GEO-EYE

ORIGINAL ARTICLE

Monitoring Land Use and Land Cover Dynamics Using Remote Sensing and GIS in Kulgam District, Jammu and Kashmir, India

Roouf Ahmad Malla[1*], **Irfan Hassan Ganaie**[1], **Sunil Yuvraj Narke**[2]

1 *Ahmednagar College, Ahmednagar, India.*
2 *Jamkhed Mahavidyalaya, Jamkhed, Ahmednagar, India.*

Abstract

Kulgam, often referred to as the "Rice Bowl of Jammu and Kashmir," has witnessed significant land use and land cover changes over the past two decades. The research reports extensive and serious transformations of different land cover classes in Kulgam district as identified via remote sensing technologies to characterize spatial and temporal patterns of comprehensive land use and land cover changes for the period from 2011 to 2021. Using the maximum likelihood classification method, a supervised classification approach, eight major land use categories were identified. The results show significant increases in horticulture (92.2%), built-up areas (18.4%), and grass lands (13.7%). Conversely, several land use classes reported a declining trend. Paddy cultivation decreased by (-38.3%), forest by (-23.2%), bare soil & rocky surface by (-11%), water bodies by (-10%), and snow contracted by (-10%). The primary drivers of land use change in the region are identified as climate change, population growth, and economic factors. However, agricultural intensity has also been an aggravating factor for land use and land cover change. The rise of horticulture, and changes in land use policies have also played a significant role in shaping the landscape dynamics of the study area.

Keywords: Land use/Land cover Change, Remote Sensing, Supervised Classification, Climate Change

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[*] **Corresponding author.**

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1 Introduction

Land use land cover (LULC) is a key aspect of several disciplines, including natural resource management and monitoring, biodiversity loss and ecosystem degradation, urban development, and unexpected changes in climate regime [43, 44]. LULC change is considered as a natural and anthropogenic process, and its impact on the local environment is essential for characterizing the socio-environment relationship [18, 31, 37]. Anthropogenic factors related to LULC changes have led into degradation of various natural resources [11]. Natural Scientists have defined land use in terms of syndromes of human activities, including agriculture, forestry and built-up areas, which change land surface processes including biogeochemistry, hydrology, and biodiversity [10].

Land cover includes the type and condition of vegetative cover (e,g, forests and grass cover as well as human structures, soil type, biodiversity, and surface and ground water [25]. The combined term Land Use Land Cover (LULC) encompasses LU and LC classes, and change assessment is crucial for investigating numerous socioeconomic and environmental issues [30]. The analysis of changes in LULC in recent years has become an important research question, as LULC change has been recognized as a major driver of environmental change globally [46]. Natural and anthropogenic activities are attributed to the changes in LULC [37], which in turn cause alterations that will hugely impact natural ecosystems [6, 21, 26]. Changes in land use and cover (LULC) — particularly owing to natural-induced factors — can enhance the vulnerability of communities and reduce their ability to preserve natural resources and supply food [12, 36]. LULC changes have been tracked over the years using the evidence collected by earth observing satellites and aerial images [35]. Land use change, land cover conversion and land use management practices have significantly transformed the majority of the earth's surface [12, 32, 40, 45]. Significant population growth, unprecedented expansion of agriculture, deforestation, and massive economic activities in the last few centuries have all contributed to an uncontrollable and surprising pace of LULC changes [24, 42].

The most common approaches to quantification, mapping, and detection of patterns of LULCC are satellite remote sensing and GIS due to their accurate geo-referencing processes, their digital format making them suitable for computer [8, 28, 32]. The process of digital change detection has been widely used for the determination and/or description of the types of major changes in LULC properties from multi-temporal remotely sensed data. The general idea of using this data for change detection is its capability to catch dissimilar changes across two or more dates. The monitoring of LULCC in various ecosystems has led many researchers to address this issue [39]. Many studies have addressed LULC change in agriculturally productive land, and arid and semi-arid land [33]. Gao & Liu (2010) [14] analyzed two Landsat images at an interval of 10 years to identify the trend of land degradation that was taking place due to soil salinization and water-logging in northeast China. Rapid and timely analysis of LULC change is crucial to tracking and assessing the consequences of these changes on the environment [15]. Rural land cover change is the result of the interaction of several socioeconomic, environmental, and institutional factors [19]. Internationally, remote sensing and GIS technologies are utilized to perform change detection studies, even for land use/land cover analysis other than accessibility [7, 17, 27] in the mountainous regions.

