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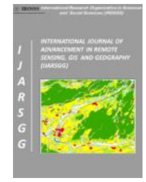

INTELLIGENT OBJECT BASED SMOOTHING: AN ALGORITHM FOR REMOVING NOISES IN THE CLASSIFIED SATELLITE IMAGE

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ABSTRACT: The existing smoothing algorithms like mean, median, majority/mode filters are not efficient in smoothing the classified image derived from the satellite data. Mean filter alters original class pattern and also it is influenced by the outliers in the neighbors. Though Median filter does not alter the values it does affect the shape of the class extent. The majority filter also suffers from a big disadvantage that it eliminates linear features and in the common edge between two classes it will blindly follow the majority rule though there is no noise. Also, these smoothing filters, by and large dependent on kernel size, pixel size and the shape of the input classes. Keeping these limitations in view the study attempted a kernel & pixel size-independent smoothing algorithm for smoothing classified satellite data, which must also cognitively, considers the neighbourhood contiguity. In this approach, spatial connectivity functions are utilized to characterize the neighborhood as objects, which are then supplemented with structuring element to selectively incorporate morphological operators like erosion and dilation for smoothing the classified image. This object oriented morphological smoothing algorithm, its effectiveness and efficiency has been studied in this research. It was found that the proposed algorithm efficiently maintained the shape and area than other conventional smoothing algorithms.

Key words: Object based smoothing, classified image, Mean filter, Median filter and Majority filter

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1. INTRODUCTION: Developments in space technology and its applications during the last three decades in India have established its ability to achieve global, national level mapping and monitoring of various natural resources. For natural resource management, remote sensing (RS) and geographic information system (GIS) plays a major role starting from compilation, manipulation, presentation, modelling and finally for monitoring. Rao (1), Kasturirangan (2), George Joseph (3) and Chandrashekhar *et al.* (4) have dealt in detail about the potential applicability of these advanced space technologies and vast literature is available in this regard. In general, Remote Sensing can be used to map the land use/ land cover of a geographical area and the classified map can be analysed in GIS by overlaying interacting biophysical (e.g. vegetation, slope, elevation, climate) and socio-economic (e.g. population growth, city growth, infrastructure influence) factors for understanding any ground processes. Remote sensing and GIS, in combination, will be an inevitable part of input preparation, standardization, modelling, and customisation process of any geoinformatics research.

Digital image processing has been of great importance in remote sensing field as it helps to enhance spatial and radiometric characteristics of satellite derived images, georeferencing satellite data with ground geographic/planimetric coordinates, fusion of multiple spatial and spectral resolution images (5), and for ultimately deriving classified land use and land cover map. The enhancement operations are vital in the initial understanding and interpretational stage. Filters are mainly used to improve the visual appeal of the multi-spectral image through a suppression of high frequency pixels or enhancing low frequency pixels which leads to visual functions like smoothing, sharpening and edge detection (in uni-direction to n-direction) over frequency domain or spatial domain. Kernel based filters are of common usage in the spatial domain. It is often noted that conventional kernel based spatial filters have been extensively used in smoothing the spatial images. Most of the existing filtering algorithms were just adopted from the electronic noise removal, high pass or lowpass filtering technique, which considers the adjacent epoch/spatial elements to characterize noise. But in satellite based image processing the ultimate aim is to derive a meaningful classified/interpreted map, in which a class may be contiguous over an area rather than limited to adjacent immediate neighbors, thus needs a different outlook in the process of filtering.

Satellite image segmentation using conventional per pixel classifiers are bound to have single pixel to few pixels smaller patches as noise, which in reality may not likely to be accounted as a separate class as it occurs within a major class. In high-resolution satellite data this type of noises are common since the high spectral variability due to high spatial resolution invariably creep into the classified scene also. The existing smoothing algorithms like mean, median, majority/mode filters are not efficient in smoothing the classified image derived from the satellite data. Mean filter or average filter is normally used to smooth any image irrespective of its type like panchromatic or multi-spectral. This filter is very easy to apply but not efficient for smoothing classified image, because in the output it produces different value than the existing class values and also it is influenced by the outliers in the neighbors. These two main disadvantages are removed by using Median filter, which is used as a better alternative for smoothing classified image, apart from being used for other type of images. But still median filter does alter the shape of the class patch and the area which is not controllable. More often majority/frequency filter is used to remove the noise which has the assumption that more the count of particular class more probable to have them at center, but this approach eliminates the linear features or narrow class patches. The majority filter suffers from a big disadvantage that in the common edge between two classes it will blindly follow the majority rule though there is no noise. More or less all the above said smoothing filters severely alter the original noise-free edges (boundary between classes) and hence change the area statistics dominantly. These smoothing filters, by and large dependent on kernel size, pixel size and the shape of the input classes.

