REVOLUTIONIZING AIRCRAFT DETECTION IN HIGH-RESOLUTION SATELLITE IMAGERY THROUGH DEEP LEARNING TECHNIQUES

Dr. A. Swetha[1*], K. Mani teja[2], N. Varun[2], G. Rani[2], A. Rajesh[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of CSE(AI&ML)

[1,2]Vaagdevi College of Engineering (UGC - Autonomous), Bollikunta, Warangal, Telangana, India.

*Corresponding Email: Dr. A. Swetha (swetha_a@vaagdevi.edu.in)

ABSTRACT

India faces frequent natural disasters such as floods, droughts, cyclones, and landslides, which significantly impact lives, infrastructure, and the environment. Between 1990 and 2020, India reported over 400 natural disasters, affecting more than 1 billion people and causing damages worth billions. With 68% of its land prone to drought, 12% to floods, and 8% to cyclones, the need for effective disaster mitigation strategies is paramount. Land cover change, driven by deforestation, urbanization, and agricultural expansion, exacerbates disaster risks, leading to soil erosion, reduced water retention, and biodiversity loss. To develop an AI-driven system for accurate and real-time classification of land cover changes, aiding in proactive natural disaster risk mitigation and improved resource management. Before AI, land cover change detection relied on manual surveys, satellite imagery interpretation, and GIS-based mapping. These methods were labor-intensive, time-consuming, and prone to human error, offering limited scalability and real-time insights. Traditional methods of land cover classification are inefficient and incapable of providing timely, accurate insights into environmental changes. This limitation hampers proactive disaster mitigation, increasing vulnerability to natural disasters. The increasing frequency and intensity of natural disasters, driven by land cover changes, highlight the need for advanced tools. AI's ability to process large datasets, detect patterns, and provide real-time insights motivates the development of GeoAware for better disaster preparedness. GeoAware leverages machine learning models such as Convolutional Neural Networks (CNN AND RANDOM FOREST CLASSIFIERs) and Random Forest Classifierand decision trees to classify land cover changes from satellite images and sensor data. These models process vast datasets to provide real-time, high-accuracy insights. By identifying deforestation, urban sprawl, and other changes, the system enables proactive disaster risk assessment, aiding policymakers and disaster management teams in making informed decisions.

Keywords: Land Cover Change, Disaster Mitigation, Resource Management, Real-time Classification, Natural Disasters.

1. INTRODUCTION

India is highly prone to natural disasters like floods, droughts, cyclones, and landslides due to its diverse geography and rapid land cover changes. Between 1990 and 2020, India experienced over 400 disasters, affecting more than 1 billion people and causing significant economic losses. Deforestation, urban expansion, and agricultural activities have intensified the frequency and impact of these disasters by reducing soil stability, water retention, and biodiversity. An AI-driven approach like GeoAware can classify land cover changes accurately and in real time, enabling policymakers to identify vulnerable areas and implement proactive mitigation measures. GeoAware aims to harness AI for classifying land cover changes to mitigate disaster risks. It identifies environmental transformations, offering high accuracy and scalability. Applications include floodplain mapping, deforestation tracking, and urban sprawl analysis. By enabling proactive decision-making, GeoAware strengthens disaster preparedness and resource management.

2. LITERATURE SURVEY

Many works have been done to examine the use of LULC analysis on remotely sensed records. From 1986 to 2001 in Pallisa District, Uganda, Otukei and Blaschke [3] carried out land cover mapping and land cover assessing using DTs, SVMs and MLCs. They explored the use of knowledge mining to find the required classification bands and thresholds for decision. The analysis assessed the efficiency of the classification models, claiming that land cover elements occur at an unpredictable pace. According to desired classes, a few image classification models are available for segmenting a multi-dimensional component space into homogenous regions and labelling segments. Parametric classifiers accept a normally distributed dataset and statistical parameters acquired properly from training data. The most broadly utilized parametric classifier is the maximum-likelihood classifier (MLC), which makes decision surfaces dependent on the mean and covariance of each class. MLC [11] was first applied to IRS LISS-III images between 2001 and 2011 and classified into eight classes. Additionally, the study used a unique methodological framework for post-classification adjustments. It considerably increased total classification accuracy from 67.84% to 82.75% in 2001 and from 71.93% to 87.43% in 2011.