According to Ahmed et al 2021 [2], Climate change has become a key global issue, and the Himalayan region is highly vulnerable to it. But in the Kashmir Valley, melting snow and changing weather patterns have rendered conventional agriculture futile and made a transition towards horticulture an imperative. The mean maximum (Tmax) and mean minimum (Tmin) temperatures are unequivocally on the rise, during the period from 1980 to 2018, Tmax increased by 1.61°C, and Tmin also increased by 0.95°C [34]. A limited amount of precipitation was recorded by various meteorological stations, showing a declining trend with different rates of 4.22 mm per year for the period of 1980 to 2016 [38]. Kashmir Valley has experienced tremendous changes over the last 30 years due to factors such as population increase& economic development, the change of farming practices, and the establishment of different development projects [3]. Although there are comprehensive studies of changes in land use and land cover (LULC) in the overall Kashmir Himalayas, the landscape of Kulgam district, located on the northern slopes and foothills of the Middle Himalayas, has not been widely studied. The socio-economic and environmental implications of LULC dynamics in Kulgam need to be understood for their ecological significance. In the last few decades, horticultural crops, especially apple, have taken up rice both in terms of area and production in Kulgam [23]. In addition, rising population growth in the South Kashmir region has added anthropogenic stress on the delicate mountain ecosystem. The Kulgam district saw a dramatic demographic upsurge from 236,899 in 1981 to 452,300 in the 2021 census data — a trend mirrored in a much larger context of expanding human settlements on the ecologically fragile landscape. As the unique, yet interwoven reconfigurations of climatic, demographic and land use changes have not yet been researched in Kulgam, our study seeks to fill this research gap and hopes to help create a more complete perspective of the changing geographical narratives of Kulgam.

1.1 Objectives

The study was intended for a comparative study/analysis of the LULCC in Kulgam by using RS and GIS tools. To this end, we set the following objectives.

1. To map and classify different LULC classes and land use transform in Kulgam between 2011 and 2021.
2. To combine supervised classification with GIS-based visual interpretation and to explore the effectiveness of combining GIS with RS techniques for understanding the spatial distribution of various LULC changes and
3. To ascertain prominent driving forces and the level of their contribution in LULC change.

1.2 Study area

Kulgam district lies in the southern part of the Kashmir valley. In terms of map references, the study area is located between $33^0 30'$N to $33^0 15'$N latitude and $74^0 30'$E to $75^0 10'$E longitude. The altitude ranges between 1569 m and 4661 m [Fig. 1].

