Investigation on the Effects of Spatial Resolution of Satellite Images on the Quality of the Extracted Information

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***Abstract*- The effects of spatial resolution on the satellite image properties as well as on the quality of the extracted information on Earth's surface properties using satellite data have been analysed. Two characteristically different surfaces (i) a relatively homogeneous surface area with relatively uniform distribution of surface classes (soil, vegetation and water) and (ii) a relatively heterogeneous (spatially) surface area with spatially non-uniform distribution of surface classes are extracted from an image of Landsat TM having a spatial resolution of 30 m. Using these two scenes of Landsat TM, images of different spatial resolutions ranging from 60 to 600 m have been prepared though degradation of the spatial resolution of the image by the application of an average filtering. The statistical properties of the spatially degraded images have been studied. Increasing degradation of spatial resolution of images decreases the image contrast. This degradation of spatial resolution causes an increase in the minimum DN value and a decrease in maximum DN value. It is also evident that different surface classes are not equally affected by degradation of spatial resolution of satellite image. Particularly, water and vegetation classes seem to be mostly affected. The cluster size of surface classes causes certain variations in classification results. For small cluster size of any surface class or classes, the spatial degradation of the image results in relatively high error on the extracted information.**

***Keywords*- spatial resolution, extracted information, Landsat TM, spatial degradation, surface classes.**

I. INTRODUCTION

Monitoring land-surface processes has become a great concern in the context of global change and increased natural hazards over the world (Ehrlich *et al.*, 1994; Charney *et al.*, 1977; Shukla and Mintz, 1982). The scale, intensity and persistence of such undesirable changes are yet to be defined and quantified to provide better understanding of the overall kinetic mechanisms. Satellite remote sensing together with its global coverage, synoptic viewing capability along with adequate spatial and temporal resolution emerges efficaciously as a potential means to serve such purpose. A vast amount of data are presently being acquired by the existing satellite sensors having varying spatial resolutions, e.g., high spatial resolution SPOT HRV or Landsat TM, large field of view NOAA AVHRR or even coarser spatial resolution Meteosat or GOES (Rahman, 1997). The quality of information contained in these remotely sensed data as well as their applications varies according to the spectral band of the sensor and their spatial and temporal resolutions.

Various factors influence the intensity of radiation that is measured at satellite altitude (Rahman, 1996a; Rahman, 1996b). Besides the atmospheric and directional effect, surface spectral responses are also governed by the spatial resolution of the sensor: The spatial resolution of satellite image plays a significant role on the quality of extracted information (Raffy, 1994). Unlike in-situ measurements, a remote sensing measurement of radiation represents a volume averaged measurements of any parameter of interest (Verstraete and Pinty, 1991). The scale of spatial representativity of such measurement is therefore defined by the size of the pixel itself. Such an averaging gives rise to contamination of the signal by the other surface classes depending on the size and spatial distribution of these classes as well as on the pixel size. An a priori knowledge of such behaviour is a necessary condition for the accurate and reliable interpretation of satellite data.

In the present work, the influences of spatial resolution on the satellite image properties as well as on the quality of extracted information from such images have been analyzed.

For the purpose, two characteristically different sub-sampled images extracted from an image of Landsat TM acquired on the 30th January, 2003 has been used. Images of different spatial resolutions have been prepared through degradation of spatial resolution of the original image by the application of average filtering with different window sizes. A focus has also been made on the surface heterogeneity in relation to information extraction.

