How degraded are Himalayan forests?

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An IRS-1D multispectral image is used to measure the extent to which central Himalayan forests are degraded. The study area covers most of the eastern half of Uttaranchal state in the Indian Himalayas. Accuracy assessment was performed on a sample taken from an Ikonos 1-meter resolution image. We estimate that 61% (48–73%) of the forested area has less than 40% crown cover, with numbers in brackets denoting the 90% confidence interval. The calculation of confidence intervals is a novel feature of the study that is important in view of the fact that satellite image interpretation is never free of error. The results show that the Forest Survey of India's widely cited figures considerably understate the extent of degradation.

Keywords: Confidence intervals, deforestation, degradation, Himalayas, satellite image.

OVER the past few decades there has been a great deal of concern about ecological degradation and deforestation in the Himalayas. The main aim of this paper is to provide estimates of the area of forest degraded in two Himalayan districts *with 90% confidence intervals* by using satellite imagery. Since all interpretation of satellite images is subject to error, it is important to provide not just point estimates, but also confidence intervals around those estimates. To the best of our knowledge, this has not been done for estimates of forest degradation in the Himalayas or elsewhere.

Degradation is measured in terms of crown cover. An IRS-1D multispectral LISS-III satellite image from May 1998 that covers an area of 20,000 square km in the Indian central Himalayas northwest of Nepal, is analysed. We present a vegetation map and estimates of the percentage of the area under forest or scrub, and the percentage of the forested area that is degraded. These figures are presented along with 90% confidence intervals, derived from crown cover counts done on a sample from an Ikonos 1-m resolution panchromatic image from April 2000.

The Forest Survey of India's biennial State of Forest Reports[1], based on interpretations of IRS imagery, have been the main source of district-wise data on the state of forests in India. However, their estimates are presented without confidence limits or error matrices, and no information about the interpretation method is given. This study finds that a greater proportion of the forest area in two districts of Uttaranchal is degraded than the Forest Survey of India estimates would suggest.

Description of the area

The study area lies in the Kumaun and Garhwal regions in the state of Uttaranchal, and includes a small area in western Nepal. It lies between 79°E; 30.5°N and 80.75°E; 29°N, and ranges from 300 to over 7000 m in altitude. Terraced agriculture is found up to a height of about 1800 m on the gentler slopes.

Four principal forest formations are identified in ref. 2. The lower elevations from the plains at 300 m up to about 1000 m contain Submontane Seasonal Broadleaf forest with *sal* (*Shorea robusta*) as the dominant species. The submontane zone has little human settlement. From 1000 to 1800 m there are *chir* pine (*Pinus roxburghii*) forests. From 1500 to 3000 m, overlapping the range of the pines, is a broadleaf forest consisting mainly of oaks, *banj* (*Quercus leucotrichophora*) and other *Quercus* species. Finally, there are the Mid-montane Needle-leaf Evergreen Forests from 1700 to 3000 m and higher, consisting of *deodar* (*Cedrus deodara*), firs, spruces and other species. Singh and Singh also identify some less common formations not described here. In some areas, grasslands occur naturally. While these forests intergrade into each other and there are mixed stands, there is, nevertheless, a strong tendency towards exclusive stands, particularly for the first three types of forest described above.

Forest degradation has resulted from a number of human uses. Overgrazing, lopping for firewood and fodder, resin tapping in the presence of fire, and commercial felling have all contributed to degradation[3]. Degradation reduces crown cover and can proceed to the point when only scrub is left. Since, except for small areas of juniper above the treeline, scrub does not occur naturally in the area[2], we treat scrub as degraded forest.