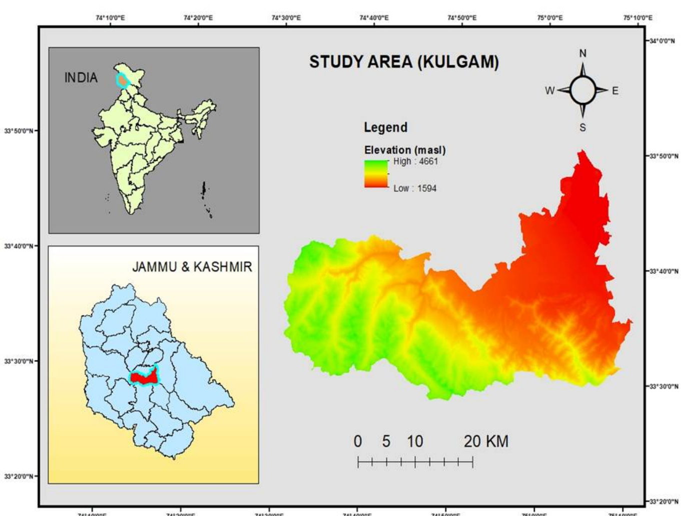

Fig. 1: Study area map

According to the 2011 census, the district has total population of 422786. The river "Veshew" passes through the middle of the district and drains the entire area and significantly contributes to the discharge of Jhelum. The river has its origin close to Kousarnag. It debouches from an elevation of 3962.4 meters above sea level. The region experiences a temperate climate with four distinct seasons: spring (March to May), summer (June to August), autumn (September to November), and winter (December to February). However, over the past few decades, the study area has experienced unprecedented LULC changes, particularly in the extension of horticulture areas and built-up.

2 Materials and methods

2.1 Data

For analysing LULC dynamics of district Kulgam, Jammu and Kashmir, two multispectral images for the study area were downloaded for two Epochs: 2011 till 2021. The satellite images utilized in this study are obtained from the United States Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov) and Copernicus Open Access hub (https://scihub.copernicus.eu) websites. The images were selected to have as little cloud as possible and to be acquired at approximate the seasonal time so that they were comparable. The study area corresponds to the Landsat frame path/row 149/035 of the Worldwide Reference System (WRS). The Landsat images of the year 2011 and Sentinel 2 of the year 2021 are used with resolutions of 30m and 10m, respectively. The data description information is available in [Table. 1].

Table 1: Details of satellite data used

Sensor	Year	Date of acquisition	Source	Spatial resolution
Landsat 5 OLI_TIRS	2011	25, September 2011	USGS earth explorer	30 meters
Sentinel 2	2021	19, September 2021	Copernicus open access hub	10 meters

The methodology of supervised classification of the satellite data was implemented on both Landsat 7 and Sentinel-2 images using a maximum likelihood classifier algorithm with training samples selected over characteristic land cover types such as built-up, paddy land, horticultural land, forest, water body, bare land, grass land and snow cover features. Training samples were delineated using expert knowledge, visual interpretation, and high resolution images in Google Earth Pro. Besides high resolution imagery, some ancillary data ware also collected, such as ground truth data, aerial photos, and topographic maps.

2.2 Image pre-processing and LULC classification

Proper pre-processing of satellite images is critical for delivering improved quality and accuracy in land cover classification and change detection studies. Data quality is thus ensured at this phase by ensuring the extracted information correlates closely with real biophysical features. Depending on platform dynamics and the geometry of the sensor, satellite images are typically subject to geometric distortions. Processing Raw Data ERDAS 2011 software was used to process the raw satellite data in order to correct these discrepancies. This process was to apply geometric correction (geo-referencing the images to a reference coordinate system). Then, the corrected Images were mosaicked and subsetted based on the defined AOI (Area of Interest). Per-pixel signatures were used and the land area was distinguished into eight classes on the basis of the specific Digital Number (DN) value of all satellites**.** The delineated classes were paddy, Built-up area, bare soil and rocky surface, Forest, Water, horticulture, grass, and snow [Table. 2]. After pre-processing, the classification process started by classifying the image into several land cover classes. This required giving the various landscape features distinct digital numbers (DN) values to make them different. One color code will allow the visualization of each type of land cover in this research. Training samples were representative of each land cover type for the classification accuracy. Polygons were created according to the regions that best represent the attributes of each group, and the spectral signature for the pixels that fell within them was stored. These spectral signatures were subsequently evaluated in order to reduce confusion between similar land cover types [14]. The initial classification of the image was done through a supervised classification method, using the maximum likelihood algorithm. This approach is heavily dependent on user-generated information because the analyst chooses the training samples that are representative of each land cover type. Next, the algorithm assigns pixels throughout the entire image to a classified category based on the statistical probability of the previously identified spectral signatures. Using this approach resulted in a complete land cover map showing all the landscape elements with a small error. Through field observation, expert information, and review of documents from both national and regional offices, the land use/land cover types were categorized into eight classes as shown in [Table. 2]. These classes represent the basis for the LULCC analysis in this study.

