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Land Cover Classification of Ucchali Wetlands Complex and Assessment of its Correlation with Temporal Climatic Changes

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Abstract: Despite the inherent dynamic system of wetlands, ecosystems are suffering from great transformations worldwide. The diverse and pervasive threats to wetlands point the need for comprehensive monitoring efforts, thus, to visualize, identify and analyze the change and impacts of change on the ecosystem services delivered by the wetland. Therefore, the present study was conducted to study the spatio-temporal variation of Land Use Land Cover (LULC) in the Ucchali Wetlands Complex (UWC). Geographic Information System (GIS) and Remote Sensing (RS) techniques added simplification and visualization by integrating multiple datasets. Five major classes were delineated (forest, agriculture, water, built-up and barren) and LULC maps, overlay maps and area shift maps were generated. The change in second half of the period was more dynamic as compared to first half. This suggested that the pattern of change and utilization of natural resources in Ucchali Wetlands Complex has been raised. Moreover, the Pearson Correlation Coefficient (PCC) analysis of land use features relative to climatic variables assisted in strengthening the results of the study by giving a clear representation of variations in terms of positive and negative changes. The results concluded that the situation requires concerted efforts instead of perfunctory actions for protection, conservation and minimization of unconstructive impact on this invaluable wetland ecosystem.

Key words: Wetland complex, LULC change, Land cover classification.

INTRODUCTION

Land use and land cover (LULC) is an integrated term, used to describe the terrestrial environment in reference to both natural as well as anthropogenic activities (Iqbal and Khan, 2014). LULC change analysis has emerged as an important research question because it plays a key role in modification of environment worldwide (Zhang *et al.*, 2011). Change detection is a process to identify and quantify the differences in LULC by observing it at different time scales (Butt *et al.*, 2015). To assess the spatiotemporal dynamics of change, GIS (Geographic Information System) and RST (Remote Sensing Technologies) have become valuable, well recognized, cost effective and time saving tools (Ahmad and Erum, 2012). It is very important to have precise, continual and periodic LULC change information for effective management of natural resources and adaptation of sustainable development program (Butt *et al.*, 2015).

LULC profoundly affects climate and vice versa. Climate variability and its vulnerability to ecosystem generate an ever-increasing demand to study patterns and impacts of LULC change in relation to climate (Salazar *et al.*, 2015).

Wetlands play an integral role in ecosystem functioning in terms of minimizing floods, recharging groundwater and provision of habitat to diverse flora, and fauna (Zorrilla *et al.*, 2014). Various stress factors, such as, climate change, urbanization, agricultural practices and deforestation, accelerate changes in wetland. These changes may be due to area fragmentation, ecological degradation, flora and fauna extinction or area shrinking, etc. (Zhang *et al.*, 2011). This all, in turn, has a profound impact at regional basis in terms of changes in climate, geology, hydrology, biodiversity and so on. An understanding of worldwide land status points toward the need to study LULC details of the wetland area at regular intervals to maintain its international status as Ramsar site and supports globally threatened wildlife.

In order to detect spatial and temporal LULC change, various GIS and RS tools and algorithms have been used widely both at national as well as international level. Out of all the methods, the study of multi-time RS images and then pre- and post classification comparison of these images is the most extensively used technique (Fan, 2008). However, this approach has its limitations in terms of accuracy, which depends on the Producers Accuracy (PA) and Consumers Accuracy (CA). Nevertheless, this

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technique can generate 'from-to' maps, which explain nature and the magnitude of change (Gao *et al.*, 2016). Many studies, addressing change in LULC, focus on wetland areas that are particularly of international importance. For this purpose, this study aims to analyze spatio-temporal land cover/land use changes in internationally important Ramsar Wetland Complex in Pakistan by applying change detection algorithm with the use of RS in combination with GIS. Moreover, it also evaluates and correlates the impact of land cover conversions with temporal climatic alterations.

Study area: Ucchali wetlands complex, a combination of three independent wetlands, Khabeki, Ucchali and Jahlar, is located in the salt range of north central Punjab, Pakistan. The complex is a Ramsar site, declared in 1996, and is a habitat to globally threatened waterfowl and endemic and endangered species of the country. With an elevation of 700-979 m, the entire study area covers an area of 745 km^2 and lies between 32° 29' to 32° 37' North latitude and 72° to 72° 15' East longitude (Fig. 1).

The area has sub-humid and sub-tropical climatic conditions with severe winter and hot to moderate summer. An average precipitation, reported for thirty years, was 855 mm, and the annual rainfall varies from 300 to 800 mm, while, relative humidity ranges from 23 to 86% (Arshad, 2011). The prevailing habitat in the area is dry sub-tropical, semi-evergreen scrub forest (Roberts**,** 1992). The level of industrial development is low, agricultural activity is very high and the principal crops, grown in the area, are vegetables in the summer and wheat in winter.

