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Exploration of Topsis (Technique for Order Preference by Similarity to Ideal Solution) as an Alternative to Traditional Classification Algorithm in Small Areas of Lohardaga District of Jharkhand, India, Using Remote Sensing Image-A Case Study

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Abstract: Supervised classification in remote sensing is widely applied to identify areas, divide the region on the image acquired by remote sensing sensors into different categories. Various algorithms like mahanlonobis classifier, maximum likelihood classifier, means cluster analysis, which are a part of the available digital image processing software, have been widely used for convenience. In the present paper, exploration of application of feasibility of using TOPSIS as a screening tool to identify small areas of similar land use in a given region is explored.

Key words: Topsis % Ground Truth % Global Positioning System (GPS) % Digital Image Processing (DIP) % Geo-Coded Satellite Image

INTRODUCTION

TOPSIS orders the feasible alternatives according to their closeness to the ideal solution [1].The weighted summation approach along with the linear transportation method for normalization criteria and the pair wise comparison method for deriving the criteria weights are used by many studies [2] in geographic information system (GIS) and remote sensing. The use of TOPSIS is specially suited for raster structure [3]. A need for new approaches to identify satellite feature on satellite imagery is explored [4], Xiao and Zhang[5] and Huang *et al*. [6]).

In the district of Lohardaga, in the state of Jharkhand, India, mining of bauxite ore started way back in 1940s [7].It is an open cast mine where the product depth ranges from 4 to 10 meters. The shallow depth encourages the local people to extract the ore on their own. Parallely there are licensed mines too.The ore is scattered all over the region, which is highly inaccessible for it being in the forest, remote sensing becomes an economical tool to identify these scattered active mining sites. Traditional methods of supervised classification with temporal data and other ancillary data along with ground truth have been successfully employed to detect the changes on the earth's surface [8].

In this paper five active mining site areas were verified during ground truth i.e. physical verification was carried out on the spot with a hand held GPS. The spectral profile of five were grouped in Table 1 and termed as observed profile. Another set of 16 active mining sites were identified on the graphic screen using the elements of image interpretation. Their spectral profiles were grouped in Table 2 and termed as data observed from the graphic screen to select areas similar to Table 1. There were 21 spectral profiles in all. TOPSIS for both the groups was performed. The aim was to explore the feasibility of making a decision to select the most likely sites closer to sites in Table 1.The values of spectral profiles of bands 1, 2 and 3 were derived from the geo-coded satellite imagery of IRS IC, LISS III sensor having four bands as displayed on the screen of a digital image processing (DIP) software. While performing TOPSIS, the maximum weight was assigned to band 2 for green reflectance of healthy vegetation useful in soil boundary and geological boundary delineation [9].

Table 1: Data of observed profiles from the graphic screen (after ground truth)

	BAND 1	BAND 2	BAND 3
PROFILE 1	166	164	149
PROFILE 2	198	210	172
PROFILE 3	183	184	160
PROFILE 4	115	132	107
PROFILE 5	122	133	112

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Table 2: Data observed from the graphic screen to select areas similar to those in Table 1

	BAND 1	BAND 2	BAND 3
PROFILE 6	213	215	167
PROFILE 7	175	181	144
PROFILE 8	170	177	147
PROFILE 9	164	178	146
PROFILE 10	149	155	129
PROFILE 11	118	124	97
PROFILE 12	117	136	111
PROFILE 13	103	92	83
PROFILE 14	90	70	83
PROFILE 15	87	66	69
PROFILE 16	87	64	58
PROFILE 17	86	67	65
PROFILE 18	84	65	73
PROFILE 19	83	60	67
PROFILE 20	83	64	63
PROFILE 21	80	60	63

METHODOLOGY

By TOPSIS we mean the technique for order preference by similarity to ideal solution, developed by Hwang and Yoon [10]. It is based on the concept that the chosen alternative should have the shortest distance from positive ideal solution (PIS) and longest distance from negative ideal solution (NIS). The ideal solution is the collection of ideal scores (ratings) in all attributes considered for a given system.

