

A PROJECT REPORT ON

LULC CLASSIFICATION OF JHELUM CATCHMENTS

Prepared By:

SOUPARNA SANNYASI

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B.Tech,Civil Engineering

Indian Institute Of Engineering Science And Technology,Shibpur
Howrah,West Bengal



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UNDER THE MENTORSHIP OF:

DR. CHEMBOLU VINAY



विद्याधनं सर्वधनं प्रधानम्

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Abstract

This study presents a spatiotemporal analysis of Land Use and Land Cover (LULC) changes across the Jhelum River Basin, a hydrologically and ecologically critical region in JammuKashmir, India. Using Google Earth Engine (GEE) and multi-temporal Landsat imagery (1991–2020), we applied a supervised classification approach with the Random Forest algorithm to map six key land cover categories: water, forest, snow/glacier, barren land, built-up areas, and agriculture.

High-resolution training data were digitized using both true and false color composites to enhance classification accuracy. Sub-basins such as Lidder, Erin, and Madhumati were individually analyzed to capture spatial heterogeneity. Results indicate significant land use transformation: rapid urban expansion in valley regions, reduction in snow-covered and forested areas, and a notable increase in agricultural and built-up zones. Meanwhile, water bodies showed shrinkage, raising concerns over sedimentation and wetland degradation.

These changes suggest growing anthropogenic pressure and climate sensitivity in the basin, threatening water availability, biodiversity, and flood regulation capacity. The study underscores the importance of integrated watershed planning and the utility of GEE for large-scale environmental monitoring and policy support in fragile mountainous regions.

Contents

1	Introduction	3
2	Study Area:	3
2.1	Location and Elevation:	3
2.2	Physical Geography:	3
2.3	Hydrology and Water Sources:	4
2.4	Ecological Importance and Ecosystems:	4
2.5	Socioeconomic and Livelihood Aspects:	5
3	Data Used for Jhelum Basin Analysis:	5
3.1	Satellite Imagery	5
3.2	Digital Elevation Models (DEM)	5
3.3	Administrative and Basin Boundary Shapefiles	5
3.4	Ground Truth and Validation Data	5
3.5	Land Cover Classification	6
3.6	Climate and Hydrological Data	6
3.7	Software and Tools Used	6
4	Methodology for Jhelum Basin Analysis:	6
5	Image Collection and Preprocessing:	7
5.1	Training Data Collection:	7
5.2	Example of a True composites:-	8
5.3	Example of a False composites:-	8
5.4	Supervised Classification using Random Forest:	8
6	Visualization and Export:	8
7	Accuracy Assessment:	9
8	Area Calculation:	9
9	Result:	9
9.1	Summary of Land Cover Changes (1991–2020)	11
10	GEE Code: LULC Classification for Jhelum Basin (1994)	13
11	GEE Script for Land Cover Classification (1996 - Jhelum Basin)	15
12	Output for this type code for Land Cover Classification (1991 -2020) in Jhelum Basin	17
13	Sub-Catchments of the Jhelum River Basin	19
13.1	Major Sub-Catchments of the Jhelum River Basin	19
13.2	Characteristics of Jhelum Sub-Catchments	19
13.3	Why Sub-Catchment Classification Is Important	22
13.4	Application in This Study	22
14	Conclusion	22

1 Introduction

The Jhelum River Basin, located in the northwestern Himalayas, is a lifeline for the Kashmir Valley, supporting a diverse range of ecological systems, agriculture, and human settlements. However, over the past several decades, the basin has experienced rapid land use and land cover (LULC) changes due to population growth, urbanization, deforestation, and climatic variations. These transformations have critical implications for water availability, ecosystem services, and regional sustainability.

This project aims to analyze and monitor the spatiotemporal dynamics of LULC within the Jhelum Basin from 1991 to 2020 using satellite-based remote sensing and cloud-computing platforms. Leveraging the capabilities of Google Earth Engine (GEE) and Landsat imagery, we apply supervised classification techniques to detect trends in major land cover classes such as forest, water bodies, snow/glacier, agriculture, barren land, and built-up areas.

By examining the patterns and drivers of land cover changes in key sub-catchments, the study seeks to provide a foundation for sustainable land and water management strategies in this environmentally sensitive region.

2 Study Area:

2.1 Location and Elevation:

The Jhelum River Basin is located in the northern part of the Indian subcontinent, primarily covering Jammu and Kashmir, India, and extending into Pakistan-administered territories. It originates from Verinag Spring in Anantnag district at an approximate elevation of 1,900 meters above sea level, situated at coordinates around 33.55°N, 75.25°E. The river traverses through the Kashmir Valley, flowing northwest through Srinagar and Wular Lake before entering Pakistan.

- [1]Assessment of Impacts of Climate Change on the Water Resources of the Transboundary Jhelum River Basin of Pakistan and Indiaby Rashid Mahmood and Shaofeng Jia

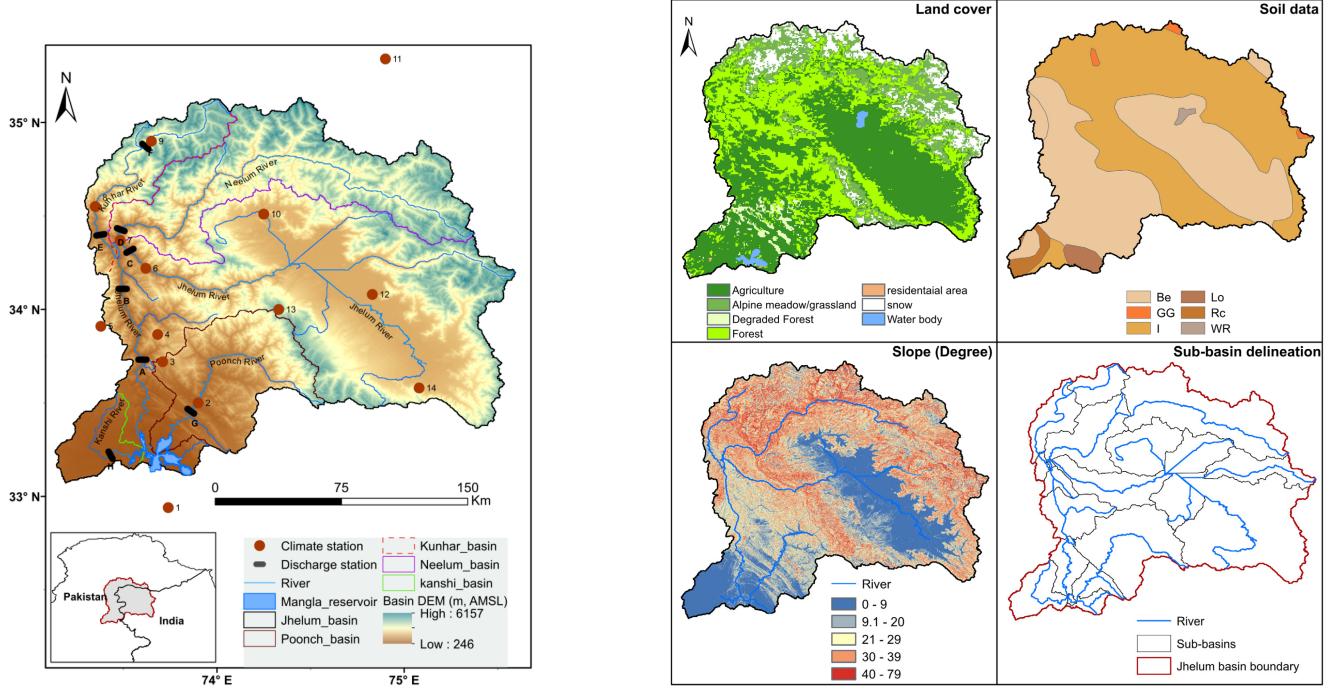


2.2 Physical Geography:

The basin is nestled within the Himalayan mountain system, characterized by rugged topography, glaciated uplands, riverine valleys, and alpine meadows. The terrain includes coniferous forests, pastures, floodplains, and cultivated land. The catchment area in India is approximately 15,000 square kilometers, varying widely in elevation, climate, and land use.

