700	0.900	**1.000**	0.788	0.788	0.929
0.827	0.800	0.827	0.776	0.788	0.776	0.542	0.639	0.755	0.788	0.842	0.646	0.735	0.776	0.827	0.827	0.788	0.842	0.788	**1.000**	1.000	0.735
0.827	0.800	0.827	0.776	0.788	0.776	0.542	0.639	0.755	0.788	0.842	0.646	0.735	0.776	0.827	0.827	0.788	0.842	0.788	1.000	**1.000**	0.735
0.859	0.900	0.900	0.735	0.878	0.900	0.613	0.735	0.900	0.765	0.765	0.813	0.859	0.755	0.776	0.755	0.692	0.878	0.929	0.735	0.735	**1.000**

Table 4 *Tolerance matrix in winter*

1.000	0.813	0.765	0.900	0.842	0.842	0.421	0.859	0.776	0.606	0.726	0.619	0.765	0.929	0.842	0.900	0.900	0.900	0.800	0.929	0.900	0.776
0.813	**1.000**	0.859	0.878	0.900	0.900	0.490	0.878	0.813	0.684	0.859	0.668	0.776	0.776	0.900	0.813	0.726	0.765	0.929	0.827	0.813	0.813
0.765	0.859	**1.000**	0.842	0.900	0.827	0.500	0.813	0.788	0.668	0.859	0.639	0.700	0.735	0.859	0.788	0.676	0.708	0.878	0.776	0.788	0.788
0.900	0.878	0.842	**1.000**	0.929	0.878	0.448	0.900	0.800	0.633	0.788	0.633	0.765	0.842	0.878	0.859	0.800	0.859	0.859	0.929	0.900	0.800
0.842	0.900	0.900	0.929	**1.000**	0.859	0.461	0.878	0.788	0.639	0.827	0.626	0.735	0.800	0.900	0.842	0.745	0.788	0.878	0.859	0.842	0.788
0.842	0.900	0.827	0.878	0.859	**1.000**	0.510	0.878	0.878	0.717	0.827	0.717	0.827	0.800	0.859	0.813	0.765	0.813	0.929	0.859	0.878	0.878
0.421	0.490	0.500	0.448	0.461	0.510	**1.000**	0.476	0.570	0.684	0.564	0.700	0.531	0.408	0.452	0.430	0.380	0.396	0.526	0.426	0.457	0.570
0.859	0.878	0.813	0.900	0.878	0.878	0.476	**1.000**	0.827	0.676	0.813	0.676	0.813	0.813	0.842	0.827	0.776	0.827	0.859	0.878	0.859	0.827
0.776	0.813	0.788	0.800	0.788	0.878	0.570	0.827	**1.000**	0.813	0.842	0.813	0.878	0.745	0.765	0.755	0.717	0.755	0.859	0.788	0.827	1.000