Islam et al. [1] used Landsat TM and Landsat 8 OLI/TIRS images to examine land use changes in Chunati Wildlife Sanctuary (CWS) from 2005 to 2015. ArcGIS and ERDAS imagine were used for land use change assessment. To derive supervised land use categorization, the maximum likelihood classification technique was applied. It was discovered that around 256 ha of the degraded forest area has increased over ten years (2005–2015), with an annual rate of change of 25.56%. Non-parametric classifiers do not accept a particular information appropriation to isolate a multi-dimensional feature space into classes. Most normally utilized non-parametric classifiers incorporate decision trees [4], support vector machines (SVM) [5] and expert systems. ML algorithms have been utilized according to pixel classifiers in remote sensing image analysis [6].

Grippa et al. [2] describes a method for mapping urban land use at the street block level, emphasizing residential usage by utilizing very-high-resolution satellite images and derived land-cover maps as input. For the classification of street blocks, a random forest (RF) classifier is utilized, which achieves accuracies of 84% and 79% for five and six land-use classifications, respectively. RF classifier applied over urban communities Dakar and Ouagadougou, cover more than 1,000 km2 altogether, with a spatial resolution of 0.5 m.

Jamali [7] compared and contrasted eight machine learning methods for image categorization in the northern region of Iran developed in the Waikato environment for knowledge analysis (WEKA) and R programming languages.

3. PROPOSED SYSTEM

Here is the overview description of the landcover changes with landsat satelite:

Uploading Dataset: Users upload their dataset by clicking the "Upload Dataset" button.

Upon clicking the button, a file dialog window appear, allowing users to navigate to and select the dataset folder containing subfolders for different classes of satellite images. Once the dataset is uploaded, a confirmation message displayed on the GUI.

Image Preprocessing: After the dataset is uploaded, the "Image preprocessing" button clicked to initiate image processing. The application utilize the VGG16 model to extract features from the satellite images in the dataset. Extracted features be saved along with their corresponding labels. The dataset be split into training and testing sets for model training and evaluation.

Training and Testing Proposed CNN AND RANDOM FOREST CLASSIFIER Model: Clicking the "Build & Train CNN AND RANDOM FOREST CLASSIFIER Model" button trigger the training of a Convolution Neural network model. The CNN AND RANDOM FOREST CLASSIFIER model be trained using the preprocessed dataset. After training, the model's performance be evaluated using similar metrics as for the logistic regression model. Evaluation results, including accuracy, precision, recall, F1-score, confusion matrix, and classification report, be displayed on the GUI.

Models Evaluation Graphs: Upon clicking the "Performance Evaluation" button, the application generate comparison graphs for evaluating the performance of both models.

Graphs display metrics such as accuracy, precision, recall, and F1-score for each model. Users visually compare the performance of the logistic regression and RFC models through these graphs.

Test Image Prediction Using Proposed CNN AND RANDOM FOREST CLASSIFIER Model: Users upload a test image by clicking the "Upload test image" button. After selecting an image, the application use the trained CNN AND RANDOM FOREST CLASSIFIER model to make predictions on the uploaded image. Predicted class labels be displayed on the image or in a separate window, indicating the land cover changes identified by the model.

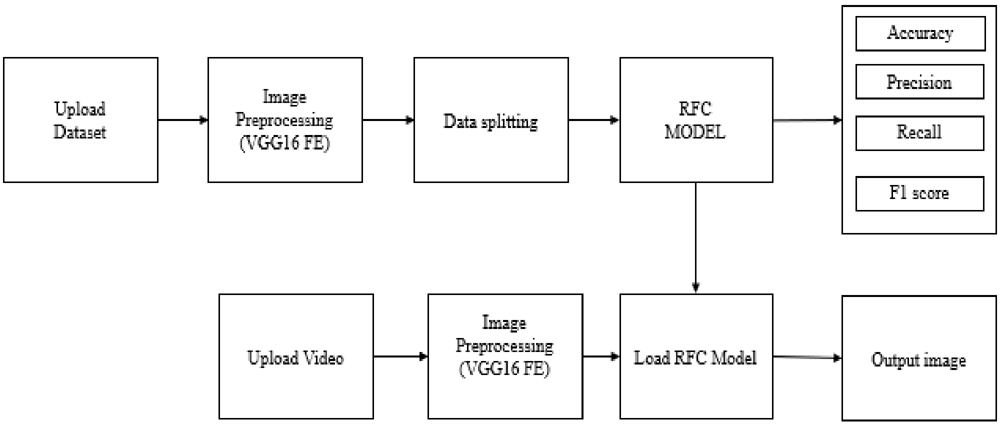

Figure.1: Block diagram of Proposed System.