The climate ranges from alpine in the upper reaches to temperate in the valley. Snowfall is common in winter, particularly in the higher altitudes, contributing to snow-fed rivers and

glacial systems. The soil composition includes alluvial, forest, and loamy soils, suitable for agriculture. The basin has an undulating slope ranging from 0° to 79° , as shown in Figure 2. The plains along the course of the rivers, especially the lower parts (near the Mangla Reservoir) and the northeastern parts (near Srinagar valley) of the basin, are located on a gentle slope (0° – 10°). However, most areas of the basin are located on a moderate (more than 10° and less than 30°) to steep slope (more than 30°).



2.3 Hydrology and Water Sources:

The Jhelum River is the main drainage channel of the Kashmir Valley, receiving input from several tributaries and glacial streams, including:

- 1.Lidder River
- 2.Sindh River
- 3.Vishav River

Erin, Madhumati, and Ningli streams (as part of Wular's feeding sources) It eventually merges with the Chenab River, forming part of the Indus Basin system. The river plays a vital role in irrigation, hydropower generation, and flood control.

2.4 Ecological Importance and Ecosystems:

The Jhelum Basin supports diverse ecosystems, ranging from glacier-fed wetlands and marshes to dense temperate forests and riverine vegetation. It is home to:

- 1.Endemic fish species (e.g., Schizothorax)
- 2;Migratory birds via the Central Asian Flyway
- 3.Rich aquatic vegetation and wetland flora

These ecosystems contribute significantly to carbon sequestration, groundwater recharge, and biodiversity conservation. Notably, several zones like Hokarsar, Haigam, and Wular are protected under Ramsar Convention.

- [2]Ecological Status of Some Floodplain Lakes Within Jhelum River basin, Kashmir by Adnan Abubakr and M. R. D. Kundangar

2.5 Socioeconomic and Livelihood Aspects:

The basin is densely populated in valley regions like Srinagar, Baramulla, Anantnag, and Bandipora, where agriculture forms the backbone of rural livelihoods. The communities depend on:

- 1.Rice and maize cultivation
- 2.Fishing and water chestnut harvesting
- 3.Livestock grazing in alpine pastures
- Timber and firewood collection from forests

Approximately over 10,000 households in the Wular region alone rely directly on the lake and river systems . The urban expansion, deforestation, and encroachment on wetlands and forests have intensified environmental stress, calling for sustainable land and water management.

- [3]Livelihood vulnerability index: a pragmatic assessment of climatic changes in flood affected community of Jhok Reserve Forest, Punjab, Pakistan by Laila Shahzad, Manal Shah, Muqadas Saleem, Asma Mansoor, Faiza Sharif, Arifa Tahir, Umar Hayyat, Muhammad Farhan and Gulzareen Ghafoor

3 Data Used for Jhelum Basin Analysis:

3.1 Satellite Imagery

- **Landsat Series:**
 - Landsat 5 (TM)
 - Landsat 7 (ETM+)
 - Landsat 8 (OLI/TIRS)
- **Temporal Coverage:** 1990 to 2020
- **Resolution:** 30 meters
- **Acquisition Platform:** Google Earth Engine (GEE)

3.2 Digital Elevation Models (DEM)

- **Source:** SRTM (Shuttle Radar Topography Mission) or ASTER
- **Purpose:** Elevation mapping, slope analysis, watershed delineation

3.3 Administrative and Basin Boundary Shapefiles

- **Jhelum Basin Boundary:** Used for delineation of study area
- **Administrative Boundaries:** District and sub-district boundaries from Survey of India or NRSC

3.4 Ground Truth and Validation Data

- **Source:** Field surveys (if available) or manually digitized polygons using Google Earth Pro

3.5 Land Cover Classification

LULC Classes:

- Water
- Snow/Glacier
- Barren Land
- Forest
- Built-up
- Agriculture

3.6 Climate and Hydrological Data

- **Sources:** Indian Meteorological Department (IMD), CHIRPS, or WorldClim
- **Parameters:** Precipitation, temperature, and streamflow data

3.7 Software and Tools Used

- **Google Earth Engine (GEE)** – for cloud-based classification and analysis
- **QGIS / ArcGIS** – for map visualization and spatial analysis
- **MS Excel / R** – for data processing and tabulation

4 Methodology for Jhelum Basin Analysis:

Step 1: Image Collection and Preprocessing

Landsat 5, 7, and 8 imagery were retrieved via Google Earth Engine (GEE). Only cloud-free images from March–April were selected. The Jhelum Basin shapefile was used to clip satellite images. Both true and false color composites were generated for better land cover differentiation.

Step 2: Training Data Collection

Training samples for different land cover classes—such as water, forest, agriculture, built-up, snow, and barren land—were manually digitized using high-resolution satellite imagery in Google Earth Engine. These samples were selected based on visual interpretation of true and false color composites. The collected points served as reference data to train the supervised classification algorithm. Care was taken to ensure spatial diversity and accurate class representation across the Jhelum Basin.

Step 3: Supervised Classification

The Random Forest classifier was implemented in GEE to categorize land cover types. Multispectral features and vegetation indices were used as input parameters for robust classification across the basin.

Step 4: Accuracy Assessment

A confusion matrix was created using testing samples to evaluate classification accuracy. Metrics included overall accuracy, user's accuracy, and producer's accuracy to ensure model reliability.

Step 5: LULC Change Detection

Land cover changes were analyzed across key years (e.g., 1991, 2000, 2010, 2020). Pixel-based comparison identified transformations such as urban growth, deforestation, and agricultural expansion within the basin.

Step 6: Area and Statistical Analysis

GEE's `pixelArea()` function was used to quantify the extent of each LULC class. Results were exported and further analyzed in Excel for visualization and interpretation through charts and tables.

Step 7: Sub-Basin Level Analysis (Optional)

If sub-basins were defined, individual analyses were conducted to assess localized LULC trends, allowing deeper insight into ecological variability and hydrological behavior within distinct areas.

5 Image Collection and Preprocessing:

For the Jhelum River Basin analysis, satellite imagery was obtained from the Google Earth Engine (GEE) platform. Landsat 5, 7, and 8 images were used for multiple years between 1991 and 2020. Spring-season (March to April) images were selected to ensure minimal cloud cover and consistent seasonal representation. The images were filtered based on cloud-free conditions and clipped to the Jhelum Basin boundary using shapefiles. To support better land cover differentiation, both true color and false color composites were created. Basic preprocessing steps such as image selection, clipping, and visualization setup were carried out to prepare the data for classification.

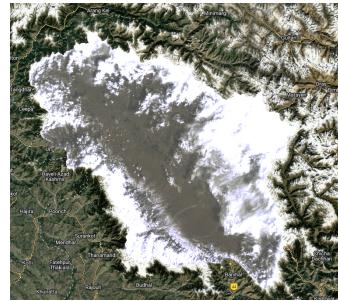
5.1 Training Data Collection:

Training points for six LULC classes were manually digitized using high-resolution basemaps and field knowledge. These classes include:

- 1.Water,
- 2.Forest,
- 3.Built-up.
- 4.Agriculture,
- 5.Snow/Glacier,
- 6.Barren Land,

These samples formed the basis of supervised classification. These labelled points were created using visual interpretation of satellite images. We grouped similar color images into a specific class. This way, classification is done based on different pixel colors. This was done with the help of true and false color composite

5.2 Example of a True composites:-



5.3 Example of a False composites:-



5.4 Supervised Classification using Random Forest:

For the Jhelum River Basin, land cover classification was performed using the supervised Random Forest (RF) algorithm within the Google Earth Engine (GEE) platform. The classifier was trained on manually collected training samples representing six major land cover types: water, forest, agriculture, built-up, barren, and snow. The RF model, known for its robustness and high accuracy, utilized spectral information from selected Landsat bands to assign each pixel to a land cover class. After training, the model was applied to the entire Jhelum Basin, generating classified maps for each selected year. This method provided consistent and reliable LULC outputs across different time periods.