Keeping these limitations in view and having sophisticated powerful computers, functions at hand, it was felt that a kernel & pixel size-independent smoothing algorithm is needed specifically for smoothing classified satellite data, which must also considers cognitively the neighborhood contiguity. In this view, in this research spatial connectivity functions are utilized to characterize the neighborhood as objects, which are then supplemented with structuring element to selectively incorporate morphological operators like erosion and dilation for smoothing the classified image. This object oriented morphological smoothing algorithm, its effectiveness and efficiency has been studied in this research.

2. THE ALGORITHM: The proposed algorithm named as Morphometric Object Based Smoothing (MOBS) was tested over a sample classified image. The algorithm mainly consists of 2 main parts. First part is converting classified image pixels into individual objects and second part is applying morphological operators through these objects.

2.1 IDENTIFYING SPATIAL CONNECTIVITY: For converting classified image pixels into individual objects the neighborhood connectivity was considered. There are two possibilities for connections over neighbouring pixels a) Four connectedness or b) Eight connectedness. Four connectedness will consider connectivity between cells of the same value only if the cells are located to the right or left, or above or below each other (i.e., the four nearest neighbors). If two cells with the same value are diagonal from one another, they are not considered as connected. Eight connectedness will consider connectivity between cells of the same value if they are within the immediate 8-cell neighborhood (i.e., eight nearest neighbors) of each other. This includes if they are to the right or left, above or below, or are diagonal to each other. The reason for converting pixels belonging to different classes into object is to differentiate the narrow and smaller patches from the bigger patches.

2.2 MORPHOLOGICAL OPERATOR: Morphological operations play an important role in distinguishing features from the background in a binary image. A morphological operator is defined by its structuring element and the applied set operator. Morphological operator process objects in the input image based on structuring element. At each pixel of the image, members of structuring element are compared with the set of the underlying pixels and if the membership of two sets match the condition defined by the set operator like if set of pixels in the structuring element is a subset of the underlying image pixels then pixel underneath is set to a pre-defined value, as it would be 0 or 1 for binary images. Dilation and Erosion are two fundamental morphological operations, which acts as a basis for other morphological operators like thinning, thickening, opening and closing. Dilation operator progressively enlarges the boundaries of regions of the foreground pixels and hence the holes within them are reduced. Erosion operator erodes the boundaries of foreground pixels, hence expands the holes within them.

Dilation of an input image S by a structuring element M is a set of all the points ‘s’ at which the intersection of S and Ms is non-empty. Erosion leads to set of all points ‘s’ such that Ms is a subset of S.

$$\text{Dilation: } S \oplus M = \{ s \mid [M_s \cap S] \subseteq S \}$$

$$\text{Erosion: } S \Theta M = \{ s \mid M_s \subseteq S \}$$

2.3 INTEGRATION: In order to smooth the classified image, the above said connectivity functions and morphological operators have to be intelligently integrated, differently from binary image. In this approach, user interested landcover class and his preferred level of noise will be of the focal attention. The input classified image will be converted into objects representing individual patches, using 8-connectivity concept. Then the patches obeying noise threshold are identified and coded with some unique code, say 1000. Now combine the user interested class objects with noise objects and dilate the noise objects. One can also do reverse by erode the user interested class. Finally integrate the output from dilation or erosion with the other objects made from the original input. In this process we have not considered any kernel size and also resolution does not come into picture as we deal with objects rather than pixels.