Table 2: Description of LULC classes identified in Kulgam district

S. No.	Class name	Description
1	Paddy	Rice fields.
2	Built-up	Encompasses residential, commercial, industrial zones, transportation networks, roads, and urban areas.
3	Bare soil and rocky surface	Covers exposed soil and unproductive lands.
4	Forest area	Represents regions with mixed forest cover.
5	Water	Comprises river lakes ponds, reservoirs, and other open water sources.
6	Horticulture	Comprises fruits like apples, pears, cherries, plum, walnuts, apricots etc.
7	Grass	High altitude areas dominated by grasses and herbaceous vegetation
8	Snow	This encompasses regions covered by perpetual snow and various glaciers, both of which constitute a substantial portion of the landscape.

2.3 Accuracy assessment

LULC maps produced were tested for accuracy to provide information, which serves as an indicator of the quality of the map and its fitness for a particular purpose [13]. Congalton (1991) [9] described how to use the confusion error matrix to test the results of the classification scheme. The user's and producer's accuracy were used to evaluate the individual class accuracy [41]. Moreover, overall accuracy and error matrix kappa coefficient were used to assess the quality of the whole type classification performance. The degree of agreement between user-assigned ratings and predetermined producer ratings is known as kappa. It is determined using a formula.

$$\text{Kappa Coefficient (T)} = \frac{(TS \times TCS) - \sum(Column\ Total \times Row}{TS^2\ - \sum(Column\ Total\ - Row\ To}$$

Where, TS = total Sample and TCS = Total Corrected Sample.

The overall accuracy for 2011 was 90.76% with a Kappa coefficient of 0.894, and for 2021, the overall accuracy was 88.57% with a Kappa of 0.869 as presented in the accuracy assessment results shown in [Table. 3] and [Table. 4] respectively.

Table 3: Error matrix table of land use/land cover of Kulgam (2011)

	References data									
	Water	**Paddy**	**Apple**	**Forest**	**Builtup**	**Snow**	**Grass**	**Bare soil**	**Row total**	**User accuracy**
Classified data										
Water	60	0	0	0	0	0	2	4	66	90.9
Paddy	4	45	0	0	0	0	0	1	50	90
Apple	0	0	62	0	3	0	2	0	67	92.53
Forest	0	0	7	55	0	0	0	0	62	88.7
Built-up	1	0	3	0	60	0	1	0	65	92.3
Snow	0	1	0	0	0	53	0	5	59	89.3
Grass	0	0	5	0	0	0	58	1	64	90.62
Baresoil	0	5	0	1	0	0	0	59	65	90.76
Column total	65	51	77	56	63	53	63	70	498	
Producer accuracy	92.3	88.23	80.51	98.21	98.41	100	92.06	84.28		

Overall classification accuracy in 1992 = 90.76% and kappa coefficient = 0.89

Table 4: Error matrix table of land use/land cover of Kulgam (2021)

	Reference data									
	Water	**Paddy**	**Apple**	**Forest**	**Builtup**	**Snow**	**Grass**	**Bare soil**	**Row total**	
Classified data										User accuracy
Water	49	2	0	0	0	2	0	6	59	83.05
Paddy	0	59	3	0	0	0	5	2	69	85.5
Apple	0	0	60	4	0	0	0	0	64	93.75
Forest	0	4	0	55	0	0	0	0	59	93.22
Built-up	0	0	0	0	52	4	0	5	61	85.24
Snow	0	0	0	4	0	57	0	2	63	90.47
Grass	2	0	0	1	3	0	55	0	61	90.16
Baresoil	0	0	4	0	0	4	0	55	63	87.3
Column total	51	65	67	64	55	67	60	70	499	
Producer accuracy	96.07	90.76	89.55	85.93	94.54	85.07	91.66	78.57		