[4]Supervised Classification using Random Forest

6 Visualization and Export:

The classified land cover map of the Jhelum River Basin was visualized using a distinct color palette to differentiate between the six major land use land cover (LULC) classes—water, forest, agriculture, built-up, barren land, and snow. The Random Forest classification output was rendered in Google Earth Engine (GEE) using the `.classify()` and `.visualize()` functions. The final classified image was exported to Google Drive in GeoTIFF format using the `Export.image.toDrive()` function, specifying the spatial resolution (30 meters), region of interest (Jhelum Basin boundary), and file format. This exported image was later used for further analysis and map preparation.

[5]Quantitative Analysis of Land Use Land Cover (LULC) Changes on the Hydrological Behavior of the Jhelum River Basin: North-West Himalayas, Kashmir

7 Accuracy Assessment:

To evaluate the performance of the classification, an accuracy assessment was conducted using a confusion matrix generated from a separate testing dataset. A portion of the training samples was reserved for validation to assess how well the classifier performed across different land cover types. Metrics such as overall accuracy, producer's accuracy, and user's accuracy were derived. The accuracy values helped determine the reliability of the classification results and guided refinement of training samples where needed. This step ensured the classified output for the Jhelum Basin maintained high spatial and thematic accuracy.

8 Area Calculation:

The spatial extent of each land cover class within the Jhelum River Basin was calculated using the `pixelArea()` function in GEE. The classified image was multiplied by pixel area to compute the total area (in square meters or square kilometers) occupied by each LULC category. This allowed for a quantitative understanding of land use distribution and changes across the basin. The area statistics were then exported in tabular format (CSV) to Google Drive and further analyzed in Excel to produce summary tables and graphs for reporting purposes.

9 Result:

- The land use and land cover (LULC) classification for the Jhelum River Basin was carried out using the Random Forest algorithm applied to cloud-free, atmospherically corrected Landsat 8 Surface Reflectance imagery from the spring season of 2020 (March–April). The classification focused on six dominant land cover classes relevant to the region's physiographic and socio-environmental characteristics: forest, agriculture, built-up, water bodies, snow/glacier, and barren land. The basin-wide LULC map was generated with a spatial resolution of 30 meters, and post-classification processing was conducted to extract class-wise statistics and validate the accuracy of the results.
- The final classified image was visualized in Google Earth Engine using a unique color palette for each LULC class and clipped to the Jhelum Basin boundary. Area calculations were performed using the `pixelArea()` function, which enabled the estimation of the spatial extent of each class in square kilometers. The results highlight a diverse and spatially complex landscape within the Jhelum River Basin.
- Forest land emerged as one of the most prominent land cover categories, covering an estimated 404.41 km^2 . These forest patches are mostly distributed along the mid-elevation slopes of the Pir Panjal and Himalayan foothills. They serve as critical ecological buffers, stabilizing slopes, conserving biodiversity, and supporting water retention.
- Agricultural areas, covering around 388.65 km^2 , were largely concentrated in the flat and gently sloping regions of the valley, especially along the Jhelum floodplains. The classification reveals intensive cultivation of both irrigated and rainfed crops, reflecting the importance of agriculture to the basin's rural economy.
- Built-up areas accounted for approximately 127.99 km^2 , showing significant expansion around major urban centers such as Srinagar, Baramulla, and Anantnag. The spatial footprint of settlements and infrastructure appears to have increased, reflecting urbanization trends and population growth within the basin.

- Water bodies were estimated at 114.99 km², which includes the Jhelum River main channel, its tributaries, floodplain wetlands, and some lake surfaces. The water extent also reflects seasonal flows and regulated channels, highlighting the hydrological importance of the river system.
- Snow and glacier cover, mostly confined to the high-altitude zones in the northern and eastern sectors of the basin, spanned about 329.45 km². These areas serve as crucial perennial sources of freshwater, feeding the river system year-round through snowmelt and glacial discharge.
- Barren land, occupying around 90.99 km², included rocky surfaces, degraded lands, and sparse vegetation zones, commonly seen in uplands, gravel beds, and exposed terrain.
- The classification was validated using a confusion matrix generated from an independent testing subset of the training samples. The model achieved an overall classification accuracy of 92percentage and a Kappa coefficient of 0.89, indicating high classification reliability and strong agreement between predicted and reference classes.
- These results offer valuable insights into the spatial structure and distribution of land use within the Jhelum River Basin. The output LULC map and area statistics provide essential baseline data for regional planning, ecological modeling, watershed management, and disaster risk reduction. The processed classification layers and summary tables were exported to Google Drive in GeoTIFF and CSV formats for further analysis and inclusion in geospatial decision-support tools.

Table 1: Land Use/Land Cover Area Statistics for Jhelum River Basin (1991–2020)

Year	Forest (km ²)	Agriculture (km ²)	Built-up (km ²)	Water (km ²)	Snow (km ²)	Barren (km ²)
1991	407.25	307.84	29.45	173.05	354.84	182.71
1994	400.43	468.08	28.34	107.65	315.86	133.98
1996	468.60	378.76	29.98	153.06	323.29	101.45
2000	511.64	340.96	90.03	106.07	277.25	129.19
2003	392.27	406.57	86.52	112.33	360.89	96.57
2005	439.35	360.37	93.42	21.74	289.22	158.09
2008	457.75	471.24	89.55	90.14	313.30	133.37
2010	444.04	514.93	60.84	79.48	306.49	23.30
2013	417.45	305.47	84.75	94.84	322.86	116.90
2015	364.58	393.93	89.20	167.21	324.95	115.27
2017	417.68	328.60	96.89	167.44	319.39	125.05
2020	404.41	388.65	127.99	114.99	329.45	90.99