0.606	0.684	0.668	0.633	0.639	0.717	0.684	0.676	0.813	**1.000**	0.776	0.900	0.776	0.588	0.626	0.606	0.558	0.582	0.726	0.613	0.646	0.813
0.726	0.859	0.859	0.788	0.827	0.827	0.564	0.813	0.842	0.776	**1.000**	0.735	0.776	0.700	0.800	0.745	0.646	0.676	0.878	0.735	0.745	0.842
0.619	0.668	0.639	0.633	0.626	0.717	0.700	0.676	0.813	0.900	0.735	**1.000**	0.800	0.600	0.613	0.606	0.582	0.606	0.708	0.626	0.661	0.813
0.765	0.776	0.700	0.765	0.735	0.827	0.531	0.813	0.878	0.776	0.776	0.800	**1.000**	0.735	0.717	0.726	0.726	0.765	0.788	0.776	0.788	0.878
0.929	0.776	0.735	0.842	0.800	0.800	0.408	0.813	0.745	0.588	0.700	0.600	0.735	**1.000**	0.827	0.929	0.929	0.842	0.765	0.859	0.842	0.745
0.842	0.900	0.859	0.878	0.900	0.859	0.452	0.842	0.765	0.626	0.800	0.613	0.717	0.827	**1.000**	0.878	0.765	0.765	0.878	0.827	0.813	0.765
0.900	0.813	0.788	0.859	0.842	0.813	0.430	0.827	0.755	0.606	0.745	0.606	0.726	0.929	0.878	**1.000**	0.859	0.800	0.800	0.842	0.827	0.755
0.900	0.726	0.676	0.800	0.745	0.765	0.380	0.776	0.717	0.558	0.646	0.582	0.726	0.929	0.765	0.859	**1.000**	0.859	0.717	0.842	0.827	0.717
0.900	0.765	0.708	0.859	0.788	0.813	0.396	0.827	0.755	0.582	0.676	0.606	0.765	0.842	0.765	0.800	0.859	**1.000**	0.755	0.929	0.900	0.755
0.800	0.929	0.878	0.859	0.878	0.929	0.526	0.859	0.859	0.726	0.878	0.708	0.788	0.765	0.878	0.800	0.717	0.755	**1.000**	0.813	0.827	0.859
0.929	0.827	0.776	0.929	0.859	0.859	0.426	0.878	0.788	0.613	0.735	0.626	0.776	0.859	0.827	0.842	0.842	0.929	0.813	**1.000**	0.929	0.788
0.900	0.813	0.788	0.900	0.842	0.878	0.457	0.859	0.827	0.646	0.745	0.661	0.788	0.842	0.813	0.827	0.827	0.900	0.827	0.929	**1.000**	0.827
0.776	0.813	0.788	0.800	0.788	0.878	0.570	0.827	1.000	0.813	0.842	0.813	0.878	0.745	0.765	0.755	0.717	0.755	0.859	0.788	0.827	**1.000**