3.1 Data preprocessing

Image preprocessing is a critical step in computer vision and image analysis tasks. It involves a series of operations to prepare raw images for further processing by algorithms or neural networks. Here's an explanation of each step in image preprocessing:

Step 1. Image Read: The first step in image preprocessing is reading the raw image from a source, typically a file on disk. Images can be in various formats, such as JPEG, PNG, BMP, or others. Image reading is performed using libraries or functions specific to the chosen programming environment or framework. The result of this step is a digital representation of the image that can be manipulated programmatically.

Step 2. Image Resize: Image resize is a common preprocessing step, especially when working with machine learning models or deep neural networks. It involves changing the dimensions (width and height) of the image. Resizing can be necessary for several reasons:

- Ensuring uniform input size: Many machine learning models, especially convolutional neural networks (CNN AND RANDOM FOREST CLASSIFIERs), require input images to have the same dimensions. Resizing allows you to standardize input sizes.
- Reducing computational complexity: Smaller images require fewer computations, which can be beneficial for faster training and inference.
- Managing memory constraints: In some cases, images need to be resized to fit within available memory constraints.

When resizing, it's essential to maintain the aspect ratio to prevent image distortion. Typically, libraries like OpenCV or Pillow provide convenient functions for resizing images.

Step 3. Image to Array: In this step, the image is converted into a numerical representation in the form of a multidimensional array or tensor. Each pixel in the image corresponds to a value in the array. The array is usually structured with dimensions representing height, width, and color channels (if applicable).

For grayscale images, the array is 2D, with each element representing the intensity of a pixel. For color images, it's a 3D or 4D array, with dimensions for height, width, color channels (e.g., Red, Green, Blue), and potentially batch size (if processing multiple images simultaneously).

The conversion from an image to an array allows for numerical manipulation and analysis, making it compatible with various data processing libraries and deep learning frameworks like NumPy or TensorFlow.

Step 4. Image to Float32: Most machine learning and computer vision algorithms expect input data to be in a specific data type, often 32-bit floating-point numbers (float32). Converting the image array to float32 ensures that the pixel values can represent a wide range of intensities between 0.0 (black) and 1.0 (white) or sometimes between -1.0 and 1.0, depending on the specific normalization used.

This step is essential for maintaining consistency in data types and enabling compatibility with various machine learning frameworks and libraries. It's typically performed by dividing the pixel values by the maximum intensity value (e.g., 255 for an 8-bit image) to scale them to the [0.0, 1.0] range.

Step 5. Image to Binary: Image binarization is a process of converting a grayscale image into a binary image, where each pixel is represented by either 0 (black) or 1 (white) based on a specified threshold. Binarization is commonly used for tasks like image segmentation, where you want to separate objects from the background.

The process involves setting a threshold value, and then for each pixel in the grayscale image, if the pixel value is greater than or equal to the threshold, it is set to 1; otherwise, it is set to 0.

Binarization simplifies the image and reduces it to essential information, which can be particularly useful in applications like character recognition or object tracking, where you need to isolate regions of interest.

3.2 ML Model Building

3.2.1 Existing Algorithm: Multinomial Naïve Bayes

Multinomial Naïve Bayes is a probabilistic classifier based on Bayes' theorem and particularly suited for discrete data, such as word counts in text classification. It assumes that the features (e.g., words) are conditionally independent given the class label. The model uses the frequency of features to calculate probabilities for classification. It works well with text data, such as spam detection, sentiment analysis, and topic classification.

How it works:

- Calculate prior probabilities for each class based on the training data.
- Compute likelihood probabilities for each feature given a class.
- Use Bayes' theorem to compute posterior probabilities for each class.
- Classify the input based on the class with the highest posterior probability.

