Research Article

Land Cover and Land Use Change Detection Using Object-Based Image Analysis in Kaghan Valley, Khyber Pakhtunkhwa

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Abstract | Since 2000, the anthropogenic and natural drivers have a great impact on the land use land cover of the Kaghan valley in Mansehra District. Rapid, unplanned and unsustainable urbanization in the area has changed the landscape of the area to a great deal. Forests are one of the worst affected land cover in a result of the changing landuse. This analysis examines the dynamics of Land Use Land Cover (LULC) changes in Kaghan Valley between 2004 and 2012 with range of observation of 4 years i.e., 2004, 2008 and 2012. The study reveals distinct shifts in various LULC categories, encompassing cropland, forest land, grassland, other land, settlements, and wetlands. Notable trends include a decrease in cropland area by 13.72%, possibly due to urbanization and shifts in agricultural practices. Forest land experienced a 5.30% decrease, likely due to deforestation and land conversion. Grassland saw a modest increase of 1.94%, potentially resulting from natural processes and land management changes. An expansion of 5.59% was observed in the "Other Land" category, which may involve complex land use changes. The most striking change was a 158.82% increase in settlements, reflecting rapid urbanization and infrastructure development. Wetlands expanded by 4.62%, possibly due to both natural fluctuations and human interventions. These changes signify the intricate interplay between human activities and natural factors, highlighting the need for informed land management strategies to ensure sustainable development in the region by using remote sensing images and Object Based Image Analysis (OBIA) techniques the changes in LULC can be examine. OBIA uses image segmentations on the basis of scale, colour, form compactness and smoothness. The research is an effort to apply OBIA and classification techniques to Landsat satellite images to detect the changes in LULC in Kaghan valley with range of observation of 4 years i.e., 2004 to 2008 and 2012.

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Keywords | Kaghan valley, Land use land cover (LULC), Urbanization Forest degradation, Land use change, Remote sensing, Object-based image classification, Landsat satellite images, Object-based image analysis (OBIA), Land use/land cover change (LULCC), Biodiversity loss, Atmospheric corrections, Maximum likelihood Zalgorithm, Multiresolution segmentation, Sustainable development planning

Introduction

Land Use/ Land Cover (LULC) is the physical composition and characteristics (e.g., grass, forest, and impervious surfaces) or human-related activities (e.g., residential, commercial, and transportation) of land elements on the earth's surface (Cihlar, 2000).

The modification of Earth's terrestrial surface by human activities is commonly known as Land use/ land cover change (LULCC) around the globe. Although modification of land by humans to obtain livelihoods and other essentials has been there for thousands of years, the extent, intensity and rate of LULCC are far greater now than were in the past. (Hassan *et al.*, 2016)

Land use/land cover (LULC) changes play a major role in the study of global change. Deforestation biodiversity loss global warming, increase of natural degradation processes i.e., flooding are largely the outcomes of land use/land cover, anthropogenic and natural modifications (Mas *et al.*, 2004; Zhao *et al.*, 2004; Dwivedi *et al.*, 2005).

To alleviate these problems, long-term dense monitoring of land use and land cover (LULC) change is of crucial important, because it provides essential information for depicting the history, current situation and future of LULC change, and for understanding biogeochemical processes and the mechanisms of LULC changes (Jinquan *et al.*, 2020) (1 to 9) at 15-, 30- and 60-meter resolution. Thermal Infrared Sensor (TIRS) consists of 2 thermal bands with a spatial resolution of 100 meters).

Study area

Kaghan valley is in Mansehra District of the Khyber Pakhtunkhwa (KPK) Province with the altitude of 2039 m, latitude and longitude is 34° 54' 27" North, 73° 38' 56" East. Figure 1. The valley is at the distance of 37 km north-east of Mansehra City. The valley is 161 km long starting from Balakot city, and covers a total area of 1735 km sq. The altitude of the area ranges from 915 m at Balakot city (the Gateway to the Kaghan Valley situated on the main road between Mansehra and the Babusar Pass) to 5280 m at Malika Parbat called 'Queen of the Mountains (Hussain *et al.*, 2006).