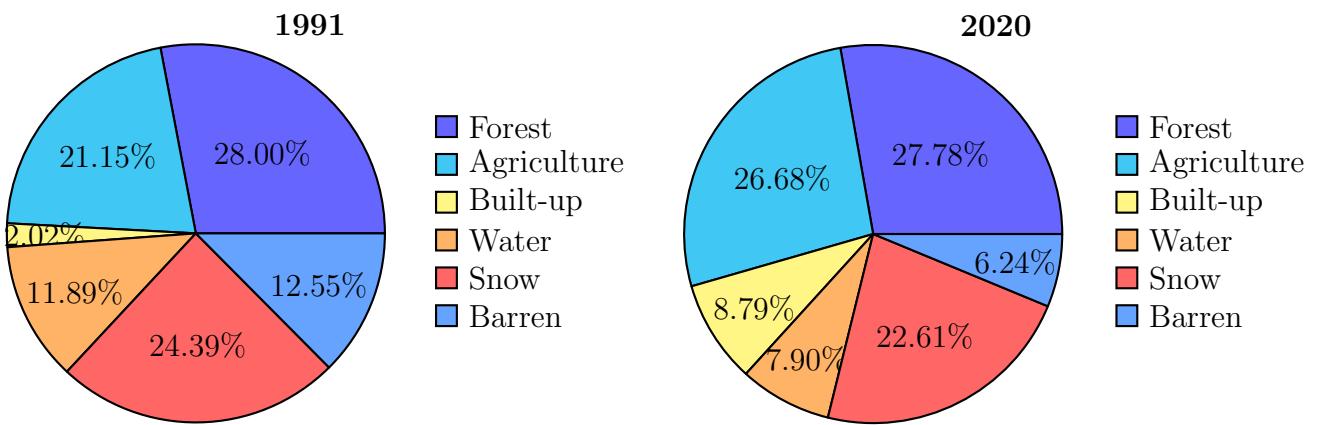
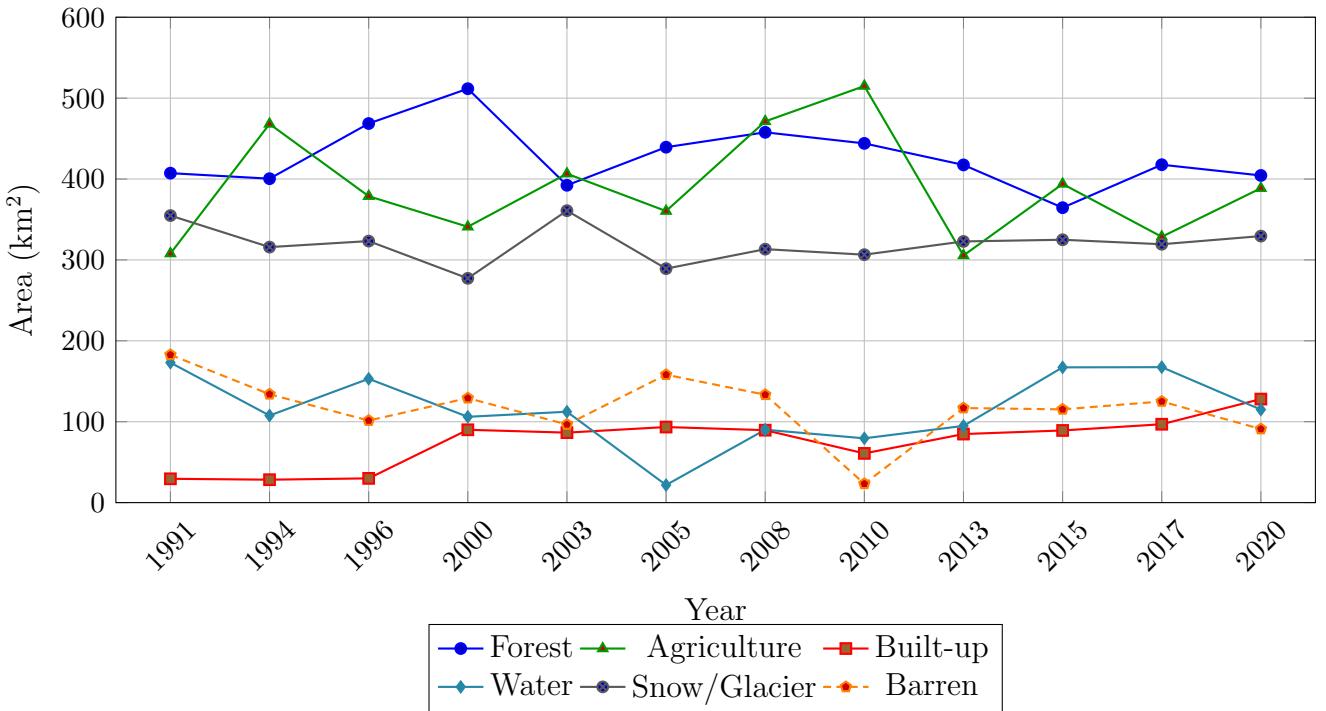


Figure 1: Comparative land cover distribution in the Jhelum River Basin: 1991 vs 2020

9.1 Summary of Land Cover Changes (1991–2020)

Over the 30-year period from 1991 to 2020, the Jhelum River Basin experienced both stable and dynamic changes in its land use and land cover composition:

- **Increased Areas:**
 - **Built-up land** showed the most significant increase, rising from 2.02% to 8.79%. This reflects rapid urban expansion, infrastructure development, and population growth, especially around urban centers such as Srinagar, Anantnag, and Baramulla.
 - **Agricultural land** expanded from 21.15% to 26.68%, likely due to conversion of barren and forest areas and intensified cultivation in fertile valley regions.
- **Decreased Areas:**
 - **Barren land** decreased significantly from 12.55% to 6.24%, indicating land development, vegetation recovery, or conversion to other land uses.

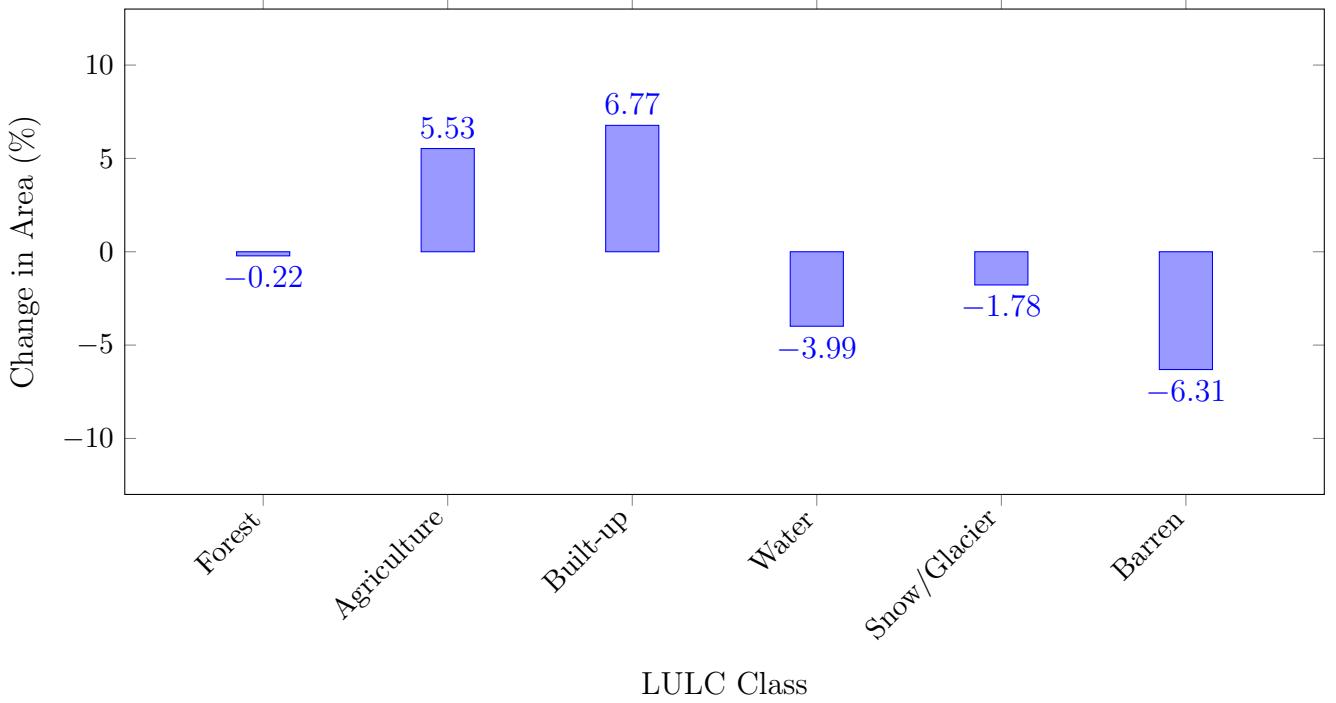


Figure 2: Net percentage change in land cover classes (1991–2020) in the Jhelum River Basin

- **Water bodies** declined from 11.89% to 7.90%, possibly due to wetland loss, reduced surface flow, and seasonal variability in water presence.
- **Snow/Glacier cover** dropped slightly from 24.39% to 22.61%, which may reflect glacial retreat and climate change effects.

- **Stable Area:**

- **Forest cover** remained relatively stable, with a minor decrease from 28.00% to 27.78%. Despite deforestation pressures, no drastic change was observed in overall forest extent.