II. Spatial Resolution and Surface Heterogeneity

The interaction of incident solar radiation with the Earth's surface takes place with the absorption, scattering and transmission of radiation (Rahman et al., 1993). A portion of the incident solar energy is reflected by the surface towards sensor. The Instantaneous Field of View (IFOV) of satellite sensor determines the effective area of the surface from which the solar energy after reflection, will be intercepted by the sensor. Eventually, the information contained within a pixel may be representative of a single or multiple classes depending on the size and spatial distribution of individual classes and also on the IFOV of the sensor. In general the spectral response from a particular pixel consisting of n number of primary classes may be represented by the following analytical equation (Rahman, 1990):

$$\rho = \frac{1}{W}\sum_{i=1}^{n} \rho_i S_i \quad (1)$$

Where, i is the number of classes within a pixel ranging from 1 to n, ρi is the spectral response of a particular class and Si is the per cent area of that class within a particular pixel. Here, Wi is an weighing factor. According to this equation, per cent area and spectral response of individual classes both are important in the determination of overall response of a pixel. In the present paper, pixels containing only one class of the three primary classes of the Earth's surface (e.g., soil, vegetation and water) will be denoted as pure pixels and those containing more than one classes within a pixel will be denoted as mixed pixels.

III. Approach

Two sub-sampled images each of about 30×30 square km area extracted from two different locations over a geometrically corrected image of Landsat TM acquired on the 30th January, 2003 have been taken as the study image. Both the images contain three major classes of the Earth's surface namely, soil, vegetation and water distributed over the image areas. However, one of the images is spatially homogeneous (with almost uniform distribution of surface classes), which we call as image 1 and the other image having relatively non-uniform spatial distribution of primary classes, we call it image 2 throughout the paper. The original image has a spatial resolution of 30 m. The images have been spatially degraded through the use of average filter having window sizes of 2×2, 4×4, 6×6, 8×8, 10×10, 12×12, 14×14, 16×16, 18×18 and 20×20. So images of 30, 60, 120, 180, 240, 300, 360, 420, 480, 540 and 600 m spatial resolutions are obtained. In this paper we will use the terms original image 1 and degraded image 1 to mean the original image 1 before degradation and after degradation respectively. Similarly, we will use the terms original image 2 and degraded image 2.

In the present study, Landsat TM bands 3, 4 and 5 have been used for the extraction of information on Earth's surface. Such a combination of bands generally yields better contrast between different surface classes within the image due to contrasted spectral response of soil, water and vegetation classes in these three spectral regions and thus, facilitates the class identification process. To characterize the image properties, we have used two different parameters namely the dynamic range (Rd) and contrast factor (CF) as given below,

$$R_d = DN_{\max} - DN_{\min} \quad (2)$$

where, DNmin and DNmax are the maximum and minimum DN values in an image for a particular spectral band.

$$CF = \frac{\sigma}{X_A} \quad (3)$$

where, a and XA are the standard deviation and mean DN value of the image for a particular band.

In general, standard deviation of an image provides an idea about the image contrast (Rahman, 1998). For a given surface, in a particular spectral band, higher value of standard deviation generally indicates higher image contrast. For comparison of image contrast between different images, we have normalized the standard deviation with respect to the mean DN value within an image for a given spectral band. A higher value of Rd and CF generally indicates a higher contrast between different surface classes within an image.

Selection of training sites are based on the DN values in bands 3, 4 and 5 following the basic spectral characteristics of three primary classes of the Earth's surface.

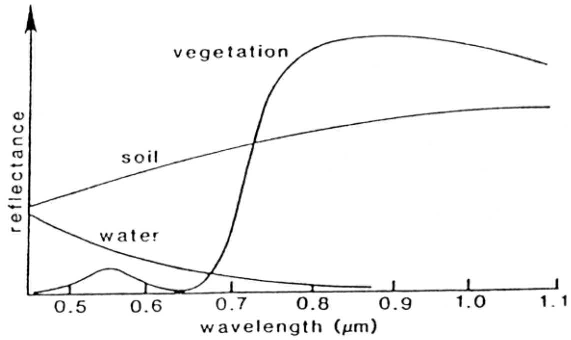

Fig. 1 Spectral response characteristics of basic Earth's surface features namely soil, vegetation and water.

Fig. 1 shows the typical spectral response characteristics of soil, vegetation and water. The basic considerations that have been made for the present study are the followings:

For green vegetation, DN value should be much lower in band 3 and higher in band 4.

1) DN value in band 5 should be higher than that in band 4.
2) For water, DN value should be higher in band 3 than that in band 4 and band 5 should have lower DN value than that in band 4.
3) For soil, DN value may have higher/lower value in band 3 than that in band 4. But band 5 should have DN value much higher than that in band 4.