The degradation of the forests has been a major blow to rural residents of the area who have suffered from the lack of firewood (the main source of energy for cooking and heating), fodder and grazing, and the adverse effects on springs which are the main water sources for villages on the slopes. Degradation may also affect areas in the plains since it may increase the runoff during the monsoon, leading

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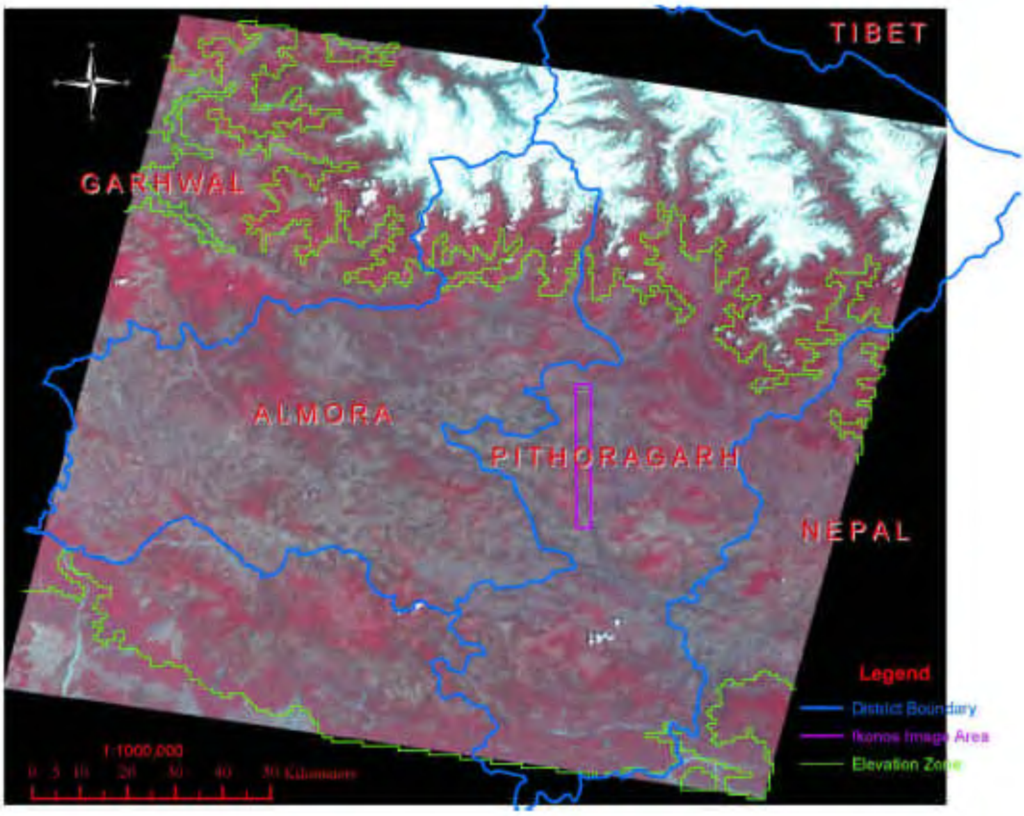

Figure 1. FCC of IRS-1D LISS III 98/50, Bands 2, 3, 4 with areas of interest.

to increased flooding during the monsoon months and reduced water supplies at other times of the year. Finally, of course, forests play a role in carbon fixation.

Methods

The aim was to obtain estimates of the area under forest or scrub and the percentage of the forest area degraded, *together with confidence intervals for these estimates*. A two-stage classification process was applied to the IRS image. In the first stage, training sites acquired during two years of fieldwork in 1997–99 were used to separate pine from broadleaf forests and forests from other classes. This was done using a supervised maximum likelihood classification into 11 classes which were subsequently concatenated. In the second stage, quantitative estimates of canopy cover from the Ikonos imagery were used to separate the two forest types into dense and degraded classes.

The Ikonos data were used to obtain sample error matrices for the classifications. These were used to compute producers' accuracies, that is the probabilities of classifying pixels from a given true class in the various classes. Point estimates of the true class proportions were obtained by inverting the producer's accuracy matrix and multiplying it by the vector of class proportions from the classified map. Confidence bounds for these point estimates were obtained by bootstrapping the sample error matrices and associated estimated true class proportions. The details are discussed below.

Classification and accuracy assessment

An IRS-1D LISS-III scene of 31 May 1998 (Path 98, Row 50) was used (Figure 1). We obtained an almost cloud-free image on a date that was close to the summer solstice. This was done so as to get an image with a sun elevation that was as high as possible (74°) in order to minimize the shadowing that occurs in steep mountain terrain at a latitude of 30°N.