The 16 selected spectral profile values were used to perform TOPSIS. Five of the observed profiles were ground truthed.These 21 profiles were divided into a set of two, one set containing five profiles (Figure 1), which were ground truthed.The 16 other profiles were grouped in Table 2 and TOPSIS was performed using the algorithm discussed in the next section.

Algorithm:

- Identify the evaluation bands for each profile. These bands have been evaluated and weighted [9].
- Choose the appropriate value (spectral profile/signature) associated with the spectral reflectance of the particular active mining site at a locale.
- Construct the decision matrix f_{ij} and normalized decision matrix r_{ij} for each observed and unobserved set of profiles. The normalized value r_{ij} is calculated as

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{J} f_{ij}^{2}}} \quad (1)$$

- Construct the weighted normalized decision matrix. The weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as

$$v_{ij} = w_i * r_{ij},\ j=1,..,m;\ i=1,\dots,n. \quad (2)$$

Where w_i is the weight of the ith band, i.e. $w=(w_1,w_2,w_3,\dots w_n)$ such that

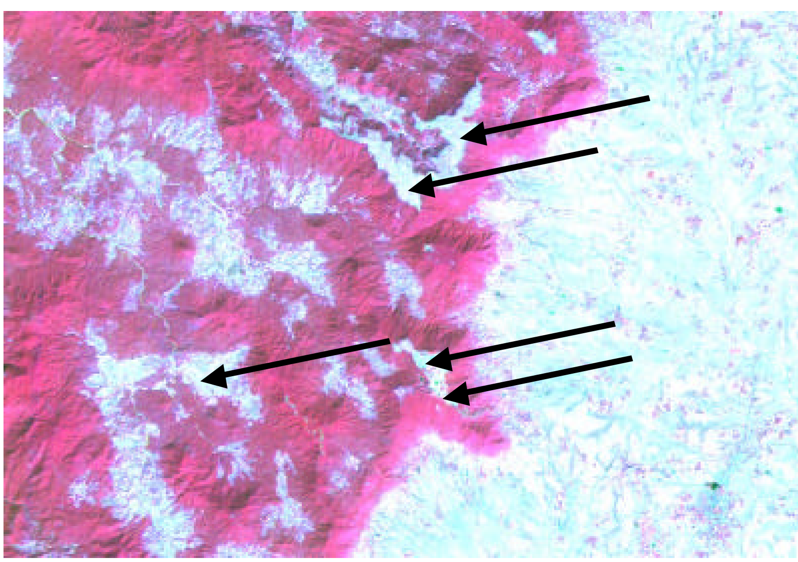

Fig. 1: Ground truth profiles as they appear on the graphic screen.

$$\sum_{i=1}^{n} w_i = 1$$

The weights of bands are also normalized by summing up the total and then dividing the individual weight of the band by this total.

- Determine Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). They are

$$A^{*} = \{ v_1^*,\ldots, v_n^*\} = \{ v_{ij} / \max v_{ij} \}$$
$$A^{-} = \{ v_1^-,\ldots,v_n^-\} = \{(v_{ij} / \min v_{ij} \} \quad (3)$$

i.e select the maximum and minimum value from each column of the weighted normalized decision matrix.

- Calculate the distance of each profile from PIS and NIS respectively. They are PIS as