Supervised classification procedure has been applied to each of the images with maximum likelihood classification technique. The processes of training sites selection and classification have been repeated three times to test the fidelity of the results. The whole image processing and classification tasks were performed using the ERDAS Imagine image processing software.

IV. Discussions

A. Effect of Spatial Degradation on Image Properties

Fig. 2a and 2b represent the grey level of the original image 1 (band 4) and image 2 (band 4) respectively. In image 1, relatively dry soil surface are exposed through most of the image area with cluster of relatively small vegetation area (very roughly of the order of about 300 to 400 m width on average) nearly uniformly distributed over the study area.

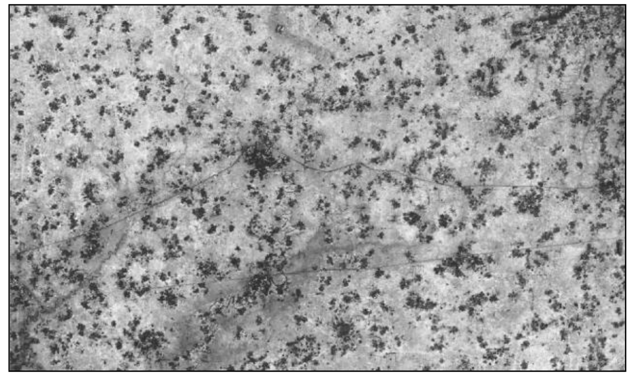

Fig. 2a Gray level image of band 4 of Landsat TM image 1 acquired on the 30th January 2010.

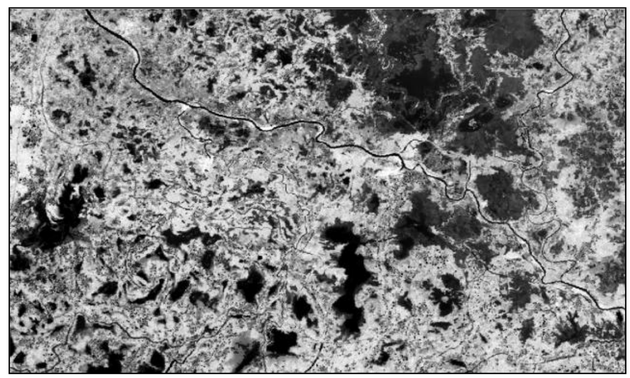

Fig 2b Same as in Fig. 2a, except for Landsat TM image 2.

While significant portion of the surface is being occupied by water as well as vegetation in addition to soil in image 2. The individual clusters are of much larger size as compared to that in image 1 and are not uniformly distributed over the study area. The relatively narrow water bodies are very much visible in the two images and soils having different moisture levels exist in both the images.

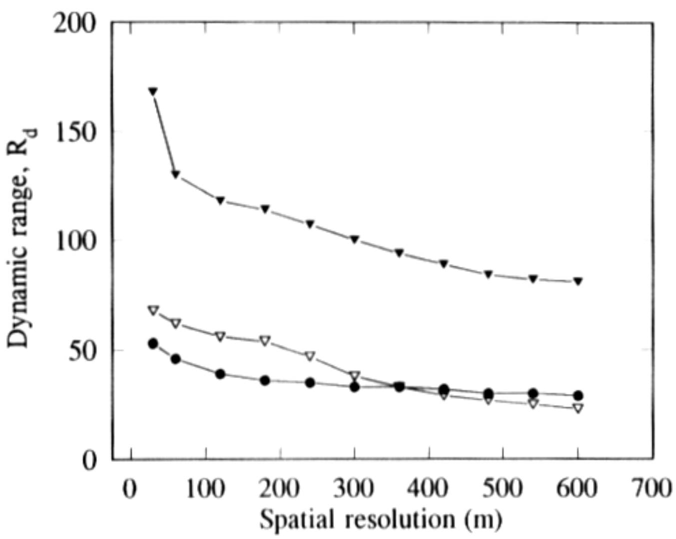

Fig 3a Plot of dynamic range (R_d) as a function of spatial resolution obtained through the degradation of spatial resolution of image 1 (extracted from an image of Landsat TM) using an average filter of varying window sizes for spectral bands (•) 3, (v) 4 and (▼) 5 of Landsat TM.