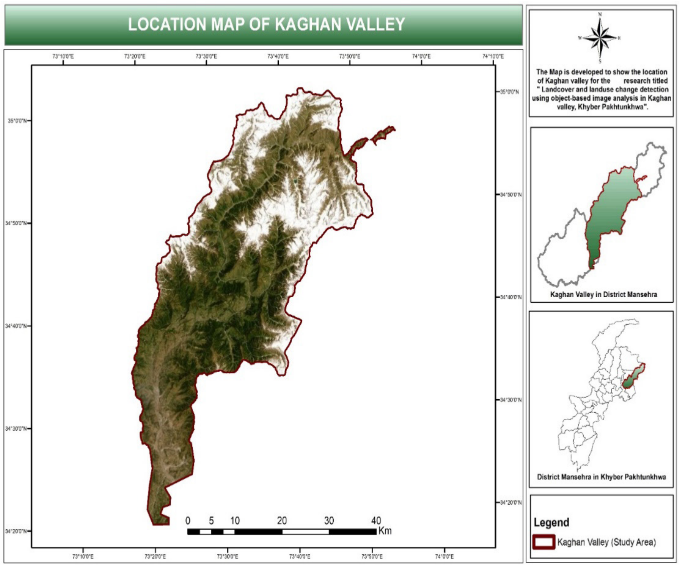

Figure 1: *Study area map.*

Table 1: *LULC area in hectares and percentage in year 2004.*

LULC of Kaghan valley in 2004		
LULC	**Area in hectares**	**Percentage%**
Cropland	11811	6.86
Forest land	64760	37.61
Grassland	36435	21.16
Other land	65137	37.83
Settlements	425	0.25
Wetland	650	0.38

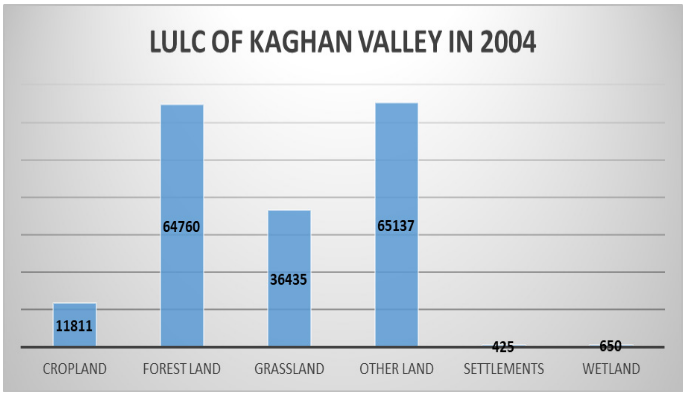

Figure 2: *LULC 2004.*

Materials and Methods

Satellite data acquisition

Orthorectified Landsat 7 and Landsat 8 satellite imageries of 2004, 2008 and 2012 (with cloud cover of less than 10 percent) were acquired for land use land cover classification. Landsat satellite imageries are freely available and have a good temporal (16 days) and moderate spatial resolution (30 metre) (Sory *et al.*, 2018).

Links Researchers

Table 2: *LULC area in hectares and percentage in year 2008.*

LULC of Kaghan valley in 2008		
	Area in hectares	**Percentage%**
Cropland	11719	6.81
Forest land	63251	36.73
Grassland	37256	21.64
Other land	65610	38.10
Settlements	710	0.41
Wetland	672	0.39

Image pre-processing and classification

Satellite image pre-processing prior to the detection of change is immensely needed and has a primary unique objective of establishing a more direct affiliation between the acquired data and biophysical phenomena (Coppin *et al.*, 2004). The data acquired from the USGS was corrected for reflectance, unregistered pixels, and atmospheric corrections before training the samples in ArcGIS environment. Then using signature file creation tool, six classes of LULC were developed i.e., water bodies, residential area, uncultivated crop land, cultivated crop land, forest, barren land. After that maximum likelihood algorithm was used for supervised classification of the images. It is the type of image classification which is mainly controlled by the analyst as the analyst selects the pixels that are representative of the desired classes. To improve classification accuracy and reduction of misclassifications, post-classification refinement was therefore used for simplicity and effectiveness of the method (Harris and Ventura, 1995). The problem of mixed pixels was addressed by visual interpretation. For the enhancement of classification accuracy and therefore the quality of the land cover/land use maps produced, visual interpretation was very important. Thus, visual analysis, reference data, as well as local knowledge, considerably improves the results obtained using the supervised algorithm.