The LISS-III sensor on an Indian Remote Sensing satellite collects reflectance in four spectral bands with wavelengths 0.52–0.59 μm (band 2, green), 0.62–0.68 μm (band 3, red), 0.77–0.86 μm (band 4, near infrared), and 1.55–1.70 μm (band 5, near infrared). (Band 1 is a panchromatic band that we did not use. For further details, see ref. 4.) The spatial resolution (pixel size) of bands 2, 3, and 4 is about 23.5 × 23.5 m, as compared to the Landsat Thematic Mapper's 28.5 × 28.5 m. When the spatial distribution of land types is highly fragmented, as is the case in mountainous subtropical landscapes[5], a relatively small pixel size is desirable to reduce the likelihood of mixed pixels, that is, pixels with more than one land cover class in them. Band 5 has a pixel size of about 70.5 m, resampled to the same resolution as bands 2, 3 and 4.

As mentioned above, the vegetation map was generated in two stages. During several visits to the field from October 1997 to September 1999, potential training sites were identified by visual inspection. These sites were chosen in contiguous patches of vegetation that were at least 100 m across and which could be accurately located on a 1 : 25000 Survey of India topographic map. Ground features, compass, altimeter, and a GPS was used to locate the training site on a map. Each site was marked as a polygon leaving a 30-m buffer of the same vegetation around the polygon to eliminate errors in the signatures arising from edge effects and registration error. After eliminating sites that were in shadow or had positional errors, 169 sites, each consisting of one of eight classes, were selected for training. These were (1) dense broad-leaved forest, (2) open broad-leaved forest, (3) broad-leaved scrub (4) dense pine forest, (5) open pine forest, (6) grassland, (7) agriculture, and (8) bare land. The broad-leaved forest with a basically closed canopy was classified as dense. Conifers, mainly pine, were classified as dense if it was not possible to see the ground when the forest was looked at from the outside, and if the trees were close enough to leave no gaps between them. Signatures for the classes (9) water bodies, (10) snow, and (11) cloud, were taken directly from the image. Since the registration error from attempting to georeference the whole IRS image was high, those parts of the satellite image containing the training sites were georeferenced with root mean square registration errors ranging from 0.45 to 1.03 pixels.

The image was classified using the method of maximum likelihood assuming that the four bands were jointly normally distributed with different parameters for each class, and with each class given a prior probability of being equally likely. The entire procedure was implemented with Erdas Imagine 8.4 software. Classes (1)–(3) of those mentioned above, were merged to form a class called broad-leaved forest (BL), (4) and (5) were merged to form Pine forest, (6) and (7) were merged into a category called Grasses, and the others were merged to form a category called Other.

After this study was underway, Ikonos 1-m resolution imagery became available. This offered an opportunity to improve the measurement of forest degradation since aerial photographs of this region are not in the public domain and were not available to us. An image from 24 April 2000, covering a transect 30 km in length from north to south and 2.5 km wide was procured from among the few images available for the area (Figure 1). This was intended to span the altitudinal zones corresponding to different vegetation types in the region. The Ikonos image was registered to the IRS image with a root mean square error of 0.7 IRS pixels.

After a field visit to prepare a key for visual interpretation, a random sample of 1024 points was taken from the transect. 75×75 m windows around these points were visually interpreted to correspond with the classes described above. The purpose of the 75×75 m windows (roughly equivalent to 3×3 IRS pixels) was to ensure that the true class of an IRS pixel at a point was correctly determined. A smaller window might have led to true classes being incorrectly determined due to registration error. An additional sample of 256 points was randomly taken from areas rich in vegetation types under-represented in the original sample. These areas were determined visually from the Ikonos image, so that the additional points were selected on the basis of the reference or true class, and *not* the map class.