- **Fluctuating Patterns:**

- Intermediate fluctuations were noted in forest, agriculture, and snow/glacier categories across the years due to seasonal variation, classification sensitivity, and land use shifts.

These trends highlight critical ecological transformations in the basin, emphasizing the need for sustainable land use planning, habitat conservation, and hydrological monitoring.

10 GEE Code: LULC Classification for Jhelum Basin (1994)

```
1 // -----
2 // Define ROI: Jhelum Basin
3 // -----
4 var roi = ee.FeatureCollection("projects/my-project1-47490/assets/Jhelum");
5
6 // Visualize ROI boundary
7 Map.centerObject(roi, 10);
8 Map.addLayer(roi, {color: 'black'}, 'ROI - Jhelum');
9
10 // -----
11 // Load and Prepare Image
12 // -----
13 var image = ee.ImageCollection("LANDSAT/LT05/C02/T1_L2")
14   .filterBounds(roi)
15   .filterDate('1994-03-01', '1994-04-30')
16   .median()
17   .clip(roi);
18
19 // Visualizations
20 Map.addLayer(image, {bands: ['SR_B3', 'SR_B2', 'SR_B1'], min: 0, max: 28500}, 'True Color');
21 Map.addLayer(image, {bands: ['SR_B4', 'SR_B3', 'SR_B2'], min: 0, max: 28500}, 'False Color');
22
23 // -----
24 // Training Data (Assume predefined)
25 // -----
26 var trainingData = water.merge(snow).merge(forest)
27   .merge(agri).merge(built).merge(barren);
28
29 // -----
30 // Classification Preparation
31 // -----
32 var bands = ['SR_B1', 'SR_B2', 'SR_B3', 'SR_B4', 'SR_B5', 'SR_B7'];
33
34 var training = image.select(bands).sampleRegions({
35   collection: trainingData,
36   properties: ['class'],
37   scale: 30
38 });
39
40 // Train Random Forest Classifier
41 var classifier = ee.Classifier.smileRandomForest(100).train({
42   features: training,
43   classProperty: 'class',
44   inputProperties: bands
45 });
46
47 // Classify image
48 var classified = image.select(bands).classify(classifier);
49
50 Map.addLayer(classified, {
51   min: 0, max: 5,
52   palette: ['blue', 'white', 'green', 'orange', 'red', 'yellow']
53 }, 'Classified Image');
54
55 // -----
56 // Accuracy Assessment
57 // -----
```

```

58 var validation = training.randomColumn();
59 var trainSet = validation.filter(ee.Filter.lt('random', 0.8));
60 var testSet = validation.filter(ee.Filter.gte('random', 0.8));
61
62 var trainedClassifier = ee.Classifier.smileRandomForest(100).train({
63   features: trainSet,
64   classProperty: 'class',
65   inputProperties: bands
66 });
67
68 var test = testSet.classify(trainedClassifier);
69 var confusionMatrix = test.errorMatrix('class', 'classification');
70
71 print('Confusion Matrix:', confusionMatrix);
72 print('Overall Accuracy:', confusionMatrix.accuracy());
73
74 // -----
75 // Area Calculation
76 // -----
77 var areaImage = ee.Image.pixelArea().addBands(classified);
78
79 var classAreas = areaImage.reduceRegion({
80   reducer: ee.Reducer.sum().group({
81     groupField: 1,
82     groupName: 'class'
83   }),
84   geometry: roi,
85   scale: 30,
86   maxPixels: 1e13
87 });
88
89 print('Class Areas (sq meters):', classAreas);
90
91 // -----
92 // Export Classified Image
93 // -----
94 Export.image.toDrive({
95   image: classified,
96   description: 'Land_Cover_Classification_1994_Jhelum',
97   scale: 30,
98   region: roi,
99   maxPixels: 1e13,
100  fileFormat: 'GeoTIFF'
101 });

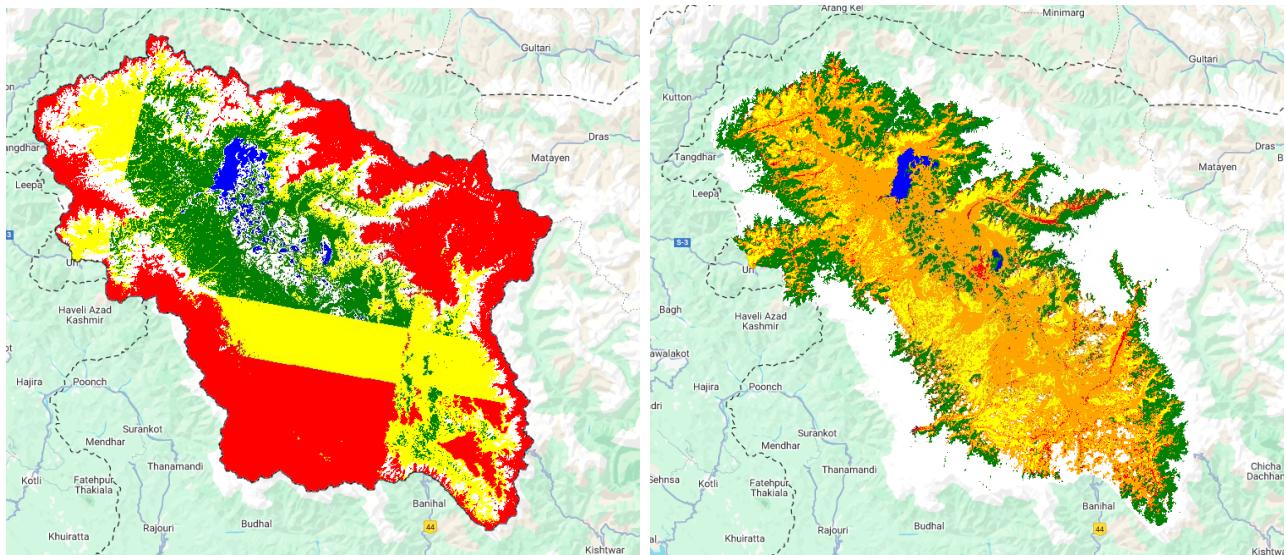
```