Image processing and interpretation

The eCognition software was used for the segmentation/classification purposes as it performs an automatically processing segmentation of the imagery. This results in a condensing of information and a knowledge-free extraction of image objects in the form of proposed land-use classes. The formation of the objects is carried out in a way that an overall homogeneous resolution is kept. The segmentation algorithm does not only rely on the single-pixel value but also pixel spatial continuity (texture, topology). The organized images objects carry not only the value and statistical information of the pixels of which they consist but also information on texture and shape as well as their position within the hierarchical network (Humano, 2000; Manakos, 2001)

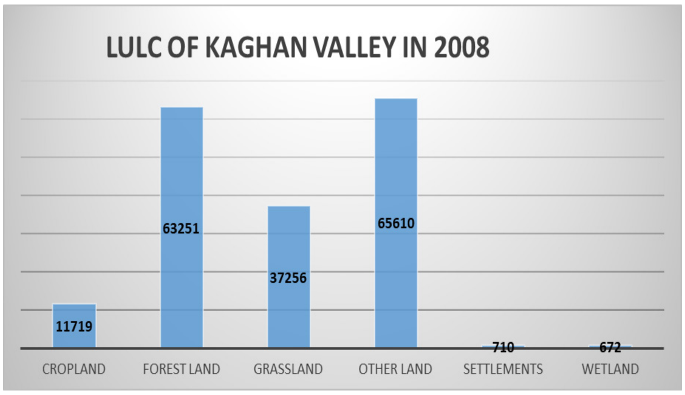

Figure 3: *LULC 2008.*

Table 3: *LULC area in hectares and percentage in year 2012.*

LULC of Kaghan valley in 2012		
LULC	**Area in hectares**	**Percentage%**
Cropland	10188	5.92
Forest land	61328	35.62
Grassland	37142	21.57
Other land	68780	39.94
Settlements	1100	0.64
Wetland	680	0.39

Keeping in view the global acceptance and reliability of Object-Based Image Analysis (OBIA), it is preferred to follow the OBIA approach. As the pixel-based image analysis relies only on the spectral information without taking into account the spatial information of the objects. Object-oriented approach is preferred because, it also takes into account the form, textures and spectral information of the objects of the scene beside the spatial information.

OBIA or Object-Oriented Classification (OOC) approach consists of two types of processes:

Segmentation: It consists of image separation into objects/ segments (groups of homogenous pixels).

Classification: It is the identification of objects depending on their attributes/characteristics/ features Classification process is based on the intrinsic values which include spectral properties, texture, shape etc. and relationships among objects which include connectivity, position to other objects.

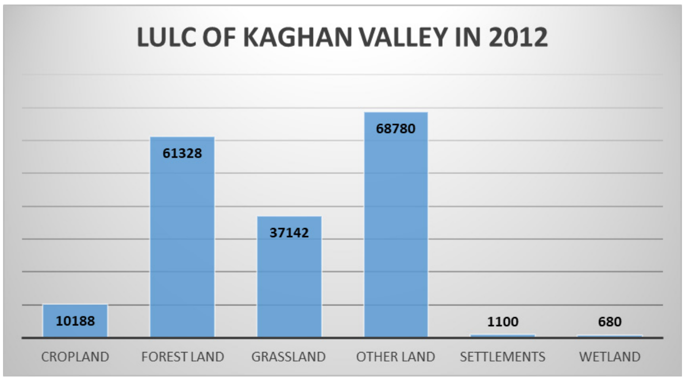

Figure 4: *LULC 2012.*

Table 4: *LULC change from year 2004 to 2008.*

LULC change in Kaghan valley 2004-2008			
	2004	**2008**	**Difference/ Change**
	Area (Ha)	**Area (Ha)**	
Cropland	11811	11719	-92
Forest land	64760	63251	-1509
Grassland	36435	37256	821
Other land	65137	65610	473
Settlements	425	710	285
Wetland	650	672	22