Six hundred and eight points for which the entire 75×75 m window fell in a single class, were retained for analysis. If the 75×75 m window contained more than one class, then we could not confidently assign the true class of the IRS pixel containing the random point, since registration error might lead to a shift in the location of the IRS pixel on the Ikonos image. A producer error matrix for this sample, $P = [p_{jk}]$, where p_{jk} is the percentage of points in class k that were classified by the maximum likelihood procedure as class j, is presented in Table 1. Here the true class k refers to the 75×75 m window about the point, while the map class j refers to the class of the IRS pixel containing the point. This error matrix presents only three classes, broad-leaved forest, pine forest, and grassland and agriculture. The Other class is not presented since its confusion with forest classes is negligible. Table 1 shows that separation of the three vegetation types is good, with over 80% producer accuracy being achieved for all three. It was found that the first stage classification done above, while differentiating quite well between different forest types and grasslands and agriculture, performed poorly in distinguishing between dense and open classes in the same type of forest. We resorted to the second stage procedure described below to separate dense and open classes.

A 10-m grid was laid on the Ikonos image and a 7×7 segment of this grid centred on each random point in the forest classes was used to measure crown cover. The proportion of the 49 squares in each segment of the grid that were covered by tree crowns was the measure of crown cover. Of the 608 points, 553 points for which reliable crown cover counts were possible were retained.

Table 1. Sample producer error matrix of vegetation types (percentages of sites in each true class mapped into different classes)

	BL (true)	Pine (true)	Grasses (true)
BL (mapped)	83	6	10
Pine (mapped)	5	94	1
Grasses (mapped)	12	0	89
Total sites	244	219	145

BL, Broad-leaved forest or scrub; Grasses, Grassland and agriculture. Percentages are rounded to whole numbers.

Crown cover was used as the indicator of degradation. Any cutoff level for classifying an area as dense or open, is, of course, arbitrary. Two cutoffs were used: 40 and 80%. Eighty per cent was thought to be appropriate since an undisturbed broad-leaved forest in this region would have a closed canopy[2]. The 40% cutoff was used for comparison with the data generated by the Forest Survey of India, which uses a 40% cutoff.

The data were topographically normalized by using the ratios of band 5 to bands 2, 3 and 4. Classification into dense and degraded classes for both cutoffs for both broad-leaved and pine types was done using the maximum likelihood classifier applied to the three band ratios and aspect. Aspect is defined as a continuous variable taking all values from 0 for south-facing pixels to 1 for north-facing pixels. The aspect variable was created in ArcMap 8 software using freely downloadable elevation data with a 90 m resolution from the SRTM (Shuttle Radar Topography Mission). (We are grateful to a referee for suggesting the use of aspect data for improving the classification accuracy which resulted in narrower confidence intervals.) The prior probabilities were chosen to roughly maximize the sum of classification accuracies of dense and degraded types while not allowing any of them to fall below 50% in the assessment sample. The resulting thematic map is presented in Figure 2.

A sample error matrix for the 40% cutoff is given in Table 2. Notice that there is still considerable misclassification of open or degraded categories as dense and vice versa, even after the use of the second-stage procedure. The fact that the different forest types are classified with a fairly high degree of accuracy, but separation of degraded from dense forest is subject to considerable error is only to be expected. There is not much difference between forests with crown cover slightly less than 40% and slightly more than 40%. There is no natural sharp distinguishing feature and so considerable misclassification is unavoidable in the latter case. For the purpose of estimating areas in the various classes, however, this *need not matter as long as the producer error matrices are estimated with sufficient accuracy*. For this purpose, classification accuracy matters only insofar as it helps to reduce the variance in the estimate of the inverse of the producer error matrix. What is important is that a large enough sample of points be taken from each true class. Sample sizes for the different classes in our study were fairly large, ranging from 70 to 145. We elaborate on these points below.

Point estimates of degradation

The producer error matrix is defined by $P = [p_{jk}]$, where p_{jk} is the probability that a pixel that is truly in class k gets classified in class j. From the vegetation map, the shares of land $s = (s_1, \ldots, s_5)$ under five classes (dense and degraded broad-leaved and pine forests, and grassland and agriculture) in the IRS image were obtained. The other classes either represented tiny fractions of the