$$D_j^* = \sqrt{\sum_{j=1}^{J} (v_{ij} - v_i^*)^2} \quad (4)$$

NIS is

$$D_j^- = \sqrt{\sum_{j=1}^{J} (v_{ij} - v_i^-)^2}$$

- Calculate the closeness coefficient. It is

$$C_j = \frac{D_j^-}{(D_j^* + D_j^-)} \qquad j = 1,\ldots,J. \quad (5)$$

Area Identification on Graphic Screen: The requirement of feature extraction from satellite images differ according to the area specific and the resolution of the satellite. The tailor made algorithms available in the digital image processing software may have to be modified or alternative statistical tools as per the users requirement may have to be explored Huang *et al*. [6]. Many new theories in information processing and data mining are ongoing to achieve this task. Mujamdar *et al*. [11] have combined two popular methods i.e. Analytical Hierarchy Process (AHP) and TOPSIS to rank cotton yarn rather than the traditional methods which are time consuming. The ranking method has been used in GIS for ranking suitable sites for soil aquifer treatment in Jerba Island (Tunisia), using RS GIS and AHP multicriteria decision analysis Makram *et al* [12]. In GIS, it has been also used as a screening tool for the managers in choosing potential candidate wetlands for rehabilitation in a region (Liu *et al* [13]).TOPSIS was used as a screening tool for the managers in choosing potential candidate wetlands for rehabilitation in this region. Liu *et al*. [13] and Chen *et al* [14] explore TOPSIS along other multicritera evaluation methods for decision making.

In the present paper TOPSIS was performed for both the sets and the closeness coefficient was calculated based on the weights given to the three bands.

A Case Study: The first five sites (Table 1) for which ground truth was done to verify the actual mining activity was treated as control points. Each profile is represented by three quantitative numbers associated with the three different spectral band of IRS LISS III camera corresponding to wavelength (BAND 1=.52 to.59 µm, BAND 2 =.62 to.68 µm, BAND 3 =.77 to.86 µm).The weights assigned to the bands are given in Table 3.

TOPSIS was performed on all the profiles together, the 16 are listed in Table 2 and their closeness coefficient was worked out (Table 14). The profile 6 was actually from the observed set and was classified into unobserved set purposely to check the correctness of the numerical method.

The maximum weight was assigned to band 2 for green reflectance of healthy vegetation useful in soil boundary and geological boundary delineation.

For performing TOPSIS, first, normalizing the data of both observed and unobserved data sets is done (Tables 4 and 5) using equation (1).The weights assigned to the various bands are also normalized (Table 6).Construction of a weighted normalized decision matrix (Tables 7 and 8) is done using equation (2). Evaluation of the positive and negative ideal solution (Tables 9 and 10) is done using equation (3). Subsequently the distance of each profile from PIS and NIS (Tables 11 and 12) is evaluated using equation (4). Finally the closeness coefficient for final evaluation of each profile is arrived at. (Tables 13 and 14).

Observations: Out of the closeness coefficient of the 16 profiles, five profiles (13, 14, 15, 17 and 18) do not show any closeness to the observed five profiles. All the profiles from Table 2 were again taken for ground truth. It was observed that the profiles of Table 14 which did not match with the TOPSIS value of Table 13 could actually be ignored for further processing in remote sensing. Thereby Topsis acted as a screening tool to identify small areas of similar land use for further treatment of the sites, which were picked up from the graphic screen showing similarity to the observed profiles after ground truth.

Table 3: Weights for various band

BANDS	BAND 1	BAND 2	BAND 3
WEIGHTS	.2	1	.4

Table 4: Normalized Decision Matrix for observed profiles obtained from Table-1

	BAND 1	BAND 2	BAND 3
PROFILE 1	0.463687	0.438503	0.468553
PROFILE 2	0.553073	0.561497	0.540881
PROFILE 3	0.511173	0.491979	0.503145
PROFILE 4	0.321229	0.352941	0.336478
PROFILE 5	0.340782	0.355615	0.352201