Table 5. *Equivalance matrix in Summer*

1.000	0.975	0.975	0.934	0.960	0.965	0.894	0.934	0.957	0.941	0.960	0.936	0.957	0.950	0.957	0.965	0.947	0.982	0.969	0.957	0.957	0.965
0.975	**1.000**	0.975	0.934	0.960	0.975	0.897	0.925	0.965	0.947	0.960	0.936	0.957	0.934	0.944	0.944	0.927	0.982	0.982	0.950	0.950	0.975
0.975	0.975	**1.000**	0.950	0.982	0.975	0.903	0.934	0.975	0.953	0.953	0.947	0.965	0.957	0.965	0.957	0.941	0.982	0.982	0.957	0.957	0.975
0.934	0.934	0.950	**1.000**	0.960	0.944	0.903	0.934	0.957	0.969	0.941	0.936	0.950	0.944	0.939	0.925	0.915	0.936	0.947	0.944	0.944	0.934
0.960	0.960	0.982	0.960	**1.000**	0.969	0.908	0.941	0.982	0.957	0.944	0.957	0.969	0.960	0.960	0.947	0.934	0.965	0.975	0.947	0.947	0.969
0.965	0.975	0.975	0.944	0.969	**1.000**	0.903	0.934	0.975	0.953	0.953	0.947	0.965	0.939	0.944	0.939	0.923	0.969	0.982	0.944	0.944	0.975
0.894	0.897	0.903	0.903	0.908	0.903	**1.000**	0.897	0.910	0.915	0.890	0.919	0.921	0.894	0.891	0.883	0.874	0.895	0.905	0.885	0.885	0.903
0.934	0.925	0.934	0.934	0.941	0.934	0.897	**1.000**	0.944	0.932	0.927	0.953	0.957	0.934	0.917	0.917	0.905	0.923	0.936	0.910	0.910	0.934
0.957	0.965	0.975	0.957	0.982	0.975	0.910	0.944	**1.000**	0.960	0.947	0.960	0.975	0.944	0.944	0.934	0.919	0.960	0.982	0.939	0.939	0.975
0.941	0.947	0.953	0.969	0.957	0.953	0.915	0.932	0.960	**1.000**	0.957	0.939	0.960	0.932	0.932	0.923	0.910	0.944	0.957	0.947	0.947	0.941
0.960	0.960	0.953	0.941	0.944	0.953	0.890	0.927	0.947	0.957	**1.000**	0.921	0.947	0.927	0.932	0.936	0.921	0.957	0.957	0.960	0.960	0.941
0.936	0.936	0.947	0.936	0.957	0.947	0.919	0.953	0.960	0.939	0.921	**1.000**	0.969	0.936	0.927	0.919	0.906	0.934	0.950	0.912	0.912	0.953
0.957	0.957	0.965	0.950	0.969	0.965	0.921	0.957	0.975	0.960	0.947	0.969	**1.000**	0.944	0.939	0.934	0.919	0.953	0.969	0.934	0.934	0.965
0.950	0.934	0.957	0.944	0.960	0.939	0.894	0.934	0.944	0.932	0.927	0.936	0.944	**1.000**	0.975	0.965	0.960	0.947	0.941	0.944	0.944	0.939
0.957	0.944	0.965	0.939	0.960	0.944	0.891	0.917	0.944	0.932	0.932	0.927	0.939	0.975	**1.000**	0.975	0.969	0.960	0.947	0.957	0.957	0.944
0.965	0.944	0.957	0.925	0.947	0.939	0.883	0.917	0.934	0.923	0.936	0.919	0.934	0.965	0.975	**1.000**	0.982	0.960	0.941	0.957	0.957	0.939
0.947	0.927	0.941	0.915	0.934	0.923	0.874	0.905	0.919	0.910	0.921	0.906	0.919	0.960	0.969	0.982	**1.000**	0.944	0.925	0.947	0.947	0.923
0.982	0.982	0.982	0.936	0.965	0.969	0.895	0.923	0.960	0.944	0.957	0.934	0.953	0.947	0.960	0.960	0.944	**1.000**	0.975	0.960	0.960	0.969
0.969	0.982	0.982	0.947	0.975	0.982	0.905	0.936	0.982	0.957	0.957	0.950	0.969	0.941	0.947	0.941	0.925	0.975	**1.000**	0.947	0.947	0.982
0.957	0.950	0.957	0.944	0.947	0.944	0.885	0.910	0.939	0.947	0.960	0.912	0.934	0.944	0.957	0.957	0.947	0.960	0.947	**1.000**	1.000	0.934
0.957	0.950	0.957	0.944	0.947	0.944	0.885	0.910	0.939	0.947	0.960	0.912	0.934	0.944	0.957	0.957	0.947	0.960	0.947	1.000	**1.000**	0.934
0.965	0.975	0.975	0.934	0.969	0.975	0.903	0.934	0.975	0.941	0.941	0.953	0.965	0.939	0.944	0.939	0.923	0.969	0.982	0.934	0.934	**1.000**