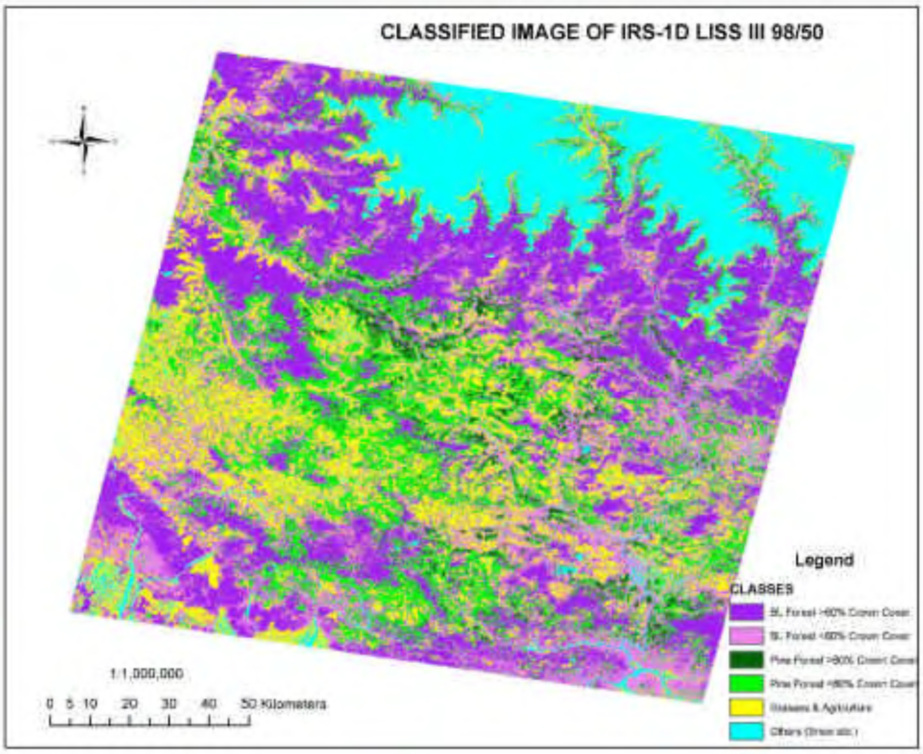

Figure 2. Classified image of IRS-1D LISS III 98/50.

Table 2. Sample producer error matrix for degradation (percentages of sites in each true class mapped into different classes)

	BL > 40% cc	BL < 40% cc	Pine > 40% cc	Pine < 40% cc	Grasses
BL > 40% cc	67 (58–75)	18	0	0	0
BL < 40% cc	33	50 (42–58)	1	11	10
Pine > 40% cc	0	0	74 (68–81)	20	0
Pine < 40% cc	0	10	25	67 (59–76)	1
Grasses	0	22	0	1	89 (84–93)
Total sites	93	125	120	70	145

BL, Broad-leaved forest or scrub; Grasses, Grassland and agriculture; cc, Crown cover.
Columns are reference or true classes, rows are map classes. Percentages are rounded to whole numbers.
To avoid clutter, 90% confidence intervals are given in brackets for the diagonal elements only.

area like bare land, or (like snow) had negligible confusion with other classes, and so were excluded from the error matrix. Now,

$$s = Ps^*,$$

where s^* is the unknown vector of true shares of land in each class. Therefore, the vector of true shares of land in each class is given by

$$s^* = P^{-1}s.$$

Let $\hat{P} = [\hat{p}_{jk}]$, where $\hat{p}_{jk}$ is the proportion of sample pixels really in class k that were classified as class j. Replacing P by $\hat{P}$ yields the following estimate, due to ref. (6), of the true shares of land in each class:

$$\hat{s}^* = \hat{P}^{-1}s.$$

$\hat{s}^*$ is a consistent (roughly speaking, unbiased in large samples) estimate of s^* if $\hat{P}$ is a consistent estimate of P. $\hat{P}$ is a consistent (in fact, unbiased) estimate of P, provided the misclassification probabilities in the Ikonos image area from which the sample was drawn are the same as the misclassification probabilities for the area as a whole, and for the subregions of interest. This is our assumption. Since the vegetation types are the same and the Ikonos image covers a transect of the area, this assumption is thought to be reasonable, although, of course, it is unlikely to be wholly accurate. The more narrowly each class is defined, the more likely it is that the assumption will hold. On the other hand, expanding the number of classes raises the cost of getting a sample of a given size for each class, and also raises the probability of infeasible estimates (class shares that are less than zero or greater than one). With these considerations in mind we chose to use five classes.