Table 5: Normalized Decision Matrix for data of Table 2

	BAND 1	BAND 2	BAND 3
PROFILE 6	0.426	0.436992	0.40048
PROFILE 7	0.35	0.367886	0.345324
PROFILE 8	0.34	0.359756	0.352518
PROFILE 9	0.328	0.361789	0.35012
PROFILE 10	0.298	0.315041	0.309353
PROFILE 11	0.236	0.252033	0.232614
PROFILE 12	0.234	0.276423	0.266187
PROFILE 13	0.206	0.186992	0.199041
PROFILE 14	0.18	0.142276	0.199041
PROFILE 15	0.174	0.134146	0.165468
PROFILE 16	0.174	0.130081	0.139089
PROFILE 17	0.172	0.136179	0.155875
PROFILE 18	0.168	0.132114	0.17506
PROFILE 19	0.166	0.121951	0.160671
PROFILE 20	0.166	0.130081	0.151079
PROFILE 21	0.16	0.121951	0.151079

Table 6: Normalized weights for various band

BANDS	BAND 1	BAND 2	BAND 3
WEIGHTS	0.125	0.625	0.25

Table 7: Weighted normalized decision matrix for observed profiles obtained from Table 1.

	BAND 1	BAND 2	BAND 3
PROFILE 1	0.057961	0.274064	0.117138
PROFILE 2	0.069134	0.350936	0.13522
PROFILE 3	0.063897	0.307487	0.125786
PROFILE 4	0.040154	0.220588	0.084119
PROFILE 5	0.042598	0.222259	0.08805

Table 8: Weighted normalized decision matrix for profiles from Table 2

	BAND 1	BAND 2	BAND 3
PROFILE 6	0.05325	0.27312	0.10012
PROFILE 7	0.04375	0.229929	0.086331
PROFILE 8	0.0425	0.224848	0.088129
PROFILE 9	0.041	0.226118	0.08753
PROFILE 10	0.03725	0.1969	0.077338
PROFILE 11	0.0295	0.15752	0.058153
PROFILE 12	0.02925	0.172764	0.066547
PROFILE 13	0.02575	0.11687	0.04976
PROFILE 14	0.0225	0.088923	0.04976
PROFILE 15	0.02175	0.083841	0.041367
PROFILE 16	0.02175	0.081301	0.034772
PROFILE 17	0.0215	0.085112	0.038969
PROFILE 18	0.021	0.082571	0.043765
PROFILE 19	0.02075	0.07622	0.040168
PROFILE 20	0.02075	0.081301	0.03777
PROFILE 21	0.02	0.07622	0.03777

Table 9:Values of NIS and PIS for observed data from Table1.

	BAND 1	BAND 2	BAND 3
PIS	0.069134	0.350936	0.13522
NIS	0.040154	0.220588	0.084119

Table 10:Values of NIS and PIS for observed data from Table 2.

	BAND 1	BAND 2	BAND 3
PIS	0.05325	0.27312	0.10012
NIS	0.02	0.07622	0.034772

Table 11:The Distance measurement for observed profile from Table 1.

	PIS (D_j*)	NIS (D_j^-)
PROFILE 1	0.079756	0.065322
PROFILE 2	0	0.142974
PROFILE 3	0.044769	0.099253
PROFILE 4	0.142974	0
PROFILE 5	0.139595	0.004921

Table 12:The Distance measurement for observed profile from Table 2.

	PIS (D_j*)	NIS (D_j^-)
PROFILE 6	0	0.210108
PROFILE 7	0.046323	0.163856
PROFILE 8	0.050888	0.15951
PROFILE 9	0.050177	0.160293
PROFILE 10	0.081144	0.129125
PROFILE 11	0.125254	0.085127
PROFILE 12	0.10851	0.102059
PROFILE 13	0.166452	0.043705
PROFILE 14	0.193417	0.019805
PROFILE 15	0.200675	0.010229
PROFILE 16	0.205078	0.005374
PROFILE 17	0.200236	0.009946
PROFILE 18	0.201308	0.011055
PROFILE 19	0.208375	0.005448
PROFILE 20	0.2043	0.005947
PROFILE 21	0.206536	0.002998

Table 13: The closeness coefficient of each observed profile from Table 1.

