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VALIDATION OF GROUND TRUTH OF REMOTELY SENSED DATA FROM SENTINEL-2 (MSI) USING SUPERVISED CLASSIFICATION, AFTER COMBINED CLOUD AND SHADOW EFFECT REMOVAL

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Abstract
SENTINEL-2 is utilized for the earth observation system to acquire optical imagery of land as well as coastal water areas with a high spatial resolution (10m to 60m). Earth observation supports various services like agricultural monitoring, ground truth classification, and identification of environmental changing effects over land cover. If images acquired are under the influence of climatic noise such as the occurrence of shadow and cloud, the clarity of ground truth images may get reduced. The present article provides an integrated method of the supervised classification, and segmentation of land cover boundaries using NDVI (Normalised Difference Vegetation Index), with detection of cloud and shadow pixels using SENTINEL-2 band images. Images of places Around Lonavala, Pavana lake, Mulashi Lake, Tamhini Ghat, Changad, Lavasa, etc. of India from 2020 to 2021 were used in experimentation. The pixels under the influence of cloud and shadow regions are detected and replaced by reconstructing an image using a reference image. Cloud and shadow, free images are further classified to validate the ground truth. The proposed system uses a Maximum Likelihood Classifier (MLC), Random Forest (RF), and Minimum Distance Classifier to examine the correctness of ground truth. Overall Accuracy achieved with the Maximum Likelihood Classifier, Random Forest Classification, and Minimum Distance Classification are 98.20%, 96.65%, and 99.65% and K-hat is 0.97, 0.95, 0.98 respectively. From statistical analysis and findings, shows that the proposed system can successfully denoise images obtained through the SENTINEL-2 satellite in preprocessing step and validated the ground truth obtained.

Keywords: **MSI (Multi-Spectral Instrument); Maximum Likelihood Classifier (MLC); Random Forest (RF); Normalized Difference Vegetation Index (NDVI);**

1. Introduction

Sentinel-2 satellite which carries multispectral scanners is developed by ESA as their second constellation.

The provision of remotely sensed data with high resolution is the main objective of the Sentinel-2 mission. Further, these data can be used for various applications like monitoring the Earth's Surface, observing changes in ground truth due to climate, or any disaster activity. [2]

Compelling development of the remote sensing mechanism has enabled humans to have astute monitoring of land cover and scene classification of images acquired through satellite, over the past decades. [3][13][14]

In optical and infrared remote sensing, if land surfaces are having clouds and their shadows, this image may become a limit to further applicability. The most critical step of pre-processing is to recognize and remove the effect of cloud and their shadows from such images.[4][16][22]

It is the prerequisite for existing techniques of cloud and shadow detection methods to get their location information previously and they absolutely failed to utilize the hidden information over the regions of a cloud and shadow. [5][23]

Normally, complimentary images are required to discover the ground truth under the cloud region, these images are known as reference images.[6] [25]

The existence of cloud and their shadows completely suppresses the clarity and visibility of remotely sensed images by limiting their use in various LULC applications such as observation of Land Cover, detection of changes in land cover, categorization of land cover, etc. [7][21]

The clouds with shadows are considered an unavoidable cause of the climatic noise in remotely sensed images, there may be a lack of adequate information required so it is a difficult task to restore the information of the region under the cloud cover. [8][24]

Due to the occurrence of Clouds and shadows over the land cover, it will create difficulty in the applicability of a cover Image for various applications, so in preprocessing step it is necessary to remove cloud and their shadows from Land Cover.[9]

The proposed method for detection and removal of clouds and their shadow's influence uses Supervised Classification using the Maximum Likelihood Algorithm, application of NDVI index to segment the land cover regions boundaries to enhance classification, B-2 to B-8A, B-11, and B-12, band images are utilized for identification of cloud, shadow pixels, remove clouds and shadows using the mask, and validate the ground truth by Accuracy Assessment.