The consistency of $\hat{P}$ does not require a simple random sample. It is sufficient that each subsample from a given true class be random. This is important since we would not have been able to obtain enough points in the rarer classes with a simple random sample.

Note that it is certainly not true that the actual shares of land in each class are the same for the sampled area and the areas of interest. This is why it is not possible to use the alternative adjustment procedures for estimating s^* proposed by Tenenbein[7] and Card[8]. Those methods rely on consistent estimates of *user* accuracies u_{jk}, that is, the probability that a pixel mapped as class j was really from class k. To get consistent estimates of user accuracies, the sample must be taken from an area with representative true class shares. This can be difficult for the following reasons.

Reference data usually come from either field observations or high-resolution imagery. Field samples are expensive. A randomly chosen point may prove to lie on the boundary of different true classes when visited in the field. This is especially likely to be the case in tropical or subtropical montane areas with high variability in landuse[5]. Using such a point is likely to result in the confusion of registration error with classification error. Dropping such points raises the cost of getting a sample of given size. High-resolution images (as in our study) are often available only for portions of the area of interest, and, therefore, are not representative of the shares of land use classes in the area of interest. Finally, if there is more than one area of interest, as in our study, methods utilizing the user error matrix would require a sample from each of these areas, thus multiplying the cost of the study.

The drawback of the method used here, which uses the producer error matrix, is that it requires a matrix inversion. This means that $\hat{s}^*$ could have elements that are less than zero or greater than one. This problem is unlikely to occur if the diagonal elements of P (the probabilities that classes are correctly classified) are sufficiently close to 1 (ref. 9), and if the class proportions are not too unequal[10]. Matrices with diagonal elements too close to zero are ill-conditioned, meaning that small changes in the elements of such a matrix can lead to large changes in its inverse. Since it is $\hat{P}^{-1}$ that is used in the calculation of the true class proportions, if it is ill-conditioned, then the estimated true class proportions will have a large variance. A simulation study[11] found that if the producer accuracies (that is, the diagonal elements) were at least 0.7, then this problem

Table 3. Comparisons of degradation with FSI estimates

	Whole image	Almora dist		Pithoragarh dist	
	This study	This study	FSI	This study	FSI
Per cent of area under forest (or scrub)	75 (71–89)	72 (68–77)	48	71 (67–75)	36
Per cent of forest area with < 40% cc	61 (48–73)	78 (68–86)	19	58 (45–70)	31

cc, Crown cover. 90% confidence intervals for our study are given in brackets. All figures rounded to whole numbers.

did not occur. This is why obtaining a classification accuracy of 70% in each class is desirable *but higher accuracies are not necessary, provided the assessment sample size in each class is large enough.*

Some of the diagonal elements in the error matrix in Table 2 are less than 70%, resulting in considerable variation in the inverse matrix. This gives wide confidence intervals as seen in Table 3. However, as we shall see below, we can still conclude that degradation has been overestimated by the Forest Survey of India. Thus, despite the low classification accuracies in some classes, we can still reach useful conclusions because the confidence intervals inform us about the limits of the likely errors.

Confidence bounds for the degradation estimates

We now come to the main contribution of this paper: computing confidence intervals for our estimated proportions of the areas in the different classes. $\hat{s}^*$ is a useful estimate only if we know how much error it is likely to contain. The 90% confidence intervals on the elements of $\hat{s}^*$ were computed as follows. One thousand random 'bootstrap' samples *with replacement* were drawn from the sample of 553 points used for accuracy assessment above, each being of the same size as the original. (See ref. 12 for a discussion of bootstrap methods in the context of estimating error rates in classification problems.) Each bootstrap sample is thus a random draw from the original sample and results in a different distribution of band ratios in each true class. Then $\hat{s}^*$ was calculated for each bootstrap sample by re-calculating $\hat{P}^{-1}$ and multiplying it by the original map proportions vector s. The 5th and 95th percentiles of the frequency distribution of $\hat{s}^*$ thus generated give us the 90% confidence intervals on $\hat{s}^*$.