Overall classification accuracy in 1992 = 88.57% and kappa coefficient = 0.86

2.4 Land use/land cover status of 2011 and 2021 in Kulgam

According to the study area's land use and land cover (LULC) analysis, agriculture has a major influence on the landscape, with horticultural land making up around 103 km² (8.15%) and paddy cultivation taking up about 209 km² (16.53%) of the total area. These agricultural categories together make up almost one-fourth of the study area, highlighting their significance in the socioeconomic structure of the area. Paddy cultivation's dominance indicates the region's ongoing reliance on traditional agriculture, which is probably influenced by the area's ideal climate, soil composition, and irrigation resources. On the other hand, the sizeable amount of horticultural land indicates a slow shift towards high-value crops, which could be linked to shifting market conditions, legislative actions, and the search for more commercially and ecologically sustainable farming practices. The comparatively small percentage of built-up area (3.11%) and the spatial distribution of agricultural land, wide grasslands (34.65%), and forests (19.46%) suggest a primarily rural character with little urban expansion. Additionally, the prevalence of rocky surfaces and bare soil (15.82%), points to potential problems with land degradation and restrictions on agricultural growth [Table. 5], [Fig. 2]. Paddy fields and horticulture are widely covered, which not only emphasizes their vital role in maintaining local livelihoods and food security but also their importance in directing future land use planning and sustainable development strategies in the area.

Table 5: Land use classification and its interpretation for 2011, detailing the area (in square kilometers) and percentage coverage of various land use types

S. No.	Land use class	Area 2011 (Sq. km)	Percentage (%)
1	Water	10	0.79
2	Paddy	209	16.53
3	horticulture	103	8.15
4	Forest	246	19.46
5	Built-up	38	3.01
6	Snow	20	1.58
7	Bare soil & Rocky surface	200	15.82
8	Grass	438	34.65
9	Total	1264	100

Table 6: Land use classification and its interpretation for 2021, detailing the area (in square kilometers) and percentage coverage of various land use types

S. No	Land use class	Area 2021 (Sq. km)	Percentage (%)
1	Water	9	0.71
2	Paddy	129	10.21
3	horticulture	198	15.66
4	Forest	189	14.95
5	Built-up	45	3.56
6	Snow	18	1.42
7	Bare soil & Rocky surface	178	14.08
8	Grass	498	39.40
9	Total	1264	100

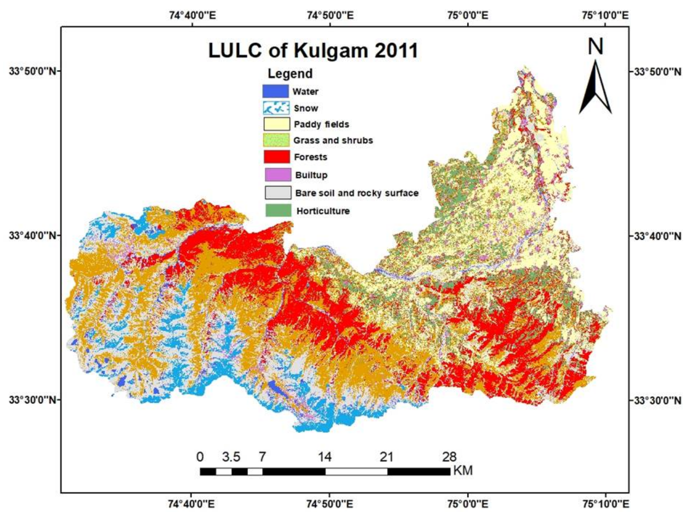

Fig. 2: LULC in Kulgam (2011)