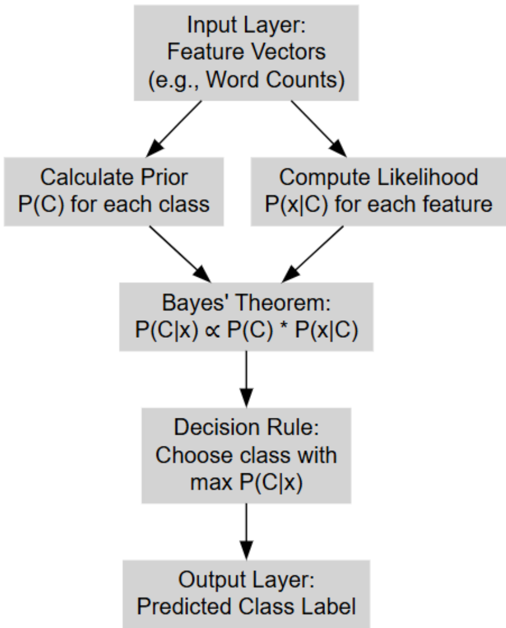

Fig. 2: internal work flow of Multinomial Naive Bayes

3.2.2 Proposed Algorithm: VGG16 Feature Extraction + Random Forest Classifier

VGG16 is a convolutional neural network (CNN AND RANDOM FOREST CLASSIFIER) known for its simplicity and efficiency in extracting high-quality features from images. In this approach, the feature maps generated by VGG16 are used as input for a Random Forest classifier, a versatile and robust ensemble learning method.

How it works:

- Load the pre-trained VGG16 model without the top classification layers.
- Pass the input images through the VGG16 model to extract feature maps.
- Flatten or pool the feature maps to create a fixed-size feature vector.

— Use the feature vectors as input for the Random Forest classifier.

— Train the Random Forest on labeled data and predict the class for new images.

Advantages:

— Combines the strength of CNN AND RANDOM FOREST CLASSIFIERs for feature extraction and ensemble methods for classification.

— Handles complex, high-dimensional image data effectively.

— Random Forest is robust to overfitting and noise.

— Pre-trained VGG16 reduces the need for large datasets for training.

— Suitable for various applications, such as image classification and object detection.

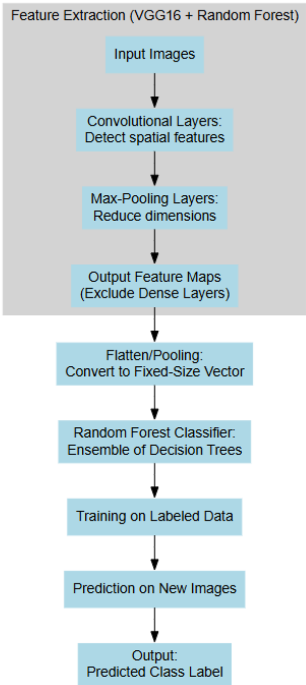

Fig. 3: Internal work flow of VGG16 Feature Extraction with Random Forest Classifier

4. RESULTS AND DISCUSSION

4.1 Dataset description

Cyclone, Earthquake, Flood, and Wildfire. Each class represents a distinct category of disaster, with visually identifiable features captured in various forms of imagery such as satellite, aerial, or ground-level photographs. Cyclone images typically exhibit swirling cloud formations, storm centers, and ocean disturbances, often captured by satellites or drones. Earthquake images depict the aftermath of seismic activity, including damaged buildings, cracked roads, and disrupted infrastructure. Flood images include submerged urban and rural areas, waterlogged streets, and aerial views of large-scale inundation. Wildfire images feature active flames, dense smoke, scorched land, and firefighting operations. This diverse and visually rich dataset provides a solid foundation for training deep learning models, enabling them to automatically recognize and classify different types of natural disasters. It serves as a valuable resource for developing intelligent systems in disaster response and management applications.

4.2 Results description

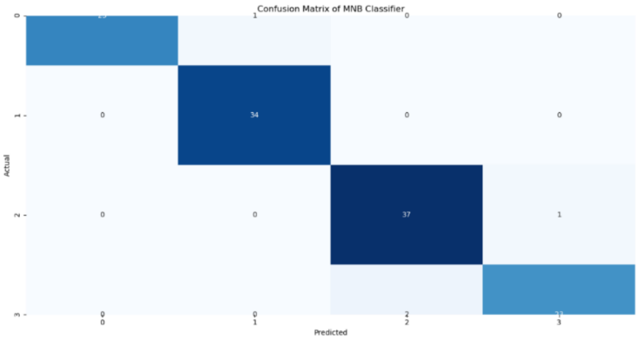

Figure 4 Confusion matrix of MNB model.