The most straightforward way to narrow the confidence intervals and increase the precision of the estimates is to use a larger sample for those classes for which the sample size is small. This will reduce the sampling variability between bootstrap samples and thus narrow the confidence intervals on the error matrix, and therefore, on the proportions of the area in different classes. An increased sample size may also improve classification by allowing better estimates of the parameters although this effect is likely to be small except when starting from a very small sample size. Of course, increasing the sample size is costly in terms of increased field visits, or acquisition, geo-registration, and visual interpretation of high-resolution images.

Results

Referring to Table 3, we see that 72% (68–77%) (throughout the paper the ranges refer to the 90% confidence interval) of the old Almora district, subsequently split into Almora and Bageshwar, was under forest or scrub in 1998. The Forest Survey of India (FSI) estimated the area under forest or scrub to be much lower: only 48%. As mentioned in the introduction, the FSI estimates are presented without any information on the interpretation methods used and without confidence bounds. In fact, the FSI estimated the area under scrub in Almora district to be only about 1% of the total area, an unbelievably low number. This probably accounts for much of the wide discrepancy between their estimates and ours. Of the forest (including scrub) area, we find that 78% (68–86%) was degraded, i.e. had a crown cover of less than 40%. The FSI estimates the forest degraded to be just 19%. Again, a good part of the discrepancy is probably due to their misclassification of scrub and other degraded forests as non-forest.

A caveat that needs to be made at once is that our IRS image does not cover the whole of both districts (Figure 1). Nevertheless, this cannot account for such huge discrepancies. The part of Almora district not in our image is very small. The part of Pithoragarh left out is larger, but most of this is under permanent snow.

The FSI's underestimation of the forest and scrub area and related underestimation of the proportion of forested area that is degraded is repeated in the Pithoragarh district (subsequently split into Pithoragarh and Champawat). We estimate the forest or scrub area in the Pithoragarh district to be 71% (67–75%) while the FSI figure is only 36%. Again, their figure for the per cent of the total area of the district under scrub is rather low: just 4%. We find that 58% (45–70%) of the forested area has a crown cover below 40% while the FSI estimate is 31%.

While there is one other large-scale study that uses visual interpretation of 1972 Landsat MSS data and aerial photographs for ground truths[13], it is unfortunately not directly comparable with ours, since they used different crown cover cutoffs and made no attempt to distinguish between scrub and grasslands. There are also a number of studies of much smaller areas in the region[14–17]. They are all based on aerial photographs from the early 1970s and they generally found smaller proportions of forest with high crown cover than we do. Tiwari and Singh[17] also included a time-change analysis using recent IRS imagery and found a decline in the extent of forests with high crown cover.

Conclusion

The results presented here suggest that the extent of forest loss in the Central Himalayas has been considerably understated in the widely cited estimates by the Forest Survey of India, partly because the extent of forest land that has been degraded has not been adequately counted. This paper has demonstrated a method for finding confidence intervals for the estimated areas under different classes. While the estimated confidence intervals for the proportion of the area forested in the two districts studied are closer, those for the proportion of forest with less than 40% crown cover are wider, a natural consequence of the fact that crown cover is a continuous variable. Despite the wide confidence intervals for degradation, the official figures lie below the lower limits of our confidence intervals in both districts. This illustrates the importance of giving confidence intervals for estimates of areas. Larger assessment samples, while more expensive, would narrow the confidence intervals, thus improving the precision of the estimates.

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ACKNOWLEDGEMENTS. Financial support from the National Science Foundation (USA) under grants SBR-9711286 and SES-9996602 is gratefully acknowledged as is support in the field by the UP Academy of Administration, Nainital, and the UP Forest Dept. We thank Preeti Rao and Sweta Patel for excellent research assistance and to three anonymous referees for comments and suggestions. Much of the research was done when R. Prabhakar was at the Institute of Rural Management and E. Somanathan was at Emory University and the University of Michigan at Ann Arbor. The Foundation for Ecological Security provided laboratory facilities.

Received 10 May 2005; revised accepted 28 March 2006