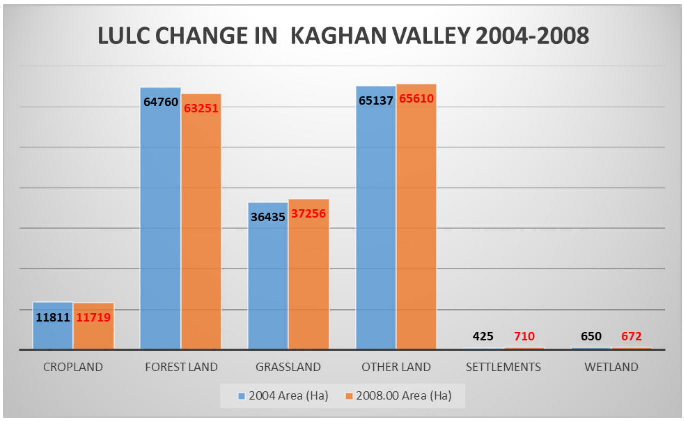

Figure 5: *LULC change from year 2004 to 2008.*

Table 5: *LULC change from 2008 to 2012.*

LULC change in Kaghan valley 2008-2012			
LULC	**2008**	**2012**	**Difference/ Change**
	Area (Ha)	**Area (Ha)**	
Cropland	11719	10188	-1531
Forest land	63251	61328	-1923
Grassland	37256	37142	-114
Other land	65610	68780	3170
Settlements	710	1100	390
Wetland	672	680	8

Segmentation approach

The eCognition developer 9 with quick map mode technique under bottom-up optimization process/ multi-resolution segmentation algorithm was applied. There are five types of Segmentation algorithms in eCognition i.e., (i) chess board segmentation, (ii) quad-tree based segmentation, (iii) multiresolution segmentation, (iv) spectral difference segmentation and (v) contrast split segmentation. Out of these five, multiresolution segmentation was selected for the mapping of the landuse classes. Multiresolution segmentation works on the principle of heterogeneity and homogeneity i.e., the output of the homogeneous areas result in larger objects and heterogeneous areas in smaller one. Different landuse classes were described in class hierarchy with specific colour combinations.

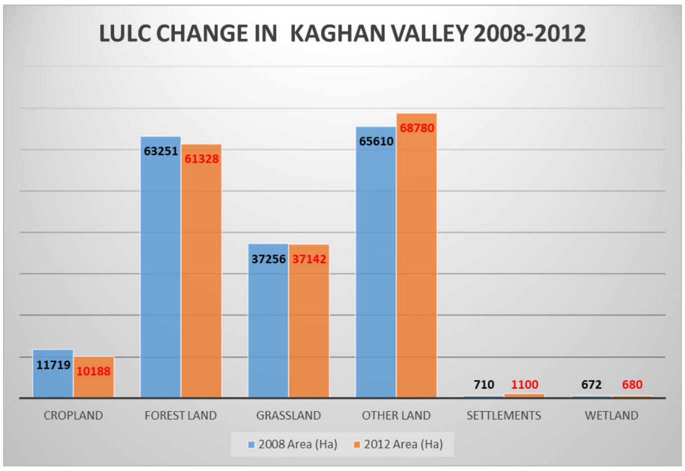

Figure 6: *LULC change from 2008 to 2012.*

Table 6: *LULC change from 2004 to 2012.*

LULC change in Kaghan valley 2004-2012			
LULC	**2004**	**2012**	**Difference/ Change**
	Area (Ha)	**Area (Ha)**	
Cropland	11811	10188	-1623
Forest land	64760	61328	-3432
Grassland	36435	37142	707
Other land	65137	68780	3643
Settlements	425	1100	675
Wetland	650	680	30

Training areas were selected randomly from the images as a sample to classify the entire for different landuse classes. Image segmentation provided spatially continuous and spectrally homogenous layer of polygons/image objects. These polygons/ image objects act as the building blocks for the subsequent image analysis. In comparison to pixels, image objects carry much more useful information. Thus, they can be characterized by far more properties such as form, texture, neighborhood or context, than pure spectral or spectral derivative information (Baatz *et al*., 2000). Each polygon represents areas with similar pixel values with respect to some characteristics such as colour, intensity or texture. This classified layer of polygons with attribute tables were exported to ArcGIS for further mapping procedures. Parameters applied in Multiresolution segmentation was, Scale: 15-30, Shape: 0.1, and Compactness 0.9. Scale is the most important parameter and affects the relative size of output polygons. Number of segment/polygons increase with the increasing value of scale. Image object hierarchy was defined followed by creation of class hierarchy. Over all six classes was assigned to the classified segments. Visual control and refinement of the digital classification was done. Accuracy assessment was done on confusion matrix.