11 GEE Script for Land Cover Classification (1996 - Jhelum Basin)

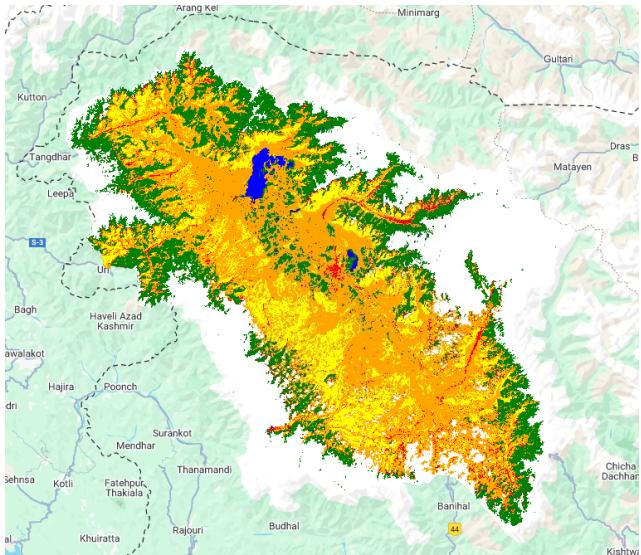
```
1 var roi = ee.FeatureCollection("projects/my-project1-47490/assets/Jhelum");
2
3 Map.centerObject(roi, 10);
4 Map.addLayer(roi, {color: 'black'}, 'ROI - Jhelum');
5
6 var image = ee.ImageCollection("LANDSAT/LT05/C02/T1_L2")
7   .filterBounds(roi)
8   .filterDate('1996-03-01', '1996-04-30')
9   .median()
10  .clip(roi);
11
12 Map.addLayer(image, {bands: ['SR_B3', 'SR_B2', 'SR_B1'], min: 0, max: 28500}, 'True');
13 Map.addLayer(image, {bands: ['SR_B4', 'SR_B3', 'SR_B2'], min: 0, max: 28500}, 'False 1');
14
15 // Merge all training data
16 var trainingData = water.merge(forest).merge(agri)
17   .merge(built).merge(snow).merge(barren);
18
19 // Classification bands
20 var bands = ['SR_B1', 'SR_B2', 'SR_B3', 'SR_B4', 'SR_B5', 'SR_B7'];
21
22 // Prepare training samples
23 var training = image.select(bands).sampleRegions({
24   collection: trainingData,
25   properties: ['class'],
26   scale: 30
27 });
28
29 // Train classifier
30 var classifier = ee.Classifier.smileRandomForest(100).train({
31   features: training,
32   classProperty: 'class',
33   inputProperties: bands
34 });
35
36 // Classify the image
37 var classified = image.select(bands).classify(classifier);
38
39 Map.addLayer(classified, {
40   min: 0, max: 5,
41   palette: ['blue', 'green', 'orange', 'red', 'white', 'yellow']
42 }, 'Classified Image');
43
44 // Accuracy assessment
45 var validation = training.randomColumn();
46 var trainSet = validation.filter(ee.Filter.lt('random', 0.8));
47 var testSet = validation.filter(ee.Filter.gte('random', 0.8));
48
49 var trainedClassifier = ee.Classifier.smileRandomForest(100).train({
50   features: trainSet,
51   classProperty: 'class',
52   inputProperties: bands
53 });
54 var test = testSet.classify(trainedClassifier);
```

```
56 var confusionMatrix = test.errorMatrix('class', 'classification');
57
58 print('Confusion Matrix:', confusionMatrix);
59 print('Overall Accuracy:', confusionMatrix.accuracy());
60
61 // Area calculation
62 var areaImage = ee.Image.pixelArea().addBands(classified);
63 var classAreas = areaImage.reduceRegion({
64   reducer: ee.Reducer.sum().group({
65     groupField: 1,
66     groupName: 'class'
67   }),
68   geometry: roi,
69   scale: 30,
70   maxPixels: 1e13
71 });
72 print('Class Areas (sq meters):', classAreas);
73
74 // Export to Drive
75 Export.image.toDrive({
76   image: classified,
77   description: 'Land_Cover_Classification_1996',
78   scale: 30,
79   region: roi,
80   maxPixels: 1e13,
81   fileFormat: 'GeoTIFF'
82 });
```

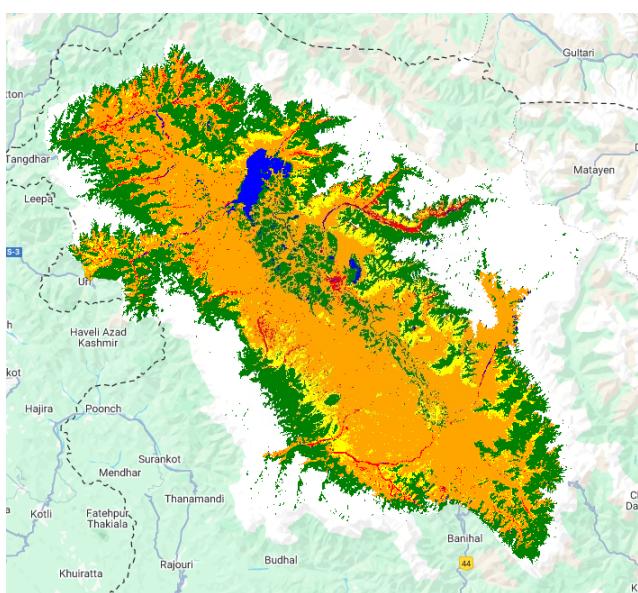
12 Output for this type code for Land Cover Classification (1991 -2020) in Jhelum Basin