Figure 4 illustrates the confusion matrix of the Multinomial Naïve Bayes (MNB) model used for classifying natural disaster categories. The matrix provides a detailed breakdown of the model's performance by showing the number of correct and incorrect predictions for each class. The diagonal elements represent the instances that were correctly classified, indicating strong model performance across categories.

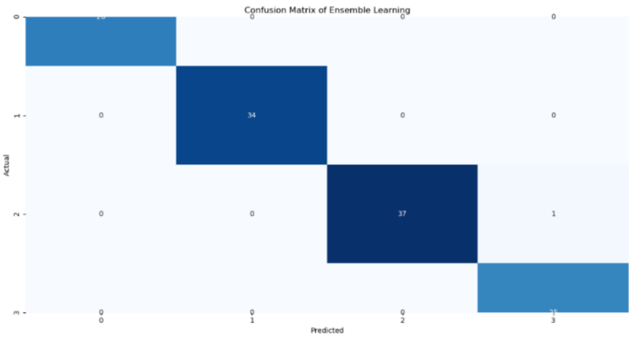

Figure 5 Confusion matrix of Ensemble model.

Figure 5 This figure presents a performance comparison count plot, depicting various evaluation metrics such as accuracy, precision, recall, and F1-score for each model. The plot allows users to visually compare the performance of different models and select the most effective one for their analysis. Figure 6: Here, the proposed Ensemble model's predictions on test images are illustrated. Users can observe the model's classifications of land cover changes based on Landsat satellite data, providing valuable insights into environmental changes over time.

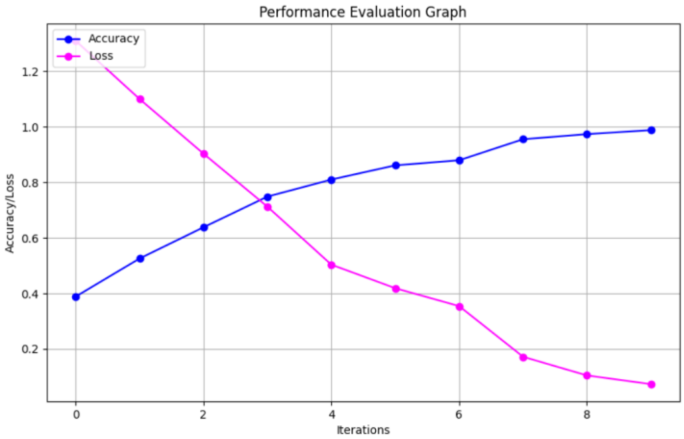

Figure 6: Performance comparison plot of each model.

Figure 6 presents the performance comparison plot of the evaluated models, highlighting key metrics such as accuracy, precision, recall, and F1-score for each. The plot visually contrasts the performance of the Multinomial Naïve Bayes (MNB) model and the proposed Ensemble model.

Figure 7: Proposed Ensemble model prediction on test images.

Figure 7 showcases the prediction results of the proposed Ensemble model on a set of test images representing different natural disasters. The figure illustrates how the model classifies each input image into categories such as cyclone, earthquake, flood, and wildfire, based on extracted visual features.

Table 1: Performance comparison of quality metrics by ALL models.

Model	MNB model	Ensemble model
Accuracy (%)	96.7	99.1
Precision (%)	96.7	99.2

Recall (%)	96.7	99.1
F1-score (%)	96.7	99.1

Table 1 showcases the performance of two models – the Multinomial Naïve Bayes (MNB) and an Ensemble Model (likely referring to a model like Random Forest or a voting ensemble). The comparison is based on four standard classification metrics: Accuracy, Precision, Recall, and F1-score.

5. Conclusion

In conclusion, the utilization of Landsat satellite data has been instrumental in monitoring and analyzing changes in land cover over the decades, contributing significantly to environmental monitoring, land use planning, and conservation efforts. The conventional methods of manual interpretation and basic change detection algorithms, while effective to some degree, have inherent limitations such as being time-consuming, subjective, and potentially overlooking subtle or intricate changes.