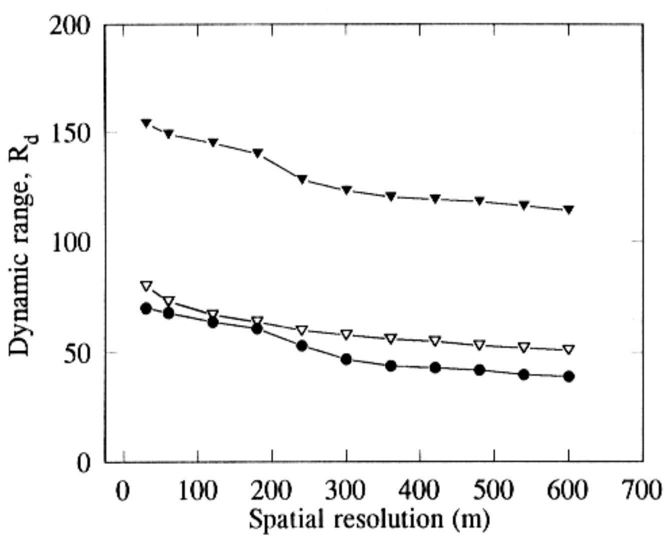

Fig 3b Plot of dynamic range (R_d) as a function of spatial resolution obtained through the degradation of spatial resolution of image 2 (extracted from an image of Landsat TM) using an average filter of varying window sizes for spectral bands (•) 3, (v) 4 and (▼) 5 of Landsat TM

TABLE 1a

Minimum and maximum of DN values in bands 3, 4 and 5 of Landsat TM for the original and spatially degraded image 1. The images of different spatial resolutions have been obtained by the application of an average filter to the original images with varying window sizes.

Spatial Resolution (m)	Image 1					
	DN minimum in Band			DN maximum in Band		
	3	4	5	3	4	5
30	36	20	12	89	88	180
60	38	21	15	84	83	145
120	38	22	17	77	78	135
180	40	22	19	76	76	133
240	40	25	24	75	72	131
300	41	32	30	74	70	130
360	41	35	35	74	68	129
420	42	37	40	74	66	129
480	43	38	44	73	65	128
540	43	39	46	73	64	128
600	44	40	47	73	63	128

TABLE 1b

Minimum and maximum of DN values in bands 3, 4 and 5 of Landsat TM for the original and spatially degraded image 2.

Spatial Resolution (m)	Image 2					
	DN minimum in Band			DN maximum in Band		
	3	4	5	3	4	5
30	26	13	5	96	93	159
60	27	15	8	95	88	157
120	28	15	9	92	82	154
180	28	15	10	89	79	150
240	29	16	10	82	76	138
300	29	16	10	76	74	133
360	29	16	10	73	72	130
420	29	17	10	72	72	129
480	29	17	10	71	70	128
540	30	17	10	70	69	126
600	30	17	10	69	68	124

TABLE 2

Results of classification of the original and spatially degraded image 1 and image 2. The spatially degraded image correspond to a spatial resolution of 300 m and is obtained through the application of an average filter with a window size of 10×10.