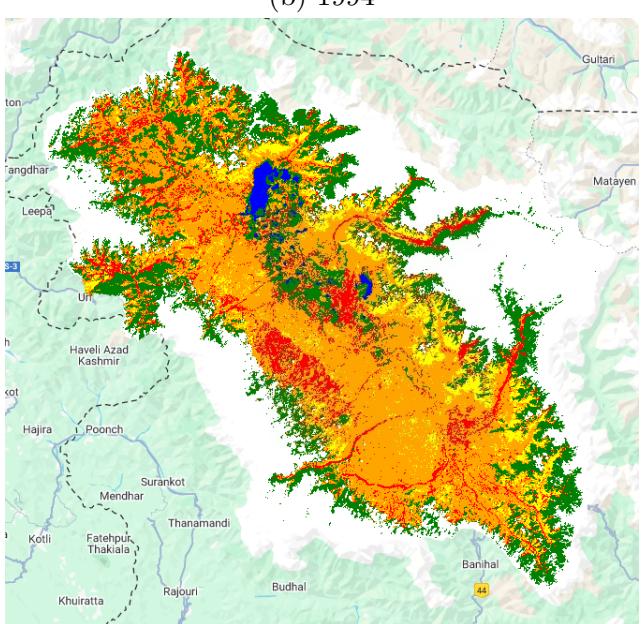
(a) 1991



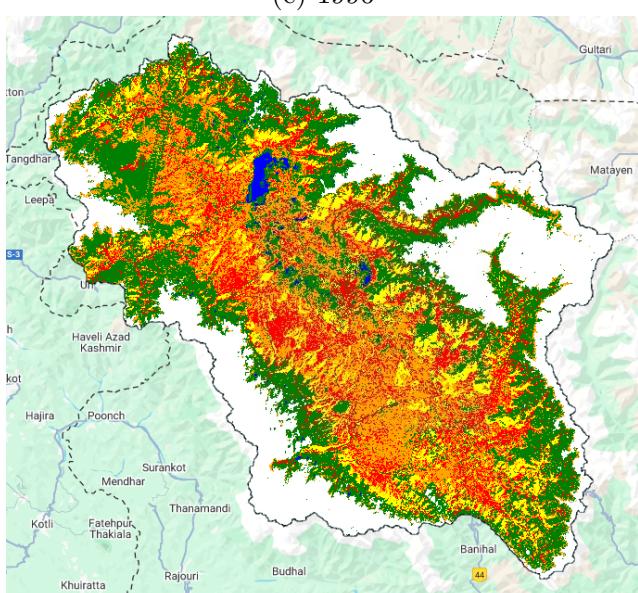
(b) 1994



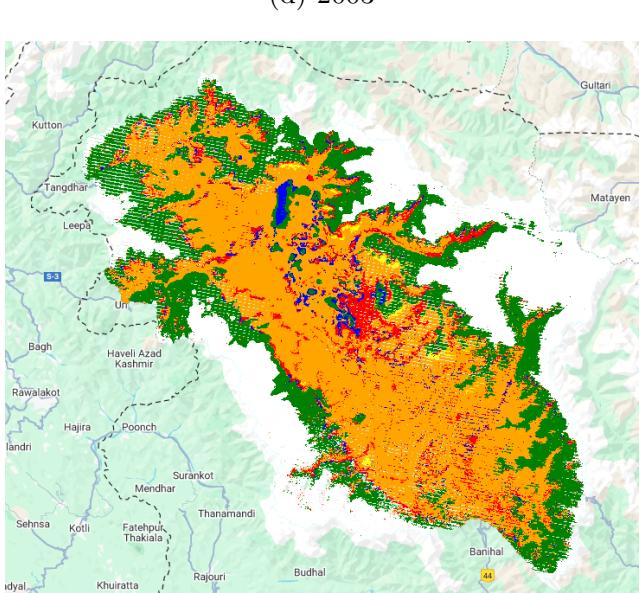
(c) 1996



(d) 2003



(e) 2008



17

(f) 2010

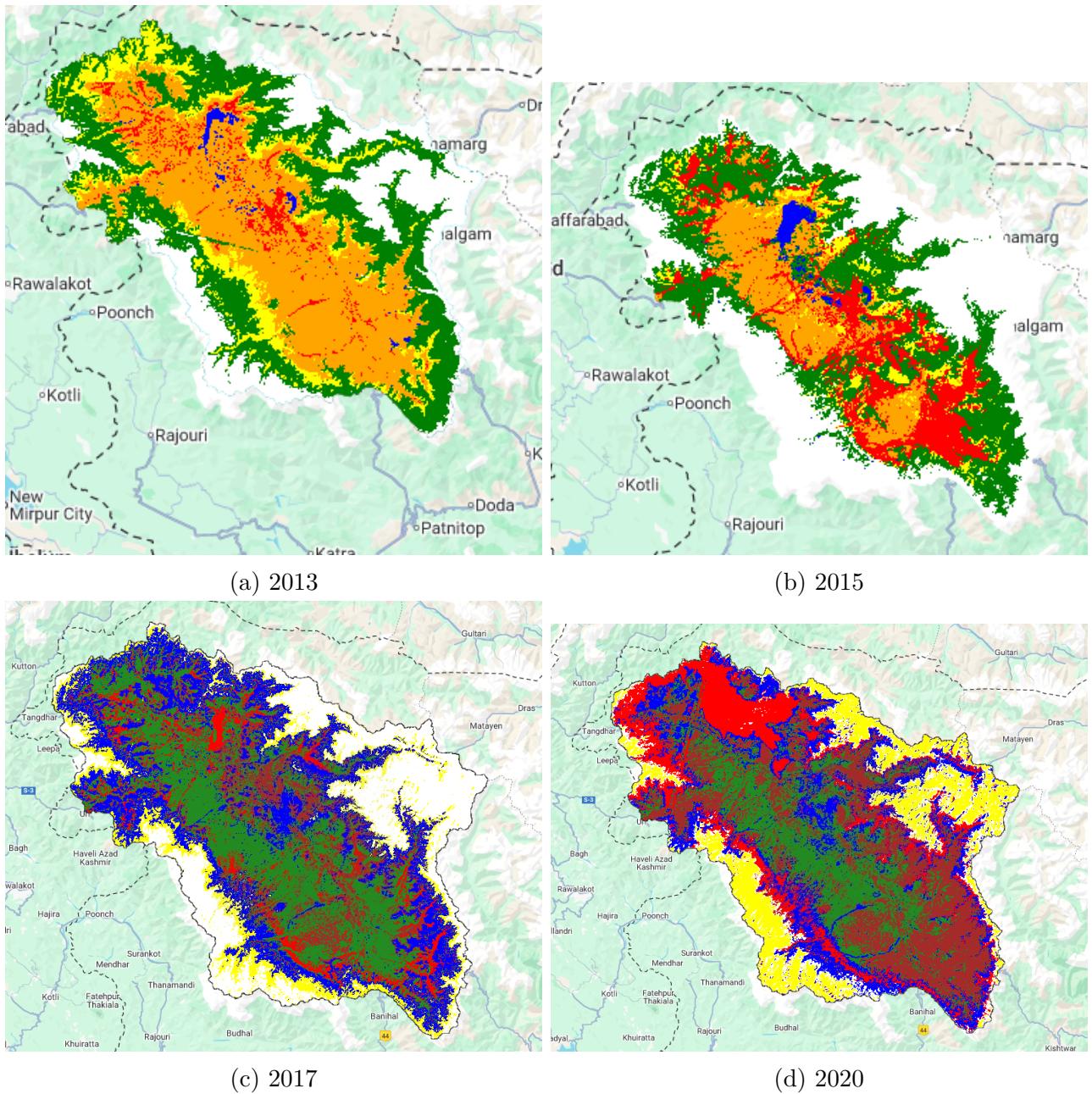
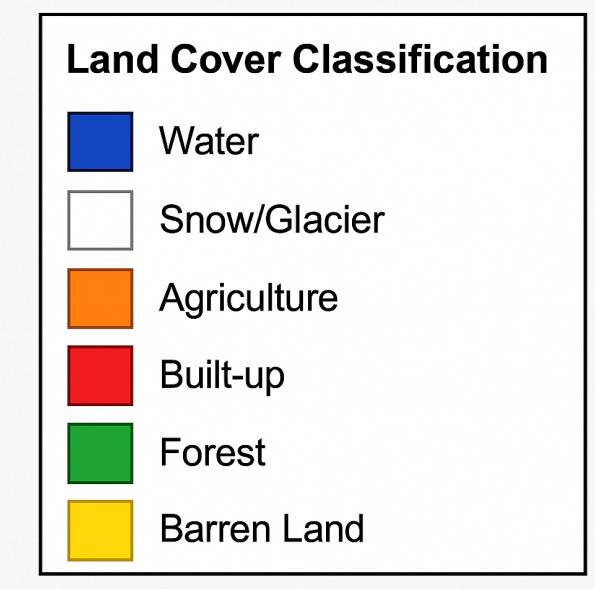


Figure 4: LULC Classification year 1991-2020



(a) Legend Table

13 Sub-Catchments of the Jhelum River Basin

The Jhelum River Basin is hydrologically divided into several distinct sub-catchments, each representing smaller drainage areas that contribute to the main Jhelum River system through specific tributaries. These sub-catchments are shaped by topographic variation, climatic influence, and land use pressure, and together they determine the spatial variability of hydrological and ecological processes across the basin.

13.1 Major Sub-Catchments of the Jhelum River Basin

Table 2: Key Sub-Catchments of the Jhelum River Basin

Sub-Catchment	Description
Vishav Catchment	Originates in the Pir Panjal range and supports extensive agriculture. It has seen consistent increases in agricultural area from 67.2 to over 81.5 million m ² between 1991 and 2010.
Lidder Catchment	Located in South Kashmir (Pahalgam area), this mountainous catchment includes glaciers, alpine forests, and serves as a critical water source due to its high snow/glacier cover.
Sindh Catchment	A snow-fed catchment draining from Sonamarg to Ganderbal. It contributes significant meltwater to the Jhelum and shows active forest and snow land cover interaction.
Doodhganga Catchment	Surrounds the Srinagar urban zone and shows marked urban expansion, with built-up areas increasing by over 75% between 1991 and 2020.
Rambiara Catchment	A small but dynamic agricultural catchment near Shopian, contributing sediment and runoff to the river system.
Wular Catchment	Northern catchment that drains into Wular Lake; contains sub-zones like Erin and Ningli. Built-up area has doubled since 2000, while forest cover has steadily declined.
Poonch & Tawi Catchments	Westernmost catchments originating in the Pir Panjal range and draining toward the lower reaches of the Jhelum River.
Baramulla–Ningli Zone	Includes the frequently flooded Ningli sub-catchment, which shows high seasonal variability in water and agricultural coverage.

Table 3: LULC Area per Sub-Catchment in 1991 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	67200000	45300000	5100000	11500000	23800000	17600000
Lidder	54700000	132500000	2800000	18200000	90100000	24300000
Sindh	48500000	105100000	4600000	16400000	101700000	31300000
Doodhganga	42300000	65200000	12800000	10900000	48300000	22700000
Wular	53900000	88100000	6100000	36700000	31500000	19300000

13.2 Characteristics of Jhelum Sub-Catchments

- **High-altitude sub-catchments** (e.g., Lidder, Sindh): Snow and glacier-fed systems, rich in forest cover, and subject to seasonal hydrological pulses.