Recognizing the pivotal role of accurate land cover change analysis in critical domains like urban planning, forestry, and environmental conservation, there is a pressing need to advance existing methodologies. The primary challenge lies in the development of a sophisticated system capable of autonomously processing and interpreting large volumes of Landsat satellite imagery, identifying nuanced changes in land use and cover, and classifying them into meaningful categories.

The proposed, "Analyzing Land Cover Changes with Landsat Satellite Data: An Application to Ensemble Learning," represents a pioneering effort to revolutionize land cover change analysis. By leveraging advanced ensemble learning techniques, which harness the collective intelligence of multiple models, the research aims to enhance the accuracy and reliability of identifying and classifying land cover changes. Ensemble learning, known for its proficiency in handling complex data and improving prediction accuracy, emerges as a promising solution to address the challenges inherent in traditional methods.

REFERENCE

[1] K. Islam, M. Jashimuddin, B. Nath, and T. K. Nath, “Land use classification and change detection by using multi-temporal remotely sensed imagery: The case of Chunati wildlife sanctuary, Bangladesh,” The Egyptian Journal of Remote Sensing and Space Science, vol. 21, no. 1, pp. 37–47, Apr. 2018, doi: 10.1016/j.ejrs.2016.12.005.

[2] C. Kok Yang, F. Pei Shan, and T. Lea Tien, “Climate change detection in Penang Island using deterministic interpolation methods,” Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), vol. 19, no. 1, pp. 412–419, Jul. 2020, doi: 10.11591/ijeecs.v19.i1.pp412-419.

[3] J. R. Otukei and T. Blaschke, “Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms,” International Journal of Applied Earth Observation and Geoinformation, vol. 12, pp. S27– S31, Feb. 2010, doi: 10.1016/j.jag.2009.11.002.

[4] L. Hua, X. Zhang, X. Chen, K. Yin, and L. Tang, “A feature-based approach of decision tree classification to map time series urban land use and land cover with Landsat 5 TM and Landsat 8 OLI in a Coastal City, China,” ISPRS International Journal of Geo-Information, vol. 6, no. 11, pp. 1–18, Oct. 2017, doi: 10.3390/ijgi6110331.

[5] I. A. Md Zin, Z. Ibrahim, D. Isa, S. Aliman, N. Sabri, and N. N. A. Mangshor, "Herbal plant recognition using deep convolutional neural network," Bulletin of Electrical Engineering and Informatics (BEEI), vol. 9, no. 5, pp. 2198–2205, Oct. 2020, doi: 10.11591/eei.v9i5.2250.

[6] Q. Weng, "Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends," Remote Sensing of Environment, vol. 117, pp. 34–49, Feb. 2012, doi: 10.1016/j.rse.2011.02.030.

[7] A. Jamali, "Evaluation and comparison of eight machine learning models in land use/land cover mapping using Landsat 8 OLI: a case study of the northern region of Iran," SN Applied Sciences, vol. 1, no. 11, Nov. 2019, Art. no. 1448, doi: 10.1007/s42452- 019-1527-8.

[8] D. K. Behera, M. Das, S. Swetanisha, and P. K. Sethy, "Hybrid model for movie recommendation system using content K-nearest neighbors and restricted Boltzmann machine," Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), vol. 23, no. 1, pp. 445–452, Jul. 2021, doi: 10.11591/ijeecs.v23.i1.pp445-452.

[9] A. A. W. Mohammed and H. T. Khamees, "Categorizing and measurement satellite image processing of fire in the forest greece using remote sensing," Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), vol. 21, no. 2, pp. 846–853, Feb. 2021, doi: 10.11591/ijeecs.v21.i2.pp846-853.

[10] Z. Deng, X. Zhu, Q. He, and L. Tang, "Land use/land cover classification using time series Landsat 8 images in a heavily urbanized area," Advances in Space Research, vol. 63, no. 7, pp. 2144–2154, Apr. 2019, doi: 10.1016/j.asr.2018.12.005.

[11] A. K. Thakkar, V. R. Desai, A. Patel, and M. B. Potdar, "Post-classification corrections in improving the classification of land use/land cover of arid region using RS and GIS: The case of Arjuni watershed, Gujarat, India," The Egyptian Journal of Remote Sensing and Space Science, vol. 20, no. 1, pp. 79–89, Jun. 2017, doi: 10.1016/j.ejrs.2016.11.