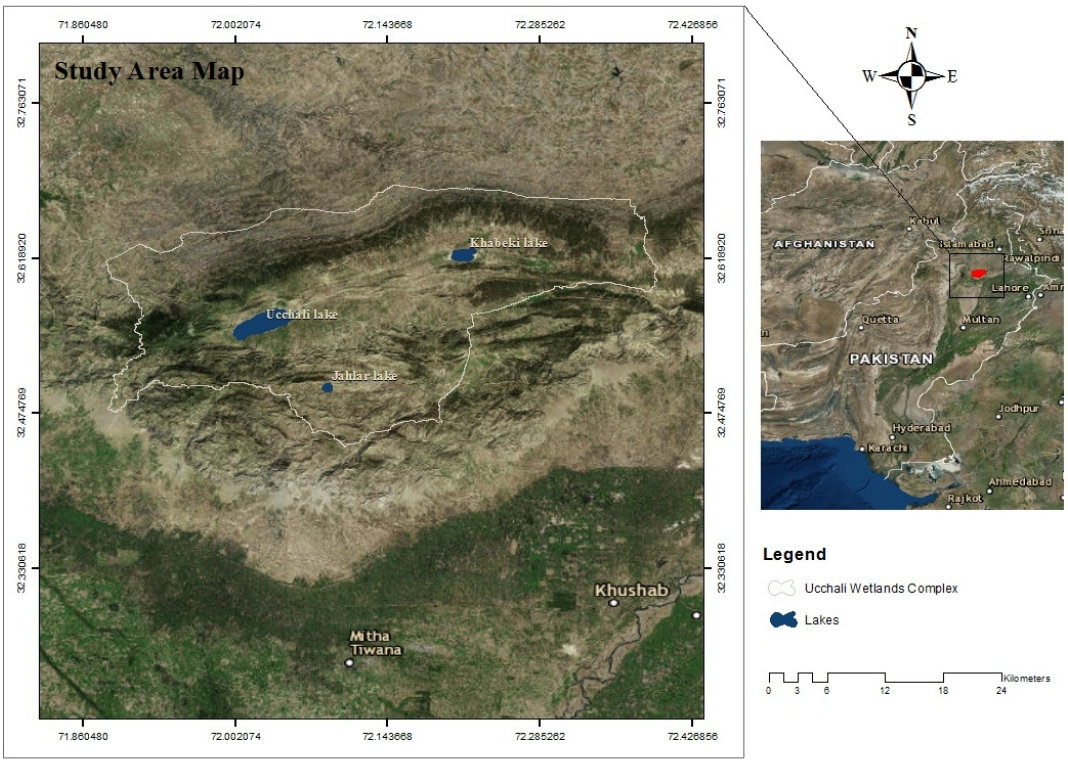

Fig. 1: Study area map.

MATERIALS AND METHODS

Data collection: For LULC change analysis, satellite imagery for the years 1990, 2003 and 2015, of Landsat 5 TM, 7 ETM and 8 OLI for the month of May, having zero cloud cover, was acquired from USGS Glovis archive and downloaded via Earth Explorer.

In addition, climatic data was employed in this research for the purpose of change analysis. The data obtained covered a period of 1990 to 2015 and included four metrological parameters, i.e., minimum and maximum temperature, rainfall, humidity and precipitation. Metrological data of Chakwal station was obtained from Pakistan Metrological Department (PMD).

LULC classification: For classifying the obtained image with maximum accuracy, the supervised classification, using Maximum Likelihood Algorithm (MLH), was used (Peter and Michael, 2003; Butt *et al.*, 2012; Iqbal and Khan, 2014; Butt *et al.*, 2015), which resulted in delineation of five classes (Table 1). Accuracy assessment was later performed to check quality of classified image by confusion/error matrix (Iqbal and Khan, 2014) and Kappa statistics (Gwet, 2002; Mather, 2004; Jensen, 2005). A total of 250 test pixels were used, following equalized random distribution pattern for determining classified images accuracy using ERDAS imagine 2011.

Table 1: LULC classification categories.

Class	Description
Forest	All the naturally growing vegetation either thick closely spaced trees with dense canopy or small dwarf trees, including herbaceous and shrubby vegetation.
Agriculture	Includes all agricultural areas, which are cultivated by humans.
Water	Includes all the water bodies, i.e., lakes, open water , streams, etc.
Barren	Bare or sparsely vegetated areas, mainly exposed soil or rock and dry lake beds.
Built-up	Artificially surfaced and built-up areas, including rural settlements, roads, residential and commercial structures, etc.

Change detection analysis: For change detection analysis of classified images, a post classification comparison was performed in ArcGIS 10.2. Area loss, gain or the area remained same was assessed.