The proposed system designed to detect and remove cloud and shadow influence utilizes Images that are acquired through the SENTINEL-2 satellite which is operated by the European company ESA. A total of 13 bands are available to capture an image of an earth's surface. Experiments are performed by using a combination of three images which are having dense, low, and no clouds of the same scene of the study area "L1C_T43QCA_A019436". The study area used in experimentation is regions covering Lonavala, Malavali, Lavasa, Mulshi Lake, Pawana Lake, etc. Cloud and Shadow influence over the landcover is detected and removed by using the proposed method of combination of band images of B-2 to B-8A, B-11, and B-12. Atmospheric correction is done by applying Dark Object Subtraction. The Maximum Likelihood Algorithm is used to classify an Image. For proper segmentation between the various classes, NDVI is used. Band-2, Band-11, and Band-12 images are used to mask cloud and shadow pixels. with the reference image pixels, the pixels under the influence of Cloud and Shadow contamination are replaced. Cloud and the shadow-free image is examined for their correctness or exactness. To validate the ground truth, Cloud and the shadow-free image is further classified with Maximum Likelihood Classifier (MLC), Random Forest (RF), and Minimum Distance Classifier. The error matrix of a classified image has been calculated and compared with the existing System. Experimentations are performed by using the Semi Classification Plugin (SCP) of QGIS.[15]

The present article is organized as section 2 explains the location and input images details, used for experimentation, in section 3, the material and methods in terms of algorithms used in preprocessing step and ground truth validation purpose are elaborated. Section 4 shows the finding and analysis for ground truth validation with accuracy assessment.

2. Study Area

For experimentation, some of the regions in the Maharashtra state of India are selected. It covers the area around Lonavala, Pawana lake, Mulashi Lake, Tamhini Ghat, Changad and Lawasa. The location of the regions selected can be viewed in Fig. 1. Dataset is downloaded from www.Copernicus.eu/en.[1]. Images are acquired through Sentinel-2 (MSI). The Scene id is "L1C_T43QCA_A019436", the output format is GeoTIFF and the spacecraft ID is T43QCA. The study area located on the map is 73° 30 000 in the East and 18° 30 000 in the North. Approximately 1,444.38 Km2 area of the region from the selected area is used for the study.

2.1. *Input Images*

The land cover is shown in Fig. 2. is of SENTINEL-2 Scene " L1C_T43QCA_A019436" acquired through SENTINEL-2. Image shown in 2(a) is acquired on 25-11-2021 with 49% Cloud Cover, 2(b) is acquired on 31-10-2021with 0.06% Cloud Cover and 2(c) is acquired on 25-11-2020 with 0% Cloud Cover. Cloud and shadow contaminated pixels from a land cover image(2(a) are identified and replaced with the reference land cover image pixels shown in 2(b) and 2(c).

Name of Data Product	Spacecraft_ID	level of Processing	Date of Sensing	Physical Bands used in Experimentation	Resolution (meters)
T43QCA	Sentinel-2A	Level-1C	25-11-2021; 31-10-2021; 25-11-2020	B2- Blue, B3- Red, B4 -Green, B8	10m
				B5 – Vegetation, B7- Vegetation	20m
				B8A, B11- SWIR, B12-SWIR	20m