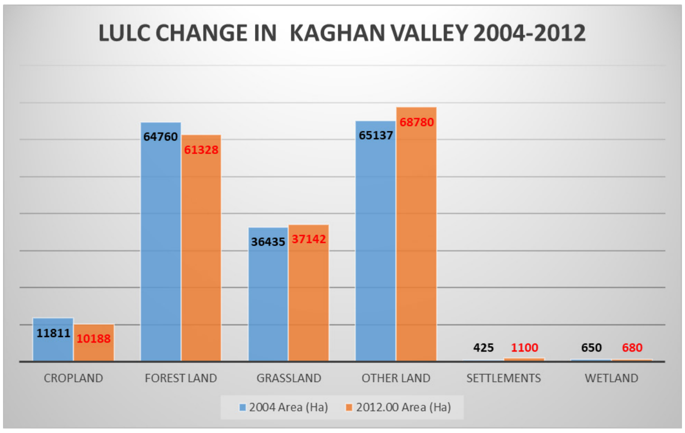

Figure 7: *LULC change from 2004 to 2012.*

Classes for landuse mapping

The images were classified into six landuse classes as per IPCC (Intergovernmental Panel on Climate Change) guidelines (Good Practice Guidance for Land Use, Land-Use Change and Forestry, 2003). These classes include the following:

Forest land: Includes all land with woody vegetation consistent with thresholds: Minimum area 0.05 ha; canopy cover more than 10%; minimum tree height 2 m at maturity.

Cropland: includes arable and tillage land, and agro-forestry systems where vegetation falls below the thresholds used for the forest land category, consistent with the selection of national definitions.

Grassland: includes rangelands and pasture land that is not considered as cropland.

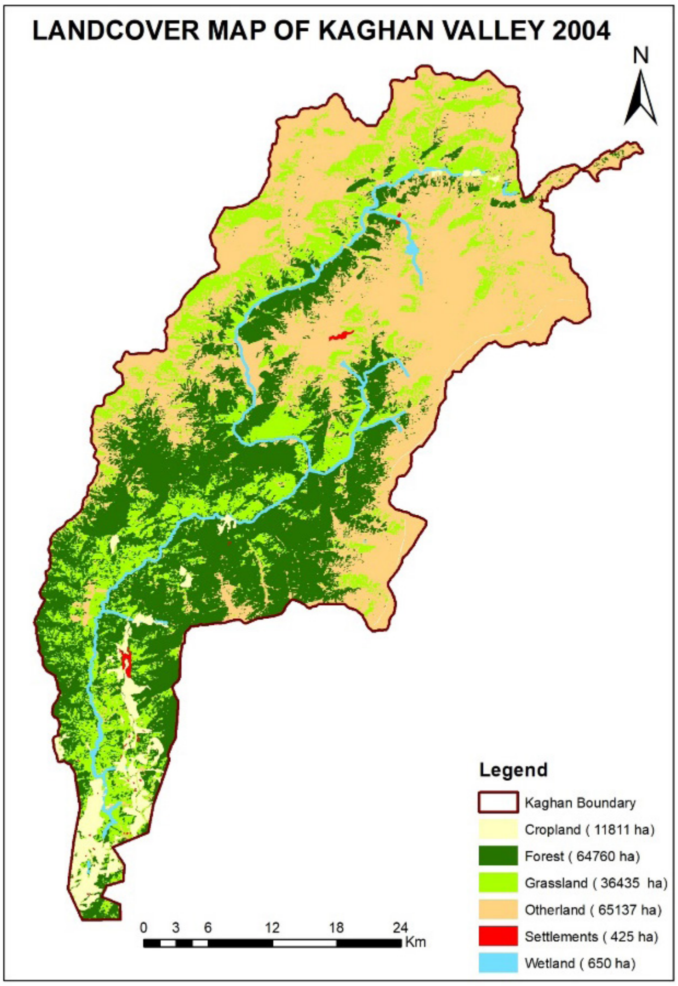

Figure 8: *LULC map 2004.*

Wetland: includes land that is covered or saturated by water for all or part of the year (e.g., peatland) and that does not fall into the forest land, cropland, grassland or settlements categories.