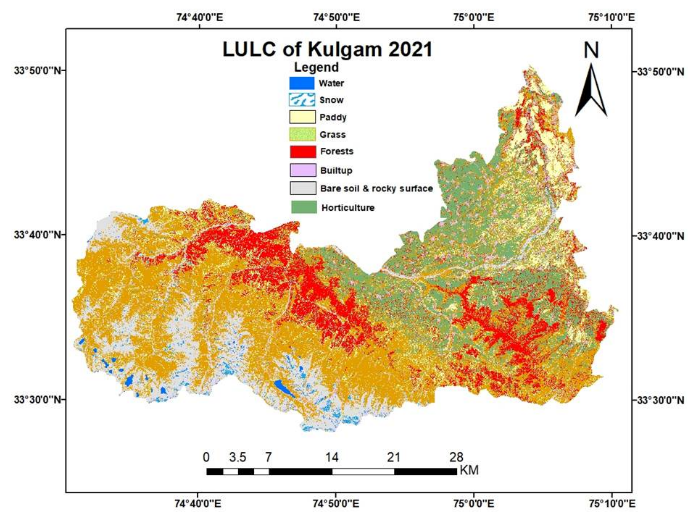

Fig. 3: LULC in Kulgam (2021)

Analysis of 2021 land use reflects a significant change in the pattern of agriculture, especially concerning paddy and Horticulture. Decline in the area under paddy cultivation was observed from 16.53% during 2011 to 10.21% in 2021, indicating a decrease in rice cultivation possibly due to changes in climatic condition, water situation, and control on agriculture. In contrast, horticulture increased from 8.15 to 15.66, almost double which reflects an emphasis on various high-value crops. Such rise could be due to the attempt being made to maximize agricultural income and the introduction of crop diversification [Table. 6] [Fig. 3].

2.5 Change detection analysis

Table review shows that there was a significant (changes in the land use/land cover status of Kulgam from 2011 to 2021. A region in the lost area under one type of land use/land cover) category has changed to some other land use/land cover category, showing an increase in the respective category [Table. 7] [Fig. 5].

- **Horticulture**

The highest positive change was recorded in Horticultural crops from 8.15% (103 sq km) in 2011 to 15.66 % (198sqkm) this time. This equates to a 92.2% increase and an additional 95 sq km of horticultural land, becoming the second largest land use category in 2021.

Table 7: The extent and variation in various LULC categories in the district Kulgam for the years 2011 and 2021

S. No	land use class	2011 Sq. km	Percentage	2021 Sq. km	Percentage	change in area (2011-2021) Sq. km	Percentage
1	Water	10	0.79	9	0.71	-1	-10.0%
2	Paddy	209	16.53	129	10.21	-80	-38.3%
3	horticulture	103	8.15	198	15.66	95	92.2%
4	Forest	246	19.46	189	14.95	-57	-23.2%
5	Builtup	38	3.01	45	3.56	7	18.4%
6	Snow	20	1.58	18	1.42	-2	-10.0%
7	Bare soil & Rocky surface	200	15.82	178	14.08	-22	-11.0%
9	Grass	438	34.65	498	39.40	60	13.7%
10	Total	1264	100	1264	100		

- **Paddy**

Among cropped areas, the largest absolute decline was noticed in traditional paddy cultivation, which went down from 209 sq km (16.53%) to 129 sq km (10.21%). The 80 sq km figure expresses a loss of agricultural area, indicating a major shift away from traditional rice farming.

- **Grassland**

Grassland, the most advanced land use class, exceeded its limit; from a much smaller area of 438 sq km (34.65%) before and swiftly stretched out to 498 sq km (39.40%). That's up to 13.7% more than right now, boosting grassland by an extra 60 sq km.

- **Forest**

But the forest area witnessed an alarming fall from 246 sq km (19.46%) to 189 sq km (14.95%), a reduction of 23.2% and loss of 57 sq km. The new annual data reveals deforestation rates are moving in the wrong direction, with potential consequences for long-term environmental sustainability.

- **Water**

The area under water bodies has decreased from 10 sq km to 9 sq km, reflecting a decrease of ten per cent. Although the change is tiny (1 sq km), this calls for concern as water resources are valuable.