Table 1. Details of Satellite Image

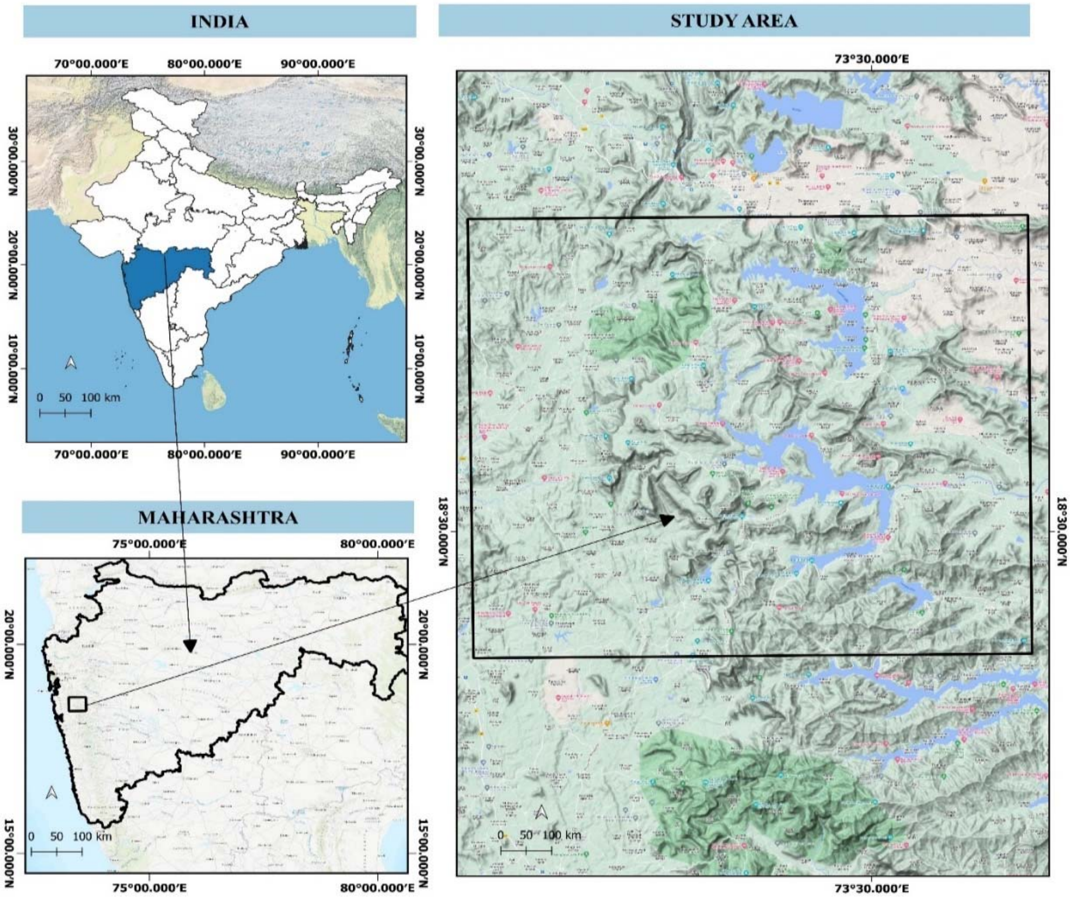


Fig. 1. Location Map of Study Area.

(a) (b) (c)

Fig. 2. SENTINEL-2 Scene " L1C_T43QCA_A019436" through SENTINEL-2 (a) Acquired on 25-11-2021 with 49% Cloud Cover (b) Acquired on 31-10-2021 with Cloud Cover of 0.06% (c) Acquired on 25-11-2020 with Cloud Cover of 0%

3. Materials and Methods

For experimentation, B-2 to B-8A, and B-11, B-12 images are used. These images are carrying scattered atmospheric reflection so it is needed to apply the atmospheric correction. In preprocessing DN to Reflectance is used to acquire actual surface reflectance.

Due to an environmental effect, the darkness that appeared in a satellite image is reduced with an image-based technique known as Dark object Subtration1(DOS1) [19], Atmospheric scattering can be obtained through dark objects of a satellite image. For reducing the atmospheric scattering, DOS1 subtracts the dark pixels identified from a satellite image.

3.1. *Supervised Classification of SENTINEL-2 by using Maximum Likelihood Algorithm.*

In the proposed system Maximum Likelihood Algorithm is used for the Classification of Images captured with the SENTINEL-2 Satellite.

Supervised classification is aimed to recognize components available on Land Cover or Earth Surface by using their spectral signatures. Land Cover may contain components such as water bodies, bare rocks, soil, snow, vegetation, constructions, mountains, etc.

In every band of satellite, there is a normal distribution of statistics belonging to all classes, this assumption is utilized by the Maximum Likelihood Algorithm for the calculation of the probability to assign the pixel to its respective class.

Pixels those are having a higher probability, that is added to their respective Class, which is also called Maximum Likelihood.

$$g_k(x) = 1np(C_k) - \frac{1}{2}1n|\Sigma_k| - \frac{1}{2}(x - y_k)^t \textstyle\sum_k^{-1}(x - y_k) \qquad (1)$$

Equation 1 is used to calculate the probability p(Ck) of a pixel with its spectral signature x, | Σ_k| is related to the image data as its covariance matrix, yk is a vector to store the spectral signature of k class. J-M distance is used for the separation required to differentiate among the surface component and its class, this value ranges from 0-2 to 0 is for overlapping and 2 is for completely separable.

After applying Maximum Likelihood classification, the input image is classified into six classes water, build-up, soil, Vegetation, Clouds, and Shadow.

3.2. *Improved Classification with NDVI (Normalized Difference Vegetation Index)*

The NDVI [17][18] value of a pixel is a scalar from -1 to 1. The pixels in regions with healthy or dense vegetation reflect more NIR light, resulting in high NDVI values. The pixels in regions with unhealthy vegetation or barren land absorb more NIR light, resulting in low or negative NDVI values.