Settlements: include all developed land, including transportation infrastructure and human settlements of any size, unless they are already included under other categories.

Other land: includes bare soil, rock, ice, and all unmanaged land areas that do not fall into any of the other five categories.

Results and Discussion

The acquired results shows that the landuse in the study area has changed up to a great deal due to different natural and anthropogenic activities (as shown in the maps Figure 8, 9 and 10). The outcomes show the change in different landuse landcover classes. The change observed are as follows.

The transformation of landscapes and the altering distribution of land use over time can provide valuable insights into the complex interplay between human activities and environmental factors. The examination of changes in the Land Use Land Cover (LULC) categories in Kaghan Valley between 2004, 2008 and 2012 reveals notable shifts that reflect both natural processes and anthropogenic influences as shown in Table 1, 2 and 3.

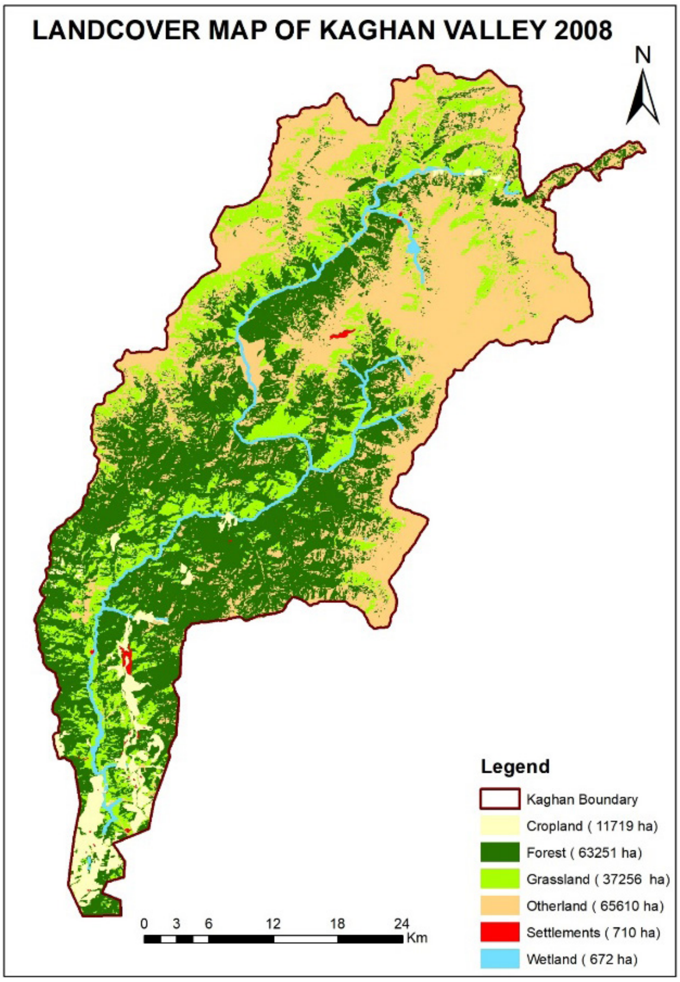

Figure 9: *LULC map 2008.*

Cropland: The cropland area witnessed a decrease of approximately 13.72% during the eight-year period. This reduction is attributed to a variety of factors such as urbanization, expansion of settlements, and changes in agricultural practices. The conversion of cropland to settlements or infrastructure also has contributed to the decline.

Forest land: The forest land area experienced a decline of overall 5.30% between 2004, 2008 and 2012 (Figure 4, 5 and 6). This decrease suggests potential deforestation, logging, or land conversion for other purposes like agriculture or development. The reduction in forest land could also be influenced by climate changes, illegal logging, or the expansion of human activities into previously forested areas.