- **Snow Cover**

According to the survey, while snow-covered areas have decreased from 20 sq km to 18 sq km depicting a decline of 10%. A change of 2 sq km reflects either climate-driven advances or retreats, or seasonal changes.

- **Built-up area**

Built-up areas increased from 38 sq km (3.01%) to 45 sq km (3.56%), an increase of 18.4%. The 7 sq km added area indicates controlled urban development and infrastructure expansion.

- **Bare soil and rocky surface**

In these areas, the number decreased by 11% from 200 sq km to 178 sq km, with a loss of 22 sq km. A decline might indicate it has been reclaimed or converted to some other productive use [Fig. 4].

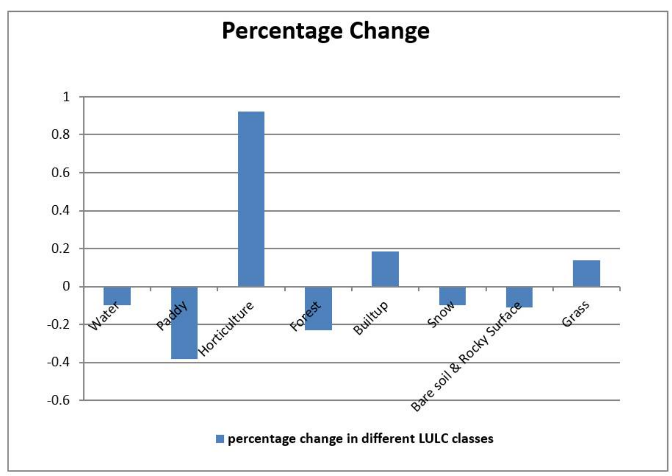

Fig. 4: Percentage change in land use/ land cover in Kulgam between 2011 and 2021

Land use in Kulgam, 2011

Source: Google Earth Pro

Land use in Kulgam, 2011

Source: Google Earth Pro

Fig. 5: Spatio-temporal changes in land use in Kulgam based on Google Earth Pro imagery showing an increase in horticultural and built-up land and decline in paddy fields (2011 and 2021)

2.6 Driving forces

The LULC changes of Kulgam are influenced by a blend of climatic, economic, and population dynamics. Besides land use land cover change is also governed by agricultural intensity. The significant variables identified as the drivers of LULC are described below.

- **Climatic**

Climate change, especially an increase in temperature and changes in precipitation pattern, has reduced snow cover and water bodies that affect both agriculture and the availability of natural resources [20]. Himachal Pradesh India is located in the Kashmir Himalayas, whose Climate studies on the Kashmir Himalayas reveal an annual increase in mean maximum temperature and mean minimum by 0.05 and 0.01 °C respectively, whereas a decrease in rainfall by 4.22 mm per annum occurred during 1980–2016 [38]. These changes in precipitation and temperature have altered the availability of water in the region as well and led to a shift from agriculture to horticulture among people of the region, because horticulture needs less water, whereas water is the prime requirement for agriculture in the form of rice. The decrease in the amount of forests and farming due to natural disasters like floods and droughts has forced farmers either to abandon their farms or to convert it for cultivation of something else. Moreover, these issues are multiplied due to extremely poor water facilities in the study area. Rain-fed agriculture has been affected by declining river flows, fluctuating rains, migrating snow covers, and disappearing glaciers. Since rice is a water-consuming crop, its cultivation is becoming less viable in water-scarce areas. Farmers have adjusted to changes by selecting for less water-dependent crops, which they find easier to relate to. The rice crop is now blocked by many floods, droughts, and hailstorms, and the frequency of these extreme events has increased. This has given rice a bad image; it is seen as being risky, and unreliable.