Segment the desired vegetation regions by performing thresholding using the NDVI values. For NDVI calculation used is NDVI= B5-B4/B5+B4

i.e., pixels from the NIR band are subtracted from Red Band and then divided by pixels from the NIR band Added with Red Band.

Classification results can be enhanced to create segments in between classes identified by using NDVI calculation.

3.3. *Cloud- Shadow Masking*

Cloud masks determine the different types of clouds. Clouds may be classified as thick clouds and cirrus clouds which are also known as thin clouds.

Cloud and Shadow contaminated pixels are selected from band-2, Band-11, and Band-12 Images, to produce the cloud and shadow mask. Fig. 3 shows images required to identify cloud and shadow pixels. With these pixel values, clouds and shadow pixel values are replaced as zero, and Mask is prepared.

After observing the result of the cloud mask, one can view the difference in each output mask. The image acquired on 25-11-2021 is having a dense amount of cloud, the image acquired on 31-10-2021 is having a low amount of cloud, and an image acquired on 25-11-2020 is having zero percentage cloud. As per the cloud contamination, cloud masks are generated.

3.4. *Reconstructing Cloud-Shadow free Image*

The pixels which are under the influence of cloud and shadow contamination are replaced with the value '0' and these particular pixels with zero are replaced with the reference image used.

Here Cloud_T1 = cloud and shadow mask of 25-11-2021, Cloud_T2 = cloud and shadow mask of 31/10/2021, Cloud_T3 = cloud and shadow mask of 25-11-2020. Cloud-Shadow free image is reconstructed by replacing the pixels of zero value of Cloud_T1 with Cloud_T2 and Cloud_T2 pixel values.

In a similar way, clod and shadow contaminated pixels masked in the second target image can be removed by taking reference from T1 and T3 masks.

Hence, the proposed system successfully recognizes and removes clouds and shadows with the combination of bands B2-B8A and B-11, B-12 reflectance with the supervised classification of the Maximum Likelihood Algorithm.

The next section displays accuracy achieved after the removal of climatic noise, to check whether the pixels are correctly mapped with their corresponding area or not?