RESULTS AND DISCUSSION

Image classification: Three landsat datasets through supervised classification technique led to the creation of five land cover classes, viz., water, forest, agriculture, barren and built-up (Fig. 4). The total area occupied by these classes came out to be 744.92 km^2.

Referring to the results in Fig. 2, the largest class in 1990 was forest, covering 68% with total area coverage of 506.65 km^2. Second major class was barren, which accounted for 27% (198.11 km^2) of total area, whilst the remaining area constituted of agriculture, water and built-up covering 27.73 km^2 (4%), 9.95 km^2 (1%) and 2.32 km^2 (0.3%) area, respectively. The percentage graph (Fig. 3) for 2003 LULC map revealed that forest, agriculture, water, barren and built-up encompassed 461.59 km^2 (62%), 233.6 km^2 (31%), 37.99 km^2 (5%), 6.83 km^2 (0.9%) and 4.7 km^2 (0.6%) of area, respectively. In 2015, the forest decreased to an area of 388.01 km^2, while agriculture class tripled to 145.26 km^2 thus becoming one of the major and prominent class of the complex, followed by barren (195.9 km^2), whereas, water and built-up occupied 2% of the total area.

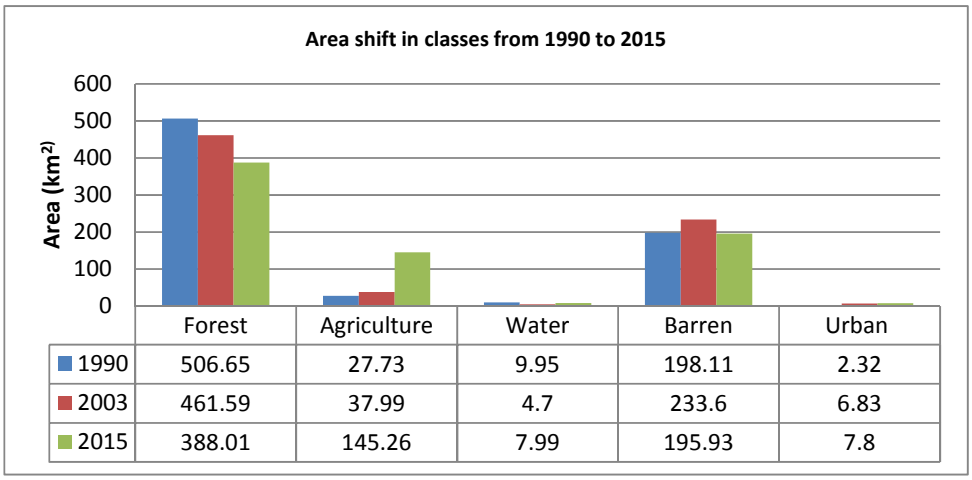

Fig. 2: Area change in each class.

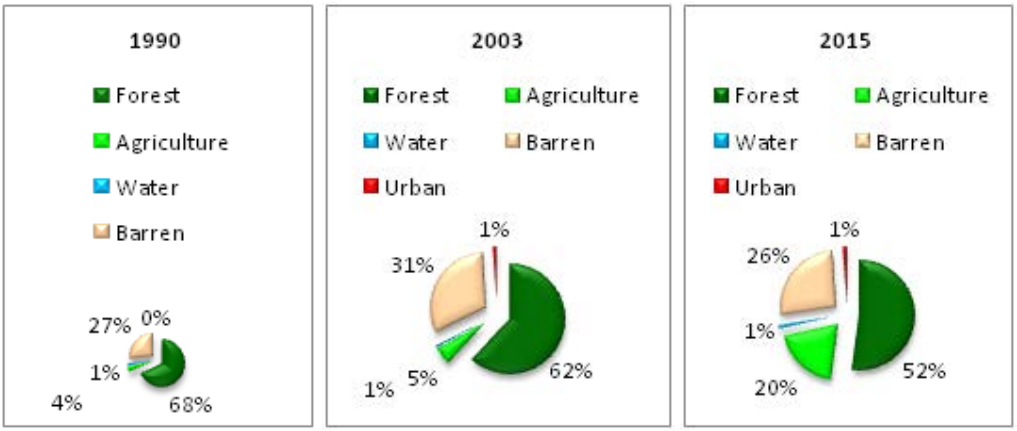

Fig. 3: Area percentage of each class.

The land use change for the two sub periods, as shown in Table 2, represents the change in second half of the period, is more dynamic, as compared to first half. This suggests that pattern of change and utilization of natural resources in Ucchali complex has been raised. The decrease of forest cover per

annum doubled in second half of the period, while an increased rate of agricultural activity was observed. In addition, water decreased from 1990-2003, leading to an increase in the barren land, while the situation reversed during a decade (Fig. 4).

Table 2: LULC change from 1990 to 2015.