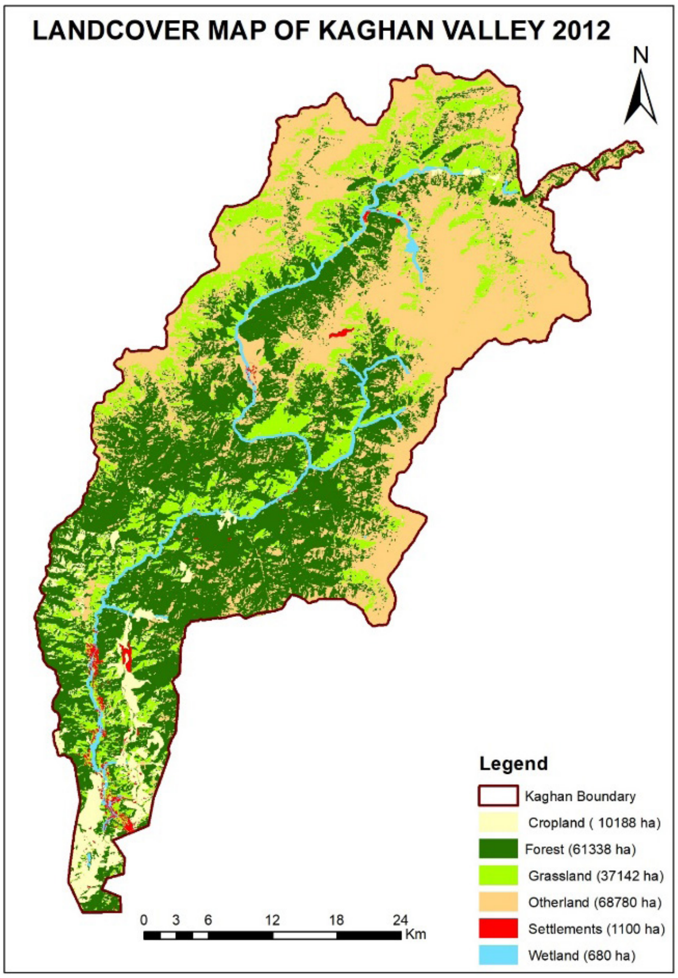

Figure 10: *LULC map 2012.*

Grassland: A modest increase of approximately 1.94% was observed in the grassland area during the study period. This change may have been caused by natural processes or changes in land management. Previously abandoned agricultural fields or underutilized land could have transitioned to grassland cover over time.

Other land: The category "Other Land" exhibited an increase of around 5.59% in area. This expansion might involve changes in land use that do not neatly fit into conventional categories. Alterations in water bodies, changes in land classification, or wetland reclamation could be contributing factors to this change.

Settlements: The most substantial change occurred in the settlements category, with an increase of approximately 158.82%. This drastic expansion points towards rapid urbanization and population growth in the region. The construction of new housing, infrastructure, and commercial areas likely drove the significant increase in settlement areas.

Wetland: Wetland area expanded by around 4.62% during the study period. This change might be influenced by natural variations in water levels, as well as human interventions aimed at wetland restoration or habitat protection.

In conclusion, the analysis of LULC changes in Kaghan Valley from 2004 to 2012 underscores the dynamic nature of landscapes (Figure 8, 9 and 10). These shifts result from a combination of natural processes and human activities. Urbanization, agricultural practices, deforestation, and conservation efforts all contribute to these changes. Understanding the reasons behind these changes is vital for informed land management decisions and sustainable development planning in the region.

Conclusions and Recommendations

The study's key findings highlight substantial transformations in land use within the Kaghan Valley due to a blend of natural forces and human actions. Over the period from 2004-2008-2012, various land use categories exhibited notable changes (Figure 7). Cropland and forest areas saw decreases, likely influenced by urbanization, settlements, and shifting agricultural practices. Conversely, grassland and "Other Land" areas experienced moderate increases, potentially due to natural shifts or altered land management. The most remarkable shift occurred in settlement areas, reflecting rapid urbanization and population growth. Wetlands also expanded, driven by both environmental dynamics and human interventions. Overall, these findings emphasize the intricate relationship between human activities and environmental processes, underscoring the importance of informed land management strategies for sustainable development.

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Novelty Statement

Kaghan valley holds a huge share of national reserved forest thus contribute in the national GDP with its tremendous potential of Tourism. The use of OBIA in land use land cover change detection of Kaghan valley will provide a base line data for the sustainable land use of the valley

Author's Contribution

Aamir Shakeel: Concieved and designed the analysis and supervised the whole research work.
Anwar Ali: Helped in writing and structuring the research paper.
Tahir Iqbal: Assisted the research work and mapping activities done for this research.
Ziad Raza: Collected the data performed the Analysis and produced the map and final draft of this paper

Conflict of interest

The authors have declared no conflict of interest.

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63
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