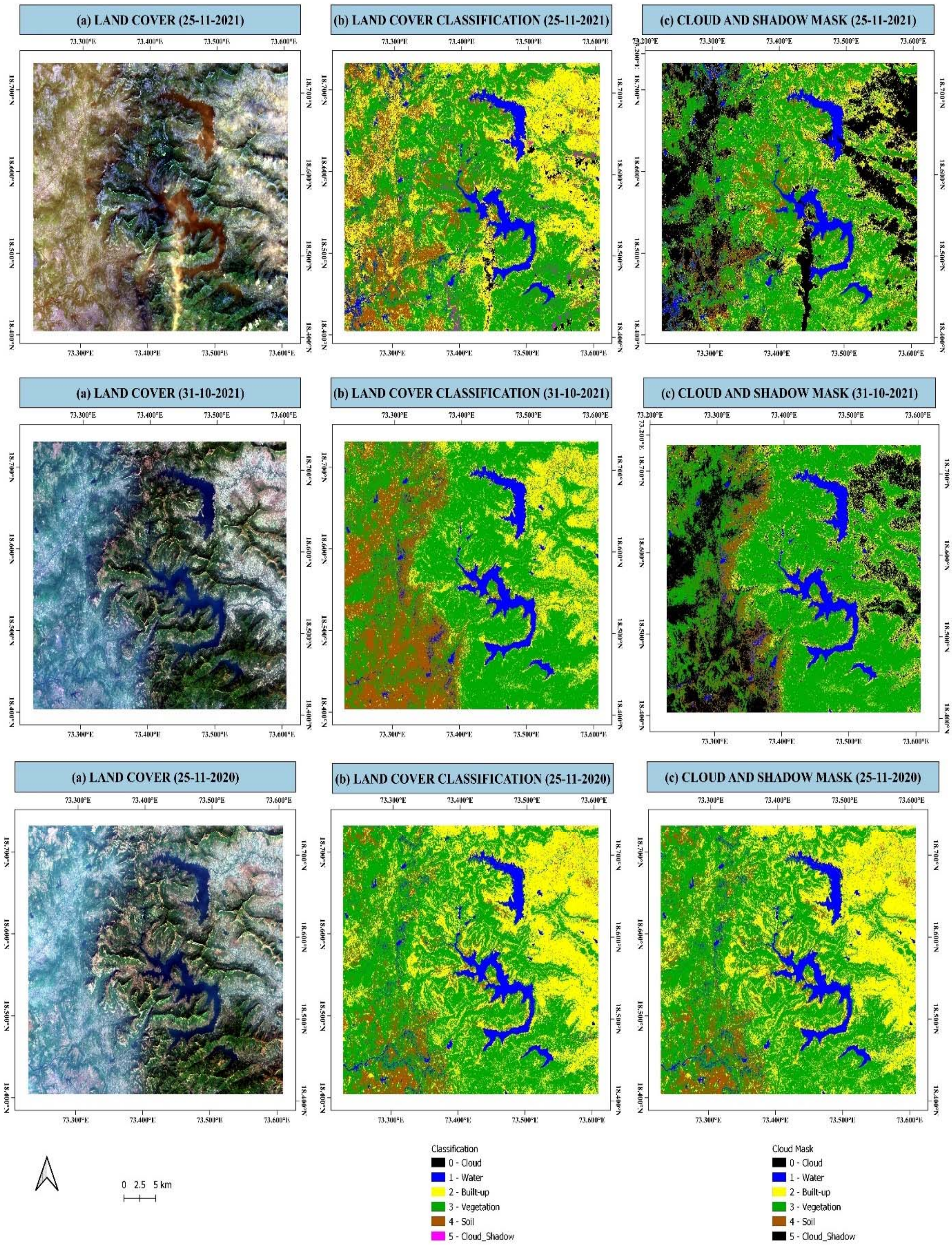
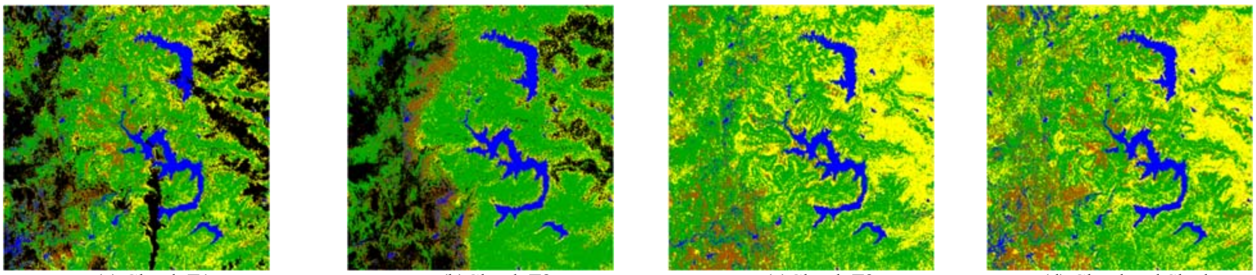


Fig. 3. Landcover Classification with Cloud and Shadow



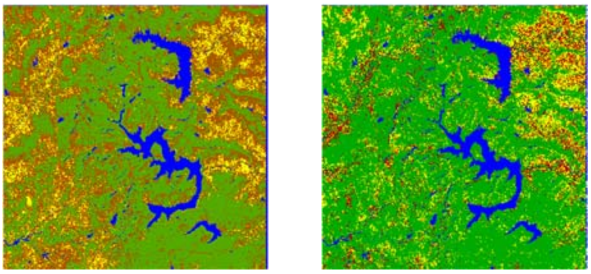
(a) Cloud_T1 (b)Cloud_T2 (c)Cloud_T3 (d) Cloud and Shadow removed from Cloud_T1

Fig. 4. Removal of cloud and shadow from Cloud_T1

4. Ground Truth Validation

After reconstructing a cloud-shadow free image of an input image acquired on 25-11-2021, the next step is to validate the ground truth data. Here the land cover classes of water, Built-up, Vegetation, and Soil are checked against map data which is known as reference data.

Ground truth is validated by applying the maximum likelihood Classifier (Fig. 4d), Random Forest Classification (Fig. 5a), and Minimum Distance Classification (Fig. 5b).