Class	Per cent area for		Mean DN value in band 3 for		Mean DN value in band 4 for		Mean DN value in band 5 for	
	O.I.	S.D.I.	O.I.	S.D.I.	O.I.	S.D.I.	O.I.	S.D.I.
RESULTS FOR IMAGE 1								
Soil 1	50.56	44.96	67.68	66.77	51.18	52.58	107.42	110.00
Soil 2	15.50	28.82	58.22	58.44	46.14	47.63	93.43	92.10
Soil 3	16.47	10.44	51.88	52.88	41.04	44.23	61.94	62.85
Vegetation	6.75	9.26	47.25	52.00	62.96	57.00	78.06	84.06
Water	1.01	0.01	53.25	53.88	29.43	35.51	23.00	33.38
RESULTS FOR IMAGE 2								

Soil 1	1.35	0.36	71.95	65.33	57.29	55.09	126.26	115.95
Soil 2	2.44	0.10	56.32	57.77	47.75	49.00	108.00	106.55
Soil 3	5.06	2.78	49.22	53.59	41.68	45.39	88.51	91.21
Soil 4	15.98	19.71	42.82	48.10	35.56	39.54	65.84	55.20
Vegetation	39.34	46.88	37.73	39.50	56.88	53.69	56.60	59.92
Water	14.46	11.16	52.43	52.32	29.20	31.08	13.88	20.11

The spatial degradation of the original image leads to certain changes in the statistical properties of the image. Fig. 3a and 3b show for image 1 and image 2 respectively, plot of dynamic range (Rd) of DN values as a function of spatial resolution obtained through spatial degradation of original images. Tables 1a and 1b provide the maximum and minimum DN values for each bands of image 1 and image 2 respectively. The fig. together with table 1a and 1b reveal that, maximum DN value decreases with degradation of spatial resolution and contrarily minimum DN value increases resulting in a reduction of dynamic range for progressive degradation of spatial resolution. This is evident from the consideration that surface contains some pixels having high DN values and simultaneously, some pixels having relatively lower DN values' exist in the neighbouring position. Due to spatial degradation, some of these lower DN valued pixels share their values with the higher DN values of the nearby pixels. As a result, the maximum DN value of the degraded image reduces. In the same way, the observed increase in minimum DN value can be explained.

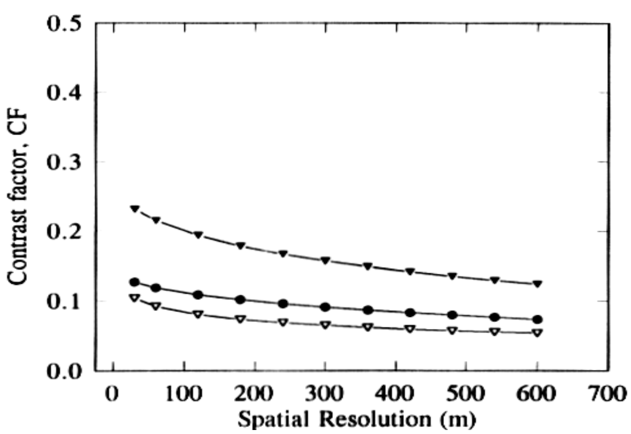

Fig 4a Plot of contrast factor (CF) as function of spatial resolution obtained through degradation spatial resolution of image 1 (extracted from an image of Landsat TM) using an average filter of varying window sizes for spectral bands (•) 3, (v) 4 and (▼) 5 of Landsat TM.