3. RESULTS AND DISCUSSION: For analyzing the effectiveness of proposed algorithm, small portion of a classified image prepared from data procured by LISS-III sensor of Indian Remote Sensing Satellite (IRS-1D) having ground resolution 23.5m, having 4 spectral bands as Green, Red, Near-Infrared and Shortwave-Infrared. The sample satellite data was classified into 15 classes using unsupervised classification algorithm so as to have highly varying clusters. Initially the sample classified image was smoothened using median, majority filters at varied kernel size and also using MOBS approach in a broad sense.

3.1 COMPARISON OF DIFFERENT SMOOTHING ALGORITHMS: Figure I. shows two different types of neighbourhood connectedness from central pixel while finding spatially connected individual objects from a given raster classified image. Figure II shows flow chart of the methodology adopted in the study. Figure III shows the original classified image and the smoothened images using different filtering approaches. Mean filter is obviously not used since it will alter the pixel value and hence not meaningful for classified/thematic images. MOBS3 represents smoothened output derived using the noise threshold as 3 pixels, means that any object which are made of less than or equal to 3 pixels will be eliminated as noise. Similarly MOBS7, MOBS15 and MOBS30 considers noise threshold as 7, 15 and 30 pixels respectively.

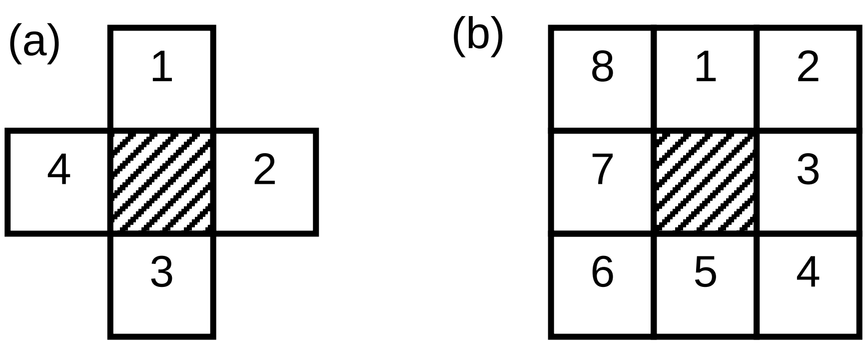


Fig. I Neighborhood relationship: a) four-connectedness and b) eight-connectedness