***Table 6** Equivalance matrix in Winter*

1.000	0.953	0.941	0.975	0.960	0.960	0.855	0.965	0.944	0.902	0.932	0.905	0.941	0.982	0.960	0.975	0.975	0.975	0.950	0.982	0.975	0.944
0.953	**1.000**	0.965	0.969	0.975	0.975	0.873	0.969	0.953	0.921	0.965	0.917	0.944	0.944	0.975	0.953	0.932	0.941	0.982	0.957	0.953	0.953
0.941	0.965	**1.000**	0.960	0.975	0.957	0.875	0.953	0.947	0.917	0.965	0.910	0.925	0.934	0.965	0.947	0.919	0.927	0.969	0.944	0.947	0.947
0.975	0.969	0.960	**1.000**	0.982	0.969	0.862	0.975	0.950	0.908	0.947	0.908	0.941	0.960	0.969	0.965	0.950	0.965	0.965	0.982	0.975	0.950
0.960	0.975	0.975	0.982	**1.000**	0.965	0.865	0.969	0.947	0.910	0.957	0.906	0.934	0.950	0.975	0.960	0.936	0.947	0.969	0.965	0.960	0.947
0.960	0.975	0.957	0.969	0.965	**1.000**	0.878	0.969	0.969	0.929	0.957	0.929	0.957	0.950	0.965	0.953	0.941	0.953	0.982	0.965	0.969	0.969
0.855	0.873	0.875	0.862	0.865	0.878	**1.000**	0.869	0.892	0.921	0.891	0.925	0.883	0.852	0.863	0.857	0.845	0.849	0.881	0.856	0.864	0.892
0.965	0.969	0.953	0.975	0.969	0.969	0.869	**1.000**	0.957	0.919	0.953	0.919	0.953	0.953	0.960	0.957	0.944	0.957	0.965	0.969	0.965	0.957
0.944	0.953	0.947	0.950	0.947	0.969	0.892	0.957	**1.000**	0.953	0.960	0.953	0.969	0.936	0.941	0.939	0.929	0.939	0.965	0.947	0.957	1.000
0.902	0.921	0.917	0.908	0.910	0.929	0.921	0.919	0.953	**1.000**	0.944	0.975	0.944	0.897	0.906	0.902	0.890	0.895	0.932	0.903	0.912	0.953
0.932	0.965	0.965	0.947	0.957	0.957	0.891	0.953	0.960	0.944	**1.000**	0.934	0.944	0.925	0.950	0.936	0.912	0.919	0.969	0.934	0.936	0.960
0.905	0.917	0.910	0.908	0.906	0.929	0.925	0.919	0.953	0.975	0.934	**1.000**	0.950	0.900	0.903	0.902	0.895	0.902	0.927	0.906	0.915	0.953
0.941	0.944	0.925	0.941	0.934	0.957	0.883	0.953	0.969	0.944	0.944	0.950	**1.000**	0.934	0.929	0.932	0.932	0.941	0.947	0.944	0.947	0.969
0.982	0.944	0.934	0.960	0.950	0.950	0.852	0.953	0.936	0.897	0.925	0.900	0.934	**1.000**	0.957	0.982	0.982	0.960	0.941	0.965	0.960	0.936
0.960	0.975	0.965	0.969	0.975	0.965	0.863	0.960	0.941	0.906	0.950	0.903	0.929	0.957	**1.000**	0.969	0.941	0.941	0.969	0.957	0.953	0.941
0.975	0.953	0.947	0.965	0.960	0.953	0.857	0.957	0.939	0.902	0.936	0.902	0.932	0.982	0.969	**1.000**	0.965	0.950	0.950	0.960	0.957	0.939
0.975	0.932	0.919	0.950	0.936	0.941	0.845	0.944	0.929	0.890	0.912	0.895	0.932	0.982	0.941	0.965	**1.000**	0.965	0.929	0.960	0.957	0.929
0.975	0.941	0.927	0.965	0.947	0.953	0.849	0.957	0.939	0.895	0.919	0.902	0.941	0.960	0.941	0.950	0.965	**1.000**	0.939	0.982	0.975	0.939
0.950	0.982	0.969	0.965	0.969	0.982	0.881	0.965	0.965	0.932	0.969	0.927	0.947	0.941	0.969	0.950	0.929	0.939	**1.000**	0.953	0.957	0.965
0.982	0.957	0.944	0.982	0.965	0.965	0.856	0.969	0.947	0.903	0.934	0.906	0.944	0.965	0.957	0.960	0.960	0.982	0.953	**1.000**	0.982	0.947
0.975	0.953	0.947	0.975	0.960	0.969	0.864	0.965	0.957	0.912	0.936	0.915	0.947	0.960	0.953	0.957	0.957	0.975	0.957	0.982	**1.000**	0.957
0.944	0.953	0.947	0.950	0.947	0.969	0.892	0.957	1.000	0.953	0.960	0.953	0.969	0.936	0.941	0.939	0.929	0.939	0.965	0.947	0.957	**1.000**

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