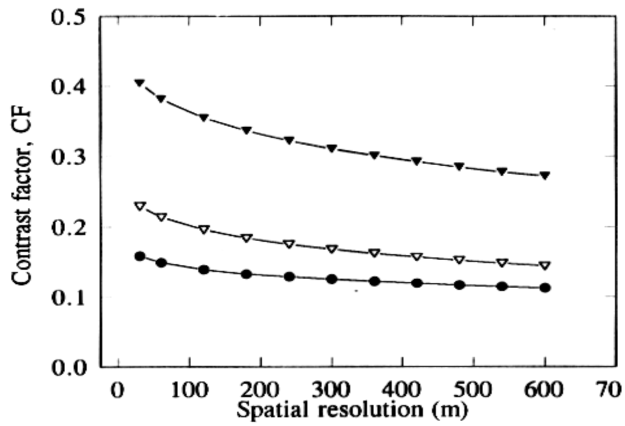

Fig 4b same as in fig. 4a except for image 2

In both images 1 and 2, the dynamic range is relatively high for band 5 as compared to that with bands 3 and 4. For image 1, the dynamic range is slightly higher in band 4 than that in band 3 upto spatial resolution of about 360 m. Beyond this, the dynamic range in band 3 marginally exceeds the dynamic range in band 4. However, for image 2, dynamic range is always slightly higher in band 4 than that in band 3. In image 1 corresponding to band 5, the value of Rd, is higher than that in image 2 of the slightly same spectral band for the original image having a spatial resolution of 30 m. However, with increasing degradation of spatial resolution of the original images, Rd reduces for both images 1 and 2. For the degraded image, the Rd values are lower in image 1 than that in image 2 for all three spectral bands under consideration. In addition, the changes in Rd values with spatial degradation are relatively higher in image 1 than that in image 2.

Fig. 4a and 4b show plot of contrast factor (CF) for image 1 and image 2 respectively as a function of spatial resolution for each of the bands 3, 4 and 5. It is evident from these fig. that with the degradation of spatial resolution of the image, contrast factor decreases in both images 1 and 2 in all three spectral bands, indicating reduction of contrast between different classes within the study image. Image 2 exhibits higher contrast than that in image 1 for all three bands. In image 1, most of the surface is uncovered soil with small cluster of vegetation distributed throughout the study area. The water represents only a small portion of image 1. As a result, the variation of surface class is small (only soil dominates largely) and that is why, contrast is relatively small in this image. Whereas, in image 2, significant portion of the surface areas are occupied by both water and vegetation in addition to uncovered soil. As a result, the total surface area under image 2 offers significant diversity of surface classes that causes a relatively high contrast value for this image.

The value of CF is much higher in band 5 than that in bands 3 and 4 for both images 1 and 2. The band 4 of image 2 shows a relatively higher CF value than that in band 3 of the same image. But in image 1, band 3 shows relatively higher CF value than that in band 4 of the same image. In image 1, most of the surface areas are uncovered soil with relatively sparse vegetation existing as clusters and a very small proportion of water also exists. The soil and vegetation both have relatively high and comparable spectral responses in band 4. As a result, contrast is relatively small in band 4 than that in band 3 of image 1. For image 2 containing significant proportions of soil, vegetation and water, the significant and different contribution from soil, vegetation and water results in relatively high contrast in band 4 as compared to that in band 3 since spectral response in band 4 is very small for water and relatively high for vegetation and soil. It is also evident from these fig. that the rate of reduction of the values of contrast factor (CF) as well as the dynamic range in both images (1 and 2) decrease with spatial degradation of spatial resolution showing a saturation trend.

B. Effect of Spatial Degradation on Classification

For the present analysis, some criteria (discussed in section 3) based on the spectral characteristics (particularly in the spectral regions corresponding to bands 3, 4 and 5 of Landsat TM) of three primary classes e.g., soil, vegetation and water have been considered. Using the classification procedure, different surface classes those having distinct spectral properties of the primary classes are separated. Table 2 provides the results of classification of the original image as well as of the spatially degraded images. Such an attempt yields a total of 5 classes in case of image 1 both for the original image and the images of degraded spatial resolutions, though the relative proportions of each class change with degradation of image spatial resolution. In case of image 2, such an attempt yields a total of 6 classes both for the original and the degraded images. As a result of spatial degradation of image spatial resolution, soil, vegetation and water class changes their spectral characteristics as demonstrated through their DN values.

The degradation of spatial resolution of satellite image does not significantly influence the classification of pixels those having only a single class element and is surrounded by pixels belonging to the same class. Such a situation does not give rise to any mixture problem due to spatial degradation. The complexity arises in the case of mixed class pixels (mixed pixels) or pixel surrounded by other pixels belonging to any other class. In such condition, the overall spectral response of pixel is influenced by more than one surface classes through both the spectral response and relative areas of individual classes within the pixel.