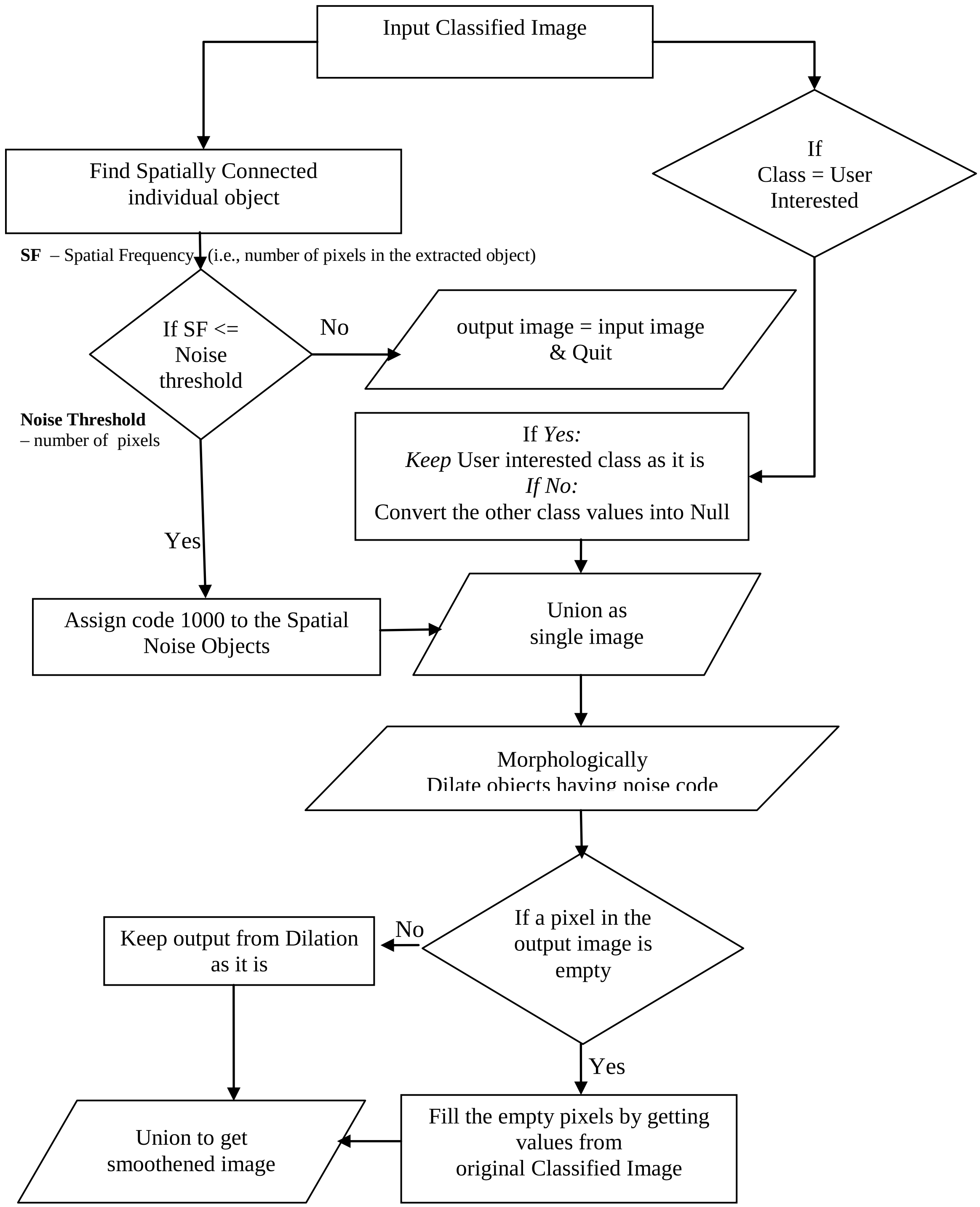


Fig. II Flow chart depicting the overall process involved in MOBS

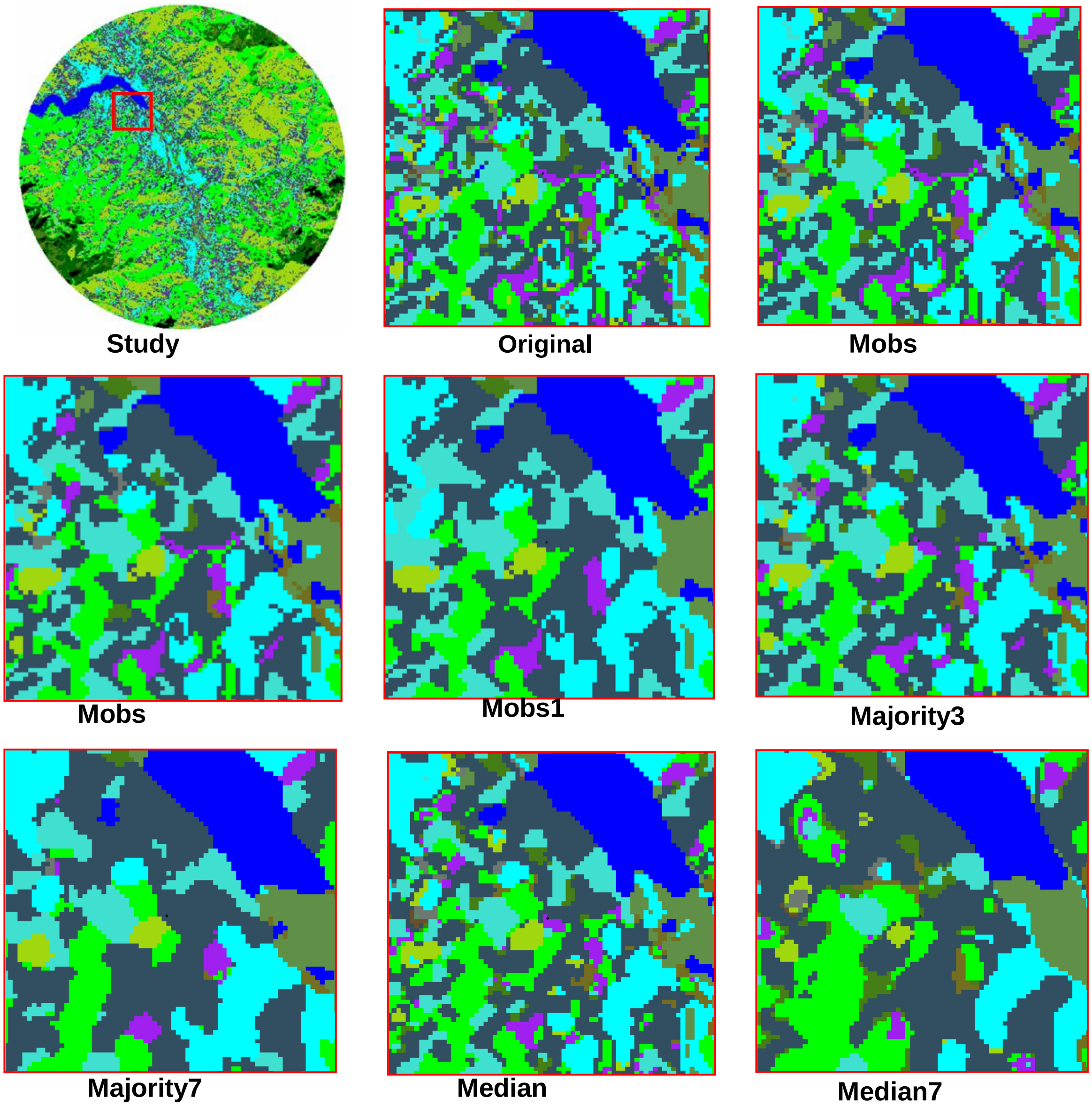


Fig. III Smoothened outputs using various algorithms

Table I shows the area statistics of the smoothened image and original image derived from various approaches. Out of all the algorithm used, only MOBS algorithm could produce the smoothened output keeping the area statistics as close as that of original. Figure IV reveals this quantitative information in a graphical manner so as to understand the area change easily. It is to be noticed that in all the conventional smoothing filters like median or majority the larger size of the window alters the area in a greater strength, but in MOBS the higher noise threshold does not alter the area much.

In Figure IV each vertical bar represents the % of different landcover classes under a particular smoothing approach. First bar represents the original class percentage and the change in the area of any class using any filtering approach can be understood by moving horizontally along that class. It is observed that till the noise threshold 15, MOBS approach has not altered the % area much. Median, Majority filters alters the area drastically even when using minimum kernel size of 3x3.