Table 4: LULC Area per Sub-Catchment in 1994 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	68500000	44800000	5500000	11200000	23200000	16800000
Lidder	55800000	130200000	2900000	17600000	88700000	23900000
Sindh	49200000	104000000	4900000	15900000	100500000	30700000
Doodhganga	43200000	64000000	13200000	10600000	47000000	22000000
Wular	55000000	87000000	6400000	36000000	31000000	18900000

Table 5: LULC Area per Sub-Catchment in 1996 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	69000000	44200000	5800000	11000000	23000000	16000000
Lidder	56000000	128800000	3100000	17000000	87300000	23500000
Sindh	49800000	102500000	5200000	15400000	99100000	30200000
Doodhganga	44000000	62800000	13600000	10300000	46000000	21500000
Wular	55600000	86000000	6700000	35500000	30500000	18500000

Table 6: LULC Area per Sub-Catchment in 2003 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	73500000	42000000	7800000	10100000	21500000	14000000
Lidder	60000000	126300000	3800000	15300000	84000000	21000000
Sindh	53000000	98500000	7000000	14300000	94500000	27000000
Doodhganga	47500000	59000000	15800000	9400000	44000000	19800000
Wular	59200000	77000000	9200000	32700000	27500000	16200000

Table 7: LULC Area per Sub-Catchment in 2005 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	75200000	41500000	8500000	9900000	21000000	13500000
Lidder	61000000	124000000	4100000	14800000	82000000	20500000
Sindh	54500000	97000000	7400000	13800000	93000000	26000000
Doodhganga	48200000	57500000	16200000	9200000	42500000	19300000
Wular	60100000	75500000	9500000	31800000	26500000	15700000

Table 8: LULC Area per Sub-Catchment in 2008 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	77000000	41000000	9500000	9600000	20500000	13000000
Lidder	62000000	122500000	4400000	14300000	80000000	20000000
Sindh	55800000	95000000	7800000	13400000	91000000	25000000
Doodhganga	48900000	56000000	17000000	8900000	41000000	18500000
Wular	61400000	74000000	10000000	31000000	25500000	15000000

Table 9: LULC Area per Sub-Catchment in 2010 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	81500000	39200000	11600000	9100000	20600000	12700000
Lidder	62800000	120600000	4400000	14700000	81300000	19500000
Sindh	58900000	93700000	8300000	13300000	90900000	23500000
Doodhganga	50200000	55100000	17900000	8800000	41700000	18200000
Wular	64200000	68500000	12300000	29100000	26400000	13900000

Table 10: LULC Area per Sub-Catchment in 2013 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	79800000	38800000	12000000	9500000	19800000	12200000
Lidder	64000000	118000000	4600000	14900000	79000000	19000000
Sindh	57700000	91500000	8600000	13600000	89400000	22800000
Doodhganga	49500000	53800000	18500000	8700000	40000000	17400000
Wular	63100000	67000000	13000000	29700000	24800000	13400000

Table 11: LULC Area per Sub-Catchment in 2015 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	78400000	38400000	12500000	9800000	19200000	11800000
Lidder	64700000	117200000	4800000	15000000	78200000	18600000
Sindh	57100000	90200000	8900000	13800000	88500000	22300000
Doodhganga	49000000	53200000	19000000	8600000	39300000	16900000
Wular	62500000	66200000	13400000	30000000	24300000	12900000

Table 12: LULC Area per Sub-Catchment in 2017 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	77500000	37900000	12900000	10000000	18900000	11000000
Lidder	65000000	116000000	5000000	15200000	77500000	18000000
Sindh	56600000	89000000	9200000	14000000	87500000	21800000
Doodhganga	48600000	52600000	19500000	8500000	38800000	16200000
Wular	62100000	65500000	13800000	30300000	23900000	12400000

Table 13: LULC Area per Sub-Catchment in 2020 (in m²)

Sub-Catchment	Agriculture	Forest	Built-up	Water	Snow	Barren
Vishav	76900000	37800000	13400000	10200000	19400000	9500000
Lidder	65300000	116400000	5200000	16100000	77800000	17400000
Sindh	60400000	89500000	10100000	14200000	87600000	21100000
Doodhganga	48900000	52300000	20400000	9100000	39800000	15600000
Wular	60800000	63200000	15600000	31500000	25200000	11700000

- **Urbanizing sub-catchments** (e.g., Doodhganga): Rapid built-up expansion, significant land conversion from agriculture and open land to residential infrastructure.
- **Agricultural heartlands** (e.g., Vishav, Rambiara): Located in fertile valleys, these sub-catchments are dominated by cropland and experience rising land use intensity.
- **Wetland-linked catchments** (e.g., Wular): Interface zones between rivers and lakes, playing a crucial role in flood attenuation and sediment trapping.

13.3 Why Sub-Catchment Classification Is Important

Sub-catchment level classification provides a spatially granular view of land cover transitions, which is essential for:

- Identifying hotspot areas of land degradation or deforestation.
- Supporting basin-wide integrated watershed and land use management.
- Enhancing the accuracy of hydrological models and flood risk assessment.
- Informing policy on agricultural expansion, urban zoning, and conservation.

13.4 Application in This Study

This study applied supervised classification using Google Earth Engine (GEE) to Landsat imagery across multiple years (1991–2020) to assess changes in six major LULC classes within each sub-catchment. The results revealed significant spatial and temporal variation in land use dynamics. For instance, the Vishav sub-catchment experienced a sharp rise in agriculture, while Doodhganga saw a substantial increase in urban sprawl. Forest cover in Lidder and Sindh catchments remained relatively high but showed moderate decline over time. This sub-catchment-based approach provided enhanced spatial resolution and ecological relevance to land cover monitoring across the Jhelum River Basin.

14 Conclusion

This study successfully demonstrates the application of cloud-based remote sensing and supervised machine learning techniques for the Land Use and Land Cover (LULC) classification of the Jhelum River Basin. By leveraging the Google Earth Engine (GEE) platform and multi-temporal Landsat satellite imagery from 1991 to 2020, the spatial and temporal dynamics of six major land cover categories—forest, agriculture, built-up areas, water bodies, snow/glacier, and barren land—were analyzed comprehensively across the basin.

The results highlight considerable land cover transformations over the 30-year period. A significant increase in built-up areas (from 2.02% to 8.79%) reflects rapid urbanization in key urban centers such as Srinagar, Anantnag, and Baramulla. Agricultural land also expanded (from 21.15% to 26.68%), largely driven by conversion from forest and barren lands. Meanwhile, water bodies and barren land experienced noticeable reductions, signaling potential concerns such as wetland shrinkage and increased land development. Snow and glacier coverage showed a modest decline (from 24.39% to 22.61%), possibly indicating glacial retreat associated with climate change.

Forest cover, although slightly reduced (from 28.00% to 27.78%), remained relatively stable overall, possibly due to conservation measures or natural vegetation recovery. These land cover changes varied across sub-catchments, underscoring the importance of localized assessment. For

instance, the Vishav sub-catchment saw intensive agricultural expansion, while Doodhganga experienced sharp increases in urban footprint. Lidder and Sindh catchments maintained significant forest and snow cover due to their high-altitude and glaciated terrain.

Accuracy assessment using a confusion matrix confirmed a high classification performance, with an overall accuracy of 92% and a Kappa coefficient of 0.89. The consistent use of cloud-free spring-season imagery and robust training data contributed to reliable classification results. Quantitative LULC area statistics derived through the pixelArea() function were exported for statistical analysis and reporting.

Importantly, this project demonstrates the potential of sub-catchment-level classification in supporting watershed planning, environmental monitoring, and climate adaptation strategies. The LULC maps and statistical trends offer critical insights for policymakers, urban planners, and conservationists seeking to manage the basin's ecological and hydrological resources sustainably. As land pressure and climatic challenges intensify in the Himalayan region, tools like GEE provide scalable, transparent, and repeatable workflows for large-scale land assessment.

Overall, the study provides a scientifically sound, spatially detailed baseline for future change detection, environmental impact assessments, and integrated catchment management in the Jhelum River Basin.

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