In cases of original and degraded image 1, about 90.3 per cent and 93.5 per cent respectively of the total areas have been classified under soil, vegetation and water classes. The remaining 9.7 and 6.5 per cent of the total areas have been found to be unclassified in cases of original and degraded image 1 respectively. In the cases of original and degraded image 2, about 78.6 and 81.0 per cent of the total areas have been classified as soil, vegetation and water groups. The remaining 21.4 and 19.0 per cent areas have been found to be unclassified in cases of original and degraded image 2 respectively. The unclassified pixels have DN values those do not correspond to the spectral characteristics of any one of the three primary classes of the Earth's surface. Such deviations of spectral characteristics are due to the mixture of two or more primary classes within a pixel.

1) Effect on Vegetation Classification:

The area obtained through classification under vegetation class significantly increases due to degradation of spatial resolution both images 1 and 2 and increases of about 37.19 per cent and 19.20 per cent respectively for images 1 and 2 are noticed in the vegetation areas. Such behaviour can be understood by considering equation 1 of section 2. In case of vegetation, band 4 has DN values significantly larger than those in band 3. Whereas, for soil (in the present case) and water, DN value shows the opposite trend, *i.e.*, DN values in band 3 are larger than those in band 4. The DN values in band 3 do not differ largely between soil, vegetation and water. As a result, when a mixing of any one of cases (ii) to (iv) occurs within a pixel, the significantly large DN value of the vegetation element in band 4 influences the overall response of the pixel in that band to increase. But DN values in band 3 of such mixed pixels do not change appreciably after degradation of spatial resolution. Consequently, such mixed pixels are classified into vegetation group that is characterized by relatively small DN value in band 3 and relatively high DN value in band 4. However, such tendency is fully dependent on the relative proportion of individual classes within a pixel.

In case of original image 1, the classification process yields a large variation in mean DN values for vegetation class between bands 3 and 4, about 47.25 and 62.96 respectively. Whereas, for degraded image 1, the classification process yields a small variation in DN values for vegetation between bands 3 and 4 of about 52.00 and 57.00 per cent respectively. This is due to the existence of soil class just near the vegetation clusters and the size of the vegetation clusters is small. Consequently, spatial averaging causes a share of DN values between vegetation and neighbouring soil and thereby, differences in DN values between bands 3 and 4 reduce. Here, it should be noted that in image 1, soil occupies about more than 80 per cent of the total area.

In case of image 2, for both original and degraded images, the classification process yields significantly large variation in mean DN values between bands 3 and 4 for vegetation class. In this case, size of vegetation clusters is relatively large. The degradation of image spatial resolution causes an averaging of DN values under the specified window size, in which the proportions of both vegetation and soil within pixels are significant. As a result, vegetation class does not undergo to a large change in DN values in bands 3 and 4. In this case, the DN values in bands 3 and 4 respectively are about 37.73 and 56.88 for the original and about 39.50 and 53.69 for the degraded image.

The classification process yields an increased vegetation area for spatially degraded image as compared to that is obtained from the original image. The increase in vegetation area obtained through classification of image 1 is much higher than that is obtained through classification of image 2. The size of vegetation clusters distributed over the soil is significantly small in image 1 than that in image 2. Relatively large number of pixels belonging to vegetation class exists just near the soil in image 1 than that in image 2. Consequently, degradation of image spatial resolution causes a mixing of vegetation with the other two classes, that is significantly large in case of image 1 than that in case of image 2. Such a condition increases the vegetation area through degradation of image spatial resolution and the increase is larger in case of image 1 than image 2. Though, the DN values in the three bands indicate a very sparse vegetation condition in this case.

2) Effect on Soil Classification:

From table 2 it is evident that, the area under pixels belonging to soil class obtained through classification does not change significantly due to degradation of image spatial resolution of both images 1 and 2. In case of original image 1, the classification procedure yields an area of about 82.5 per cent of the total areas under three different soil classes. The spatially degraded image yields a total of about 83.7 per cent of the total areas under three different classes of soil. That is no significant change in the areas belonging to soil class is noticed due to degradation of spatial resolution of the image. The rest portion of the study area remains unclassified. The soil has been classified into three different groups having three different ranges of moisture levels and is based on the differences in DN values in band 5. These three soil classes namely soil 1, soil 2 and soil 3 represent nearly dry, medium moist and moist soil respectively. It is evident from table 2 that after degradation, areas belonging to dry and moist soils decrease and contrarily, areas belonging to medium moist soil increases. This may be due to averaging of either dry soil and moist soil or dry soil with water that result in mixed pixel having characteristics of medium moist soil.