Filters	Class1	Class2	Class3	Class4	Class5	Class6	Class7	Class8	Class9	Class10	Class11	Class12	Class13	Class14	Class15
Original	1512.46	358.40	1092.76	5073.06	331.58	130.98	3054.02	178.27	138.07	4185.77	437.91	952.94	201.50	342.53	283.91
Mobs3	1482.36	293.01	1103.92	5152.30	292.75	121.93	3080.58	156.85	108.87	4305.64	401.30	958.34	188.54	347.13	280.63
Mobs7	1396.67	213.87	1103.55	5293.44	256.35	117.28	3136.76	119.98	78.45	4446.88	356.81	958.87	170.97	347.98	276.30
Mobs15	1271.03	130.66	1102.97	5539.74	217.79	102.26	3105.34	78.93	41.16	4672.66	272.01	975.85	150.92	349.83	263.02
Mobs30	1067.68	69.46	1110.27	5921.94	198.64	77.55	2976.26	51.68	11.96	4898.22	184.14	991.40	127.86	343.96	243.13
Maj33	1411.95	246.30	1104.23	5276.25	266.09	114.85	3009.11	141.93	97.34	4462.17	360.30	970.72	176.95	347.61	270.32
Maj77	1049.01	86.23	1093.71	5777.21	191.39	90.88	2948.96	71.47	27.51	4949.54	185.84	994.20	141.82	355.28	233.13
Med33	1024.88	227.58	1066.57	5574.02	338.72	159.44	3300.38	194.46	122.36	4362.56	283.86	893.43	135.53	333.16	257.20
Med77	335.17	97.81	957.49	6309.44	363.42	215.25	3803.62	203.24	106.81	4421.28	98.18	788.74	64.11	318.25	191.34
Mean33	1850.81	660.14	1078.31	4373.08	530.06	166.48	3411.04	276.35	249.85	3272.18	641.31	885.18	279.36	323.80	336.39
Mean77	2574.85	1638.00	1014.52	2437.95	1141.90	255.67	2769.53	660.40	664.21	1802.04	1392.33	1001.19	512.71	278.78	417.38