	Closeness Coefficient (C_j)
PROFILE 1	0.450256
PROFILE 2	1
PROFILE 3	0.689152
PROFILE 4	0
PROFILE 5	0.034053

Table 14:The closeness coefficient of each unobserved profile from Table 2

	Closeness Coefficient (C_j)
PROFILE 6	1
PROFILE 7	0.779601
PROFILE 8	0.758136
PROFILE 9	0.761594
PROFILE 10	0.614093
PROFILE 11	0.404634
PROFILE 12	0.484681
PROFILE 13	0.207963
PROFILE 14	0.092886
PROFILE 15	0.048503
PROFILE 16	0.025534
PROFILE 17	0.047322
PROFILE 18	0.052057
PROFILE 19	0.025478
PROFILE 20	0.028285
PROFILE 21	0.014307

Conclusions and Scope for Future Research: In as small patch of area (800 sq. km), the study area of Lohardaga district, on the basis of TOPSIS a decision could be reached at to select where further investigations could be made. In a further stage of study the fuzzy ranking approach could be incorporated for achieving a more accurate result. The study could also be expanded to test the approach for extracting more than one feature. Spatial Risk management of natural hazards, in GIS environment using multicriteria evaluation (MCE) along with artificial intelligence based methods are now being probed at (Chen *et al*.[15]).

REFERENCES

1. Malezewski, J., 1996. A GIS based approach to multiple criteria group decision making. International Journal Geographic Information system, 10(8).
2. Malezewski, J., 2006. GIS based multicriteria decision analysis: a survey of the literature. International Journal of Geographical Information Sci., 20(7): 703-726.
3. Malczewski, J., 1999. GIS and Multicriteria decision analysis. John Wiley and Sons.
4. Chen, J., M. Luo, L.L. Daoliangli, C. Zhang, Y. Huang and Y. Jiang, 2008. Comparation and Analysis Methods of Moderate Resolution Satellite Remote Sensing Image Classification. WSEAS Transactions on Computers, 7.
5. Su, W., C. Zhang, M. Luo, L.I. Li, J. Wang, J.U. Zhengshan and L.I. Daoliang, 2008. Object oriented implementation monitoring method of zone feature in land consolidation engineering using SPOT 5 imagery. WSEAS Transactions on Computers, 7.
6. Huang, Y., A. Yue, S. Wei, D. Li, M. Luo, Y. Jiang and C. Zhang, 2008. Texture feature extraction for land cover classification of Remote Sensing data in Land consolidation district using semi-variogram analysis.WSEAS Transactions on Computers, 7(7).
7. Roy, M.K., 1998. Need for reassessment of Bauxite Deposits of Bihar, Proc. Mineral Exploration and development in Bihar held at Ranchi from May, pp: 28-29.
8. Jhanwar, M.L., 1996. Application of Remote Sensing for environmental monitoring in Bijolia area of Rajasthan. Journal. Indian Society Remote Sensing, 24(4): 264.
9. Jensen, J.R., 2003. Remote sensing of the environment-An earth resource perspective. Pearson Education.
10. Hwang, C.L. and K. Yoon, 1981. Multiple Attributes Decision Making Methods and Applications, Berlin, Heidelberg: Springer.
11. Majumdar, A., B. Sarkar and P.K. Majumdar, 2005. Determination of quality value of cotton fiber using hybrid AHP-TOPSIS method of multicriteria-decision making. Journal of the Textile Institute, 96(5): 303-309.
12. Anane, M., H. Kallali, S. Jellali and M. Ouessar, 2008. Ranking suitable sites for Soil Aquifer Treatment in Jerba Island (Tunisia) using remote sensing, GIS and AHP-multicriteria decision analysis. International Journal of Water, 4(1-2): 121-135.
13. Liu, C., P. Frazier, L. Kumar, C. Macgrgorand and N. Blake, 2006. Catchment wide wetland assessment and prioritization using the multi-criteria decision making method (TOPSIS). Earth and Environ. Sci., 38(2): 316-326.