In case of image 2, the original image yields an area of about 24.83 per cent of the total areas under four different soil classes, whereas, the spatially degraded image yields a total of about 22.9 per cent (a decrease of about 7.6 per cent in soil areas with respect to the soil area obtained through classification of original image 2) of the total areas under four different classes of soil. When soil mixed with water within a pixel, DN values in bands 3 and 4 do not change drastically. However, DN value in band 5 of the degraded image decreases depending on the proportion of soil and water within the pixel. Thereby, the spectral characteristics of such pixels change and some of them do not belong to the characteristics of any primary classes. Rather than, such combination of classes in pixels goes towards unclassified group. The classification process applied to the spatially degraded image yields a reduced mean DN value in band 5 for different soil classes as compared to that is obtained from the original image. The soil has been classified into four different classes depending on the moisture content as demonstrated through the DN values in band 5. In this case, areas belonging to comparatively dry and medium soil classes decrease and that belonging to moist soil class increase due to degradation of spatial resolution of images.

3) Effect on Water Classification:

The spatial degradation of satellite image results in a decrease of water areas in both image 1 and image 2 as obtained through classification. In case of image 1, the water area obtained through classification reduces from a value of 1.01 per cent to a value of about 0.01 per cent. In case of image 2, the water areas are found to be about 14.46 (for the original image) and 11.16 (for the spatially degraded image). That is in both cases, significant decreases in water areas are caused by degradation of spatial resolution of the images.

In both images 1 and 2, the degradation of spatial resolution results in increased mean DN values in spectral bands 4 and 5 and no significant changes in band 3 for water class. The DN values in band 3 do not differ largely between soil, water and vegetation. Consequently, mixture of these classes in any proportion does not change the DN values in band 3 of the degraded image. Contrarily, the DN values in bands 4 and 5 are relatively higher for soil and vegetation than that for water. In consequence, spatial degradation of image that incorporates a mixing of either cases (i), (ii) or (iv) (section 3.2) results in augmentation of DN values in bands 4 and 5. Consequently, when a pixel contains both water and soil, the overall response of the pixel tends to go towards soil group after spatial degradation and in such a way, water area has been reduced.

V. CONCLUSIONS

Satellite based remote sensing measurements of radiation over terrestrial surface represents a volume averaged measurements and are related to different Earth's surface parameters. Such an averaging process gives rise to contamination of the signal by different neighbouring surface classes depending on the size and spatial distribution of surface class or classes within a pixel as well as on the pixel size. In the present paper, the effects of spatial resolution on satellite image properties as well as on the quality of the extracted information from such images have been studied using two different sub-sampled images extracted from an image of Landsat TM having different surface characteristics. An average filter with varying window sizes has been used to produce images of different spatial resolution.

Variations in spatial resolution of satellite images incorporate certain changes in image properties. Degradation of spatial resolution results in an increase in minimum DN value and decrease in maximum DN value of the image. A decrease in image contrast is also associated with such degradation. The rate of reduction of both contrast and dynamic range of the image decreases with increased degradation of spatial resolution. The effect is relatively higher in a uniform surface with relatively small cluster size of surface class than that due to a non-uniform surface with relatively large cluster size.

The study also reveals that, spatial resolution of satellite images has significant influence on the quality of the extracted information. The quality of the extracted information is deteriorated by spatial degradation of the image. The spatial distribution and size of different surface classes have significant influences on the quality of the extracted information. For small cluster size of any class, the change in spectral characteristics of a resulting pixel is significantly large than that of relatively large cluster size of that class. Different surface classes are not equally affected due to such degradation. Vegetation area seems to be increased and water area seems to be decreased due to spatial degradation of satellite data.

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