Table II: Comparison Area Statistics (in Ha) of each class using various filters for smoothing the classified image

CLASS	Area variation (after applying MOBS algorithms)										
	original classified image	MOBS1	MOBS2	MOBS3	MOBS4	MOBS5	diff01	diff12	diff23	diff34	diff45
1	1512.46	1503.10	1491.57	1482.36	1465.91	1446.60	9.36	4.72	3.83	3.68	2.69
2	358.40	341.42	317.93	293.01	265.13	247.68	16.98	4.71	4.4	3.86	2.75
3	1092.76	1096.93	1102.70	1103.92	1105.24	1101.85	-4.18	1.07	1.24	0.86	0.74
4	5073.06	5096.54	5120.77	5152.30	5189.23	5219.64	-23.49	3.09	2.56	2.16	1.97
5	331.58	319.57	305.71	292.75	279.95	271.17	12.01	2.63	2.35	2.34	1.45
6	130.98	127.59	124.32	121.93	120.24	118.71	3.39	1.95	1.67	1.28	1
7	3054.02	3063.02	3071.85	3080.58	3098.30	3119.99	-8.99	6.19	5.26	4.94	3.68
8	178.27	172.77	165.21	156.85	146.48	139.29	5.50	3.03	2.61	2.48	1.8
9	138.07	129.87	120.56	108.87	99.24	88.55	8.20	2.95	3.35	2.52	2.18
10	4185.77	4216.39	4260.72	4305.64	4347.64	4379.75	-30.63	3.32	2.9	2.42	1.98
11	437.91	427.59	414.58	401.30	387.12	378.29	10.32	4.13	3.25	3.08	2.51
12	952.94	954.90	958.02	958.34	959.02	958.65	-1.96	2.66	2.04	1.79	1.52
13	201.50	197.95	194.09	188.54	182.51	176.47	3.54	2.46	1.96	1.87	1.59
14	342.53	343.48	344.33	347.13	348.66	349.09	-0.95	0.19	0.27	0.07	0.13
15	283.91	283.02	281.80	280.63	279.47	278.41	0.90	0.36	0.52	0.28	0.22

Table II: Comparison of Area variation using MOBS algorithms having different noise threshold

CLASS	original classified image	Shape Index after smoothening								
		MOBS1	**MOBS2**	**MOBS3**	**MOBS4**	**MOBS5**	**MAJ33**	**MAJ77**	**MED33**	**MED77**
1	*71.05*	66.91	62.19	58.36	54.68	51.99	48.69	26.38	41.06	17.10
2	*47.95*	43.96	39.25	34.85	30.99	28.24	28.58	11.13	30.40	16.98
3	*30.82*	29.75	28.68	27.44	26.58	25.84	21.80	12.42	21.91	13.09
4	*59.17*	56.54	53.45	50.89	48.73	46.76	41.36	23.78	46.07	27.42
5	*30.88*	28.2	25.57	23.22	20.88	19.43	17.41	8.02	26.48	26.83
6	*23.69*	22.01	20.06	18.39	17.11	16.11	15.52	8.66	20.87	17.87
7	*100.71*	95.43	89.24	83.98	79.04	75.36	63.60	34.64	72.99	45.75
8	*31.58*	28.75	25.72	23.11	20.63	18.83	20.39	8.54	26.59	23.18
9	*30.56*	27.58	24.63	21.28	18.76	16.58	19.14	7.02	23.91	20.75
10	*56.33*	53.22	49.9	47	44.58	42.6	36.32	20.87	36.66	21.10
11	*47.52*	43.92	39.79	36.54	33.46	30.95	30.10	14.68	27.60	14.79
12	*38.66*	36.3	33.64	31.6	29.81	28.29	24.17	13.41	22.85	12.00
13	*29.12*	27.08	24.62	22.66	20.79	19.2	17.97	8.97	15.91	7.31
14	*5.85*	5.71	5.52	5.25	5.18	5.05	4.69	3.34	4.17	2.80
15	*14.74*	14.23	13.87	13.35	13.07	12.85	11.34	6.80	10.78	5.95