(a) Random Forest (b) Minimum Distance

Fig. 5. Ground Truth Classification

4.1. *Random Forest*

Random forest classifier contains ensembles that may be referred to as enormous decision trees. In experimentation 100 decision trees to get a more accurate classifier. More than 8000 pixels are used in training. The evaluated performance of the random forest classifier is 99.36%, and RMSE is 0.15. Overall Classification Accuracy obtained for ground truth validation is 96.95 % which can be visualized in Table. 3.

4.2. *Minimum Distance*

Minimum Distance Classification is used to assign a pixel to its nearest class. Mean vectors of each class are used for the calculation of the Euclidean distance of each unknown pixel with it. So, the pixel is assigned to the class on the basis of the spectral signature which one is closer to it by using the Euclidean Distance measure. [16]

Ground truth validation using minimum distance gives overall accuracy of 99.65%, as shown in Table. 4.

5. Accuracy Assessment

Table 2 data is interpreted as for Water class 9273 pixels are correctly classified as water class from map data, one pixel is misclassified as built-up, 1425 water pixels are incorrectly classified as vegetation and 0 pixels of water class are misclassified as soil pixels from total 94219 water pixels. similarly, other rows can be interpreted.

The accuracy Matrix is represented with an error matrix as shown in Table 2. Table 2 highlights pixel-based accuracy. Pixels of reference data that are correctly mapped to classes identified are known as Overall Accuracy.

The overall accuracy obtained for the classification of MLC is 98.20 % (Pixel Wise), and K-hat statistics calculated pixel-wise are also closer to one that is 0.97. In a similar way Table 3 and Table, 4 can be interpreted.

From the accuracies obtained and reduced error percentage of omission and commission errors, it can be concluded that ground truth is successfully validated with the proposed system.

IV_Classified		REFERENCE DATA				
		1(Water)	**2(Built-up)**	**3(Vegetation)**	**4(Soil)**	**Total**
CLASSIFIED DATA	**1(Water)**	92793	1	1425	0	94219
	2(Built-up)	0	91750	1970	1776	95496
	3(Vegetation)	0	3	105255	1263	106521
	4(Soil)	0	0	0	62928	62928
	Total	92793	91754	108650	65967	359164
	PA	100	99.99	96.87	95.39	**98.06**
	UA	98.48	97.37	98.81	100	**98.66**
	OE	0	0.00	0.03	0.04	**0.02**
	CE	0.01	0.03	0.01	0	**0.01**
Overall accuracy [%] = 98.20 %, Kappa hat classification = 0.97						

Table 2. Error Matrix of Maximum Likelihood Classifier (MLC)

IV_Classified		REFERENCE DATA				
		1(Water)	**2(Built-up)**	**3(Vegetation)**	**4(Soil)**	**Total**
CLASSIFIED DATA	**1(Water)**	61420	0	0	0	61420
	2(Built-up)	0	2719	4	197	2920
	3(Vegetation)	15	10	13462	155	13642
	4(Soil)	0	305	11	6001	6317
	Total	61435	3034	13477	6353	84299
	PA	99.98	89.62	99.89	94.46	**95.99**
	UA	100.00	93.12	98.68	95.00	**96.70**
	OE	0.00	0.10	0.00	0.06	**0.05**
	CE	0.00	0.07	0.01	0.05	**0.03**
Overall accuracy [%] = 96.95 %, Kappa hat classification = 0.95						

Table 3. Error Matrix of Random Forest

IV_Classified		REFERENCE DATA				
		1(Water)	**2(Built-up)**	**3(Vegetation)**	**4(Soil)**	**Total**
CLASSIFIED DATA	**1(Water)**	1300787	158	19	18	1300982
	2(Built-up)	1421	8594693	295	503	8596912
	3(Vegetation)	44411	0	3681327	73	3725811
	4(Soil)	0	581	0	8732	9313
	Total	1346619	8595432	3681641	9326	13633018
	PA	96.60	99.99	99.99	93.63	**97.55**
	UA	99.99	99.97	98.81	94	**98.19**
	OE	3.40	0.01	0.01	6.37	**2.45**
	CE	0.01	0.03	1.19	6.24	**1.87**
Overall accuracy [%] = 99.65%, Kappa hat classification = 0.98						

Table 4. Error Matrix of Minimum Distance

Following is the graphical presentation of Overall accuracies, Omission errors and Commission errors, k-hat statistics using Maximum Likelihood Classifier, Random Forest Classification and Minimum Distance Classification.