- **Economic**

Rice cultivation is being perceived by the people as not so revenue fetching as is the growing of other high value crops such as apple, saffron and other horticultural items. Rice is being replaced by horticulture as it earns more than traditional paddy fields. The shift in land use between 2011 and 2021 is predominantly economically motivated. The switch from paddy cultivation to horticulture is driven by the increasing profitability of high-value crops that provide higher returns for farmers who are increasingly bearing the brunt of competing for scarce water and land resources. Easy access to markets and technologies with high productivity potential also contributes to the trend towards more input- and management-intensive farming systems i.e horticulture. With the enhanced availability of imported rice and government distribution systems (e.g., Public Distribution System, PDS, in India), self-sufficiency in rice production is no longer perceived as critical. This has lessened the cultural and economic reliance on rice cultivation. Moreover, the trend of urbanization and urban development has also led to the conversion of agricultural land and forest areas to built-up areas. With rapid industrialization and rising demand for residential and commercial spaces, rural land is being converted to accommodate expanding urban populations [47].

- **Demographic**

One of the direct driving forces of land use and land cover (LULC) change in any area is the rising human population

[5]. Population growth, particularly in rural areas, is exerting pressure on land resources. This may lead to agricultural land being used for residential and commercial purposes or to forests being cut down to make way for more settlements. The increasing anthropogenic intervention resulting from increasing population pressure has led to the degradation of the mountain ecosystem and biological resource base to dimensions hard to ignore. The study area has seen population expansion rapidly, and horticultural commodities in and outflow have been for feeding the dense population. "Additionally, transport networks have been well established, which assist in the transfer of local produce to the national market to fetch better prices. Fresh vegetable supply is increasing to meet global demands and is increasingly shifting towards rural and semi-urban practice of horticulture. Rapid population growth has accelerated the growth of built-up areas, illustrating the combined effect of demographic and economy imposed as well as environment driven pressures on the land use. For many, there is a migration to the city or other non-agricultural employment for additional income, which is resulting in labor shortages and a decrease in the perception of farming as a primary occupation. A change in mindset with generations sees it as old-fashioned and less attractive compared to the modern professions among younger generations.

- **Agricultural intensity**

Agricultural intensity, particularly in horticulture, is a major driver of land use and land cover changes in Kulgam, where apple orchards and other fruit cultivation have expanded significantly. A numbers of high-density apple orchards are coming up in the Kulgam district, occupying either rice fields or old traditional orchards [23]. The region's favorable climate and economic viability of horticulture have led to the conversion of traditional farmlands, forests, and even pastures into high-density fruit orchards. Farmers increasingly adopt intensive practices such as high-density plantation, chemical fertilizers, and irrigation systems to enhance productivity. While this shift has boosted local incomes and employment, it has also contributed to soil degradation, water resource depletion, and loss of natural vegetation. The rapid expansion of horticulture continues to reshape Kulgam's landscape, necessitating sustainable land management strategies to mitigate environmental impacts while ensuring long-term agricultural prosperity.

3 Conclusion

The current study utilized remote sensing and GIS methods to evaluate LULC and monitor change between 2011 and 2021. The accuracy assessment showed that both the overall classification accuracies (90.76% and 88.57%) were high, and the substantial or even almost perfect kappa values indicated high reliability of the classification results. Analysis revealed an exceptional agricultural transition characterized by a substantial decrease in paddy area (38.3%) and an increase in horticultural land (92.2%), indicating adaptation to climatic variability. Forrest cover was reduced by 23.2%, together with a 13.7% increase of grassland, which suggested ecosystem degradation and loss of carbon sequestration capacity. Population growth and urban expansion led to built-up areas rising by 18.4%. The driving factors of these observed changes are climatic variation, economic change from low-value to high-value crop production, demographic pressure, and agricultural intensification. These changes illustrate challenges related to environmental degradation, as well as opportunities for mimicking sustainable land management, adaptive water resource planning, conservation of forests, and sustainable agricultural practices that can sustain the climate. The results offer significant implications for understanding the spatio-temporal dynamics of Kulgam and for the regional climate change adaptation and sustainable development planning.

4 Disclosure

Ethical declarations: All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

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