Table III: Comparison of Shape Complexity variation using different smoothing algorithm

Moreover it is also important to analyse the impact of noise over landcover classes and type of noise present in the image, meaning whether the dominant noise is from a single pixel noise or two pixel noise and which class it is affecting. Conventional smoothing algorithms do not provide means to study this effect. For this purpose smoothening using Noise threshold as 1pixel, 2 pixels, 3, 4 & 5 pixels are done using MOBS algorithm, so that the minute variations in the area due to noise clusters can be analysed in a better manner. Table II compares the area statistics of original classified image with the smoothened using MOBS1, MOBS2, MOBS3, MOBS4 and MOBS5. The column DIFF01 represents the difference between the original area and area derived after MOBS. Similarly DIFF12 represents the difference between area from MOBS1 and MOBS2 and DIFF23, DIFF34, DIFF45 are respective difference in areas between successive smoothening. Figure V represents these variations graphically, where one can easily identify which type of noise is dominating in a particular class. For example for the class7, the dominant noise is 5 pixel clusters, but for class10 dominant noise is 3pixel clusters and for the class4 it is 4pixel clusters. Dominant noise is a cluster of pixels, when removed from the image it changes (positively or negatively) the area statistics of that class more than other noise clusters. In the graph positive value means that the class has lost that much hectares due to smoothening, this is due to subtraction from the previous smoothening, negative value means the class area has increased after smoothening.

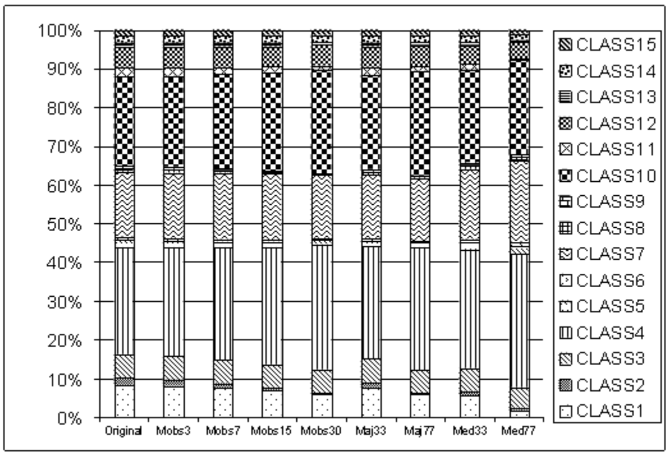


Fig. IV: Area Variations of input classes in different smoothing algorithms 1% of area = 182.74 ha for the current study