It can be observed from Fig.6 that Minimum Distance Classification gives more overall accuracy than Maximum Likelihood Classifier and Random Forest, but it has more commission and omission error, so as per the evaluation Maximum Likelihood Algorithm gives better results than minimum distance classification and Random Forest Classification.

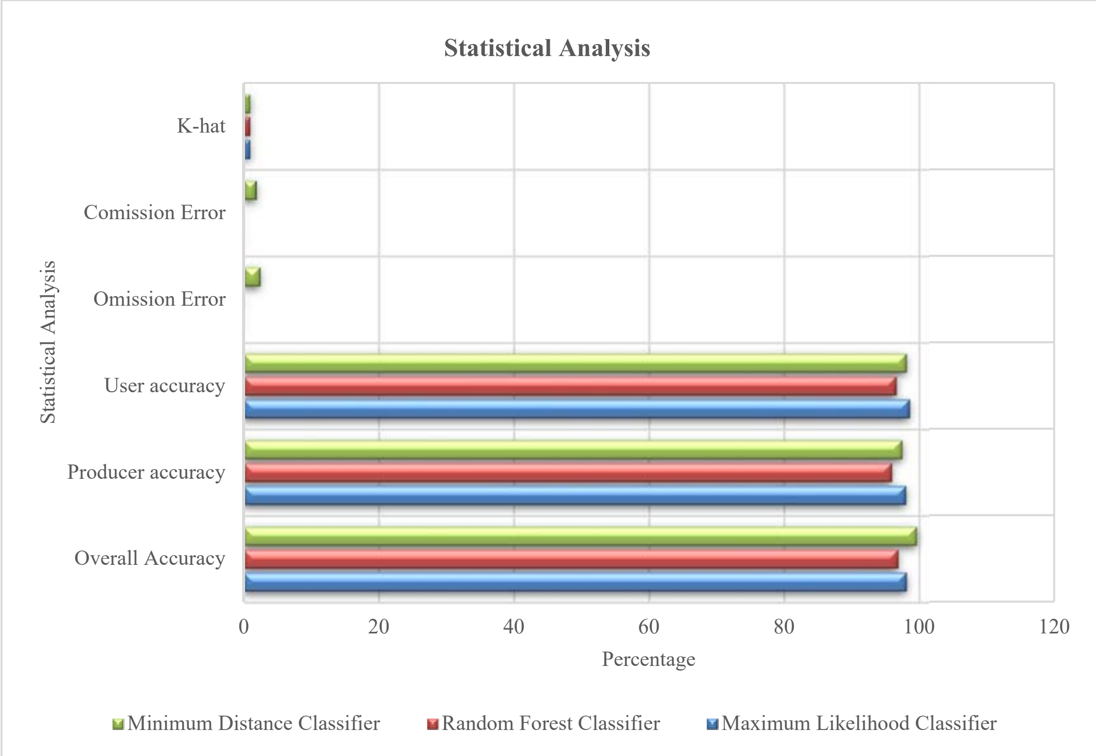


Fig. 6 Statistical Analysis for Ground Truth validation

Conclusion

Proposed the system for ground truth validation after denoising the cloud and shadow images is acquired through the SENTINEL-2 satellite, three images which are having dense, low, and no cloud of the same scene of the study area "L1C_T43QCA_A019436" are used to perform the experimentations. The study area used in experimentation is an area of Lonavala, Malavali, Lavasa, Mulshi Lake, Pawana Lake, etc. Atmospheric interference is reduced by applying Dark Object Subtraction

Ground truth is validated with supervised classification techniques (Maximum Likelihood Algorithm, Random Forest, Minimum Distance Classification) are used in the present article B-2 to B-8A and B-11, B-12are used for recognizing denoising pixels of under cloud and shadow to build a mask. Reference Images which are having low and no cloud contamination are used to replace these pixels. Accuracy Assessment has been calculated and compared with the existing System. Overall Accuracy was achieved with the Maximum Likelihood Classifier, Random Forest Classification and Minimum Distance Classification are 98.20%, 96.65%, and 99.65% and K-hat is 0.97, 0.95, 0.98 respectively. From statistical analysis and findings, it is concluded that the proposed system can successfully denoise images obtained through the SENTINEL-2 satellite in preprocessing step and validated the ground truth obtained.

Conflicts of interest

"The authors have no conflicts of interest to declare"

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