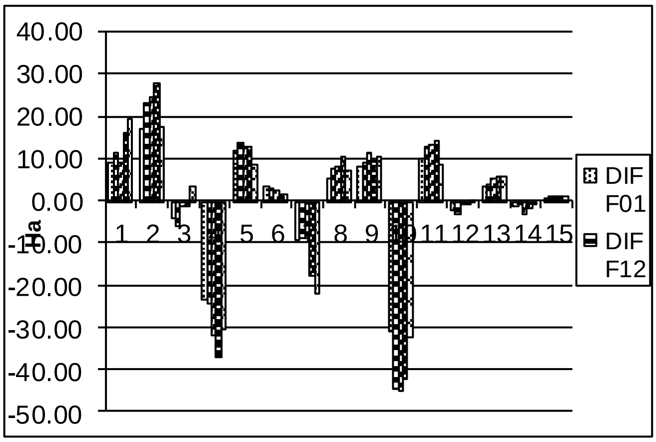
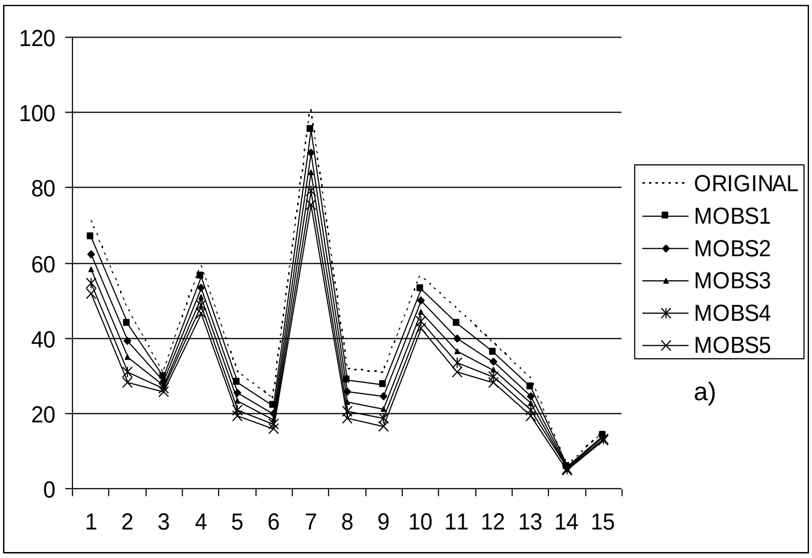


Fig. V Impact of different noise threshold on area of different classes (x-axis represents Class Number; y-axis represents Class Area in ha

In the ecological point of view, shape of a landcover class plays an important role over interaction between patches as it represents the degree of human disturbance. Hence the change in shape index due to smoothening is also been studied. Robert C. Frohn (6) have proposed an elegant shape complexity index, which is better than fractal dimension index. The Equation for finding Shape complexity is as below:

Shape Complexity Index = Perimeter / (4 * sqrt(area))

The value of this index increases from 0 to infinity, as the complexity increases. Table III represents the variations in the shape complexity values after applying different smoothing algorithms. Figure VI graphically represents this variation. It is found from Fig. IVa that the MOBS algorithm kept the variations in the shape complexity of different classes relatively in the same manner, but other algorithms with different kernel size have drastically altered the shape complexity of different classes in a different manner. Hence a user shall not worry about the impact of the proposed algorithm in altering their ecological interpretations.



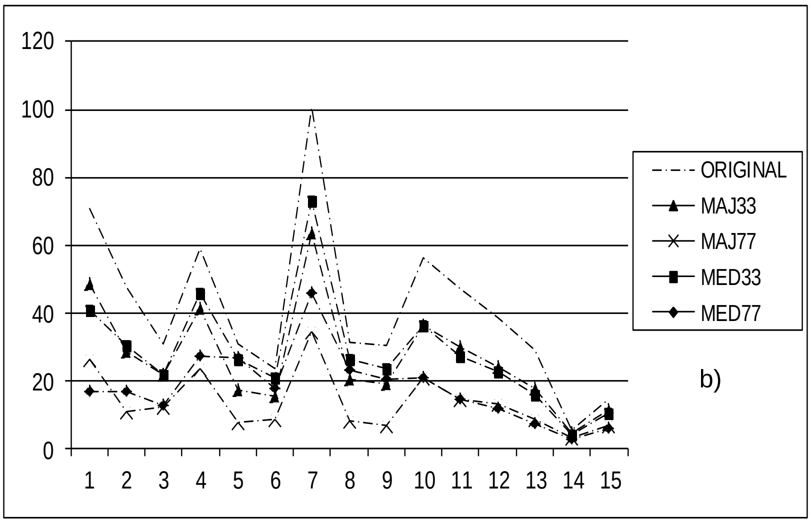


Fig. VI Variations on Shape Complexity: a) Shape Complexity variation after applying MOBS b) Shape Complexity variation after applying Median & Majority (x-axis represents the class number ; y-axis represents the shape index)

4. CONCLUSION: Visually, graphically and quantitatively it is evident from the above arguments that the current MOBS approach has not altered the shape and area much, which is not handled diligently using other approaches. This approach has also provided a possibility to study the type of noises and its impact on varied land cover classes. This approach would provide a big relief to the quantitative analysts, whom otherwise been using uncontrollable smoothing algorithms so far.

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