Class Type	Area (km^2)			Annual average change (km^2/year)		
	1990	2003	2015	1990-2003	2003-2015	1990-2015
Forest	506.65	461.59	388.01	– 3.47	– 6.13	– 2.94
Agriculture	27.73	37.99	145.26	0.79	8.94	4.70
Water	9.95	4.7	7.99	– 0.40	0.27	– 0.08
Barren	198.11	233.6	195.93	2.73	– 3.14	– 0.09
Built-up	2.32	6.83	7.8	0.35	0.08	0.22

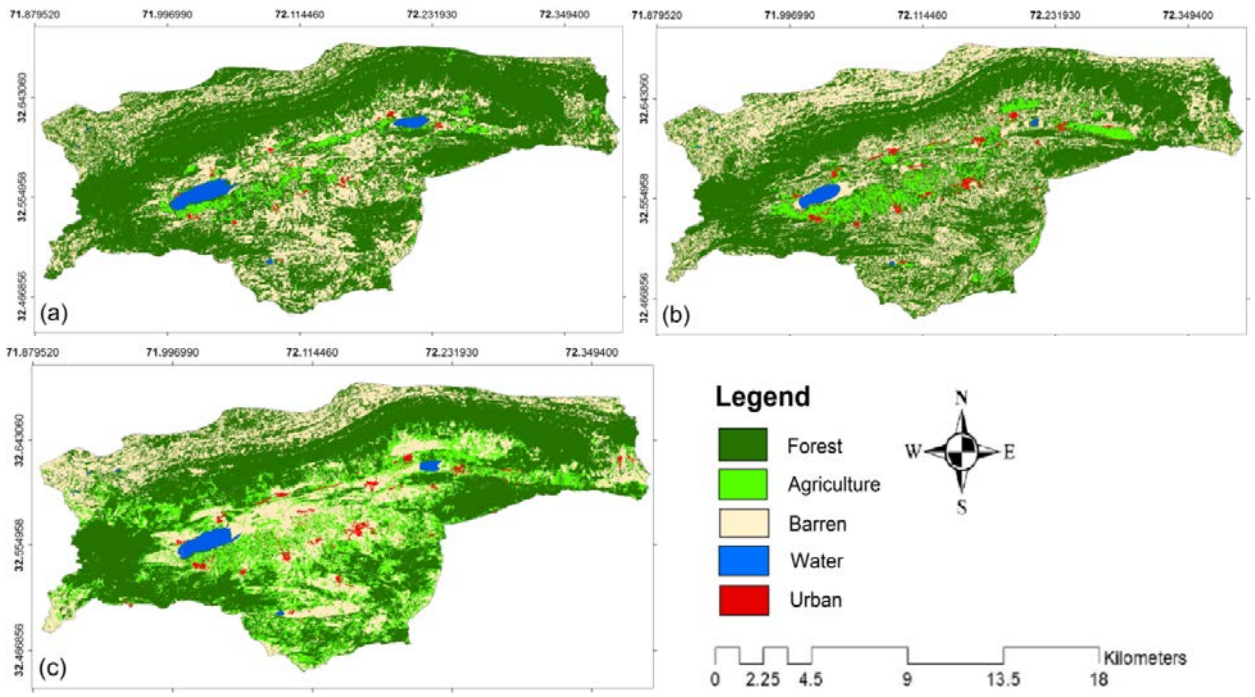

Fig. 4: Land use Map of Ucchali Wetlands Complex for the year (a) 1990, (b) 2003, (c) 2015.

Accuracy assessment: The overall accuracy from three Landsat data sets of 1990, 2003 and 2015 appeared to be 94%, 93.6% and 92.8%, respectively, whereas, the results for Kappa statistics turned out to be 0.9250, 0.9200 and 0.9100 (Table 3). Hence, as recommended by Lea and Curtis (2010), the accuracy level is in agreement with the set standards.

Table 3: Classification accuracy assessment using Confusion matrix.

	1990	2003	2015
Overall classification accuracy (%)	94.00	93.60	92.80
Overall Kappa statistics	0.9250	0.9200	0.9100

LULC change detection: In 1990, the forest covered an area of 506.65 km^2, thus representing almost 70% of Ucchali wetlands complex (Fig. 3). With an average annual decrease of 3.47 km^2, the forest occupied 461.59 km^2 in 2003. Furthermore, after total loss of 118.4 km^2 ever since the forest cover became 388.01 km^2 in 2015 (Fig. 5a). On the other hand, agriculture area showed a rapid increase over a period of 25 years. Even the lake beds were cultivated with crops. The abrupt agriculture area has been increased from 27.73 km^2 in 1990 to 145.26 km^2 in 2015 (Fig. 5b). Area calculation indicated that water covered an area of 9.95 km^2 in 1990. While in 2003, the water decreased to 4.7 km^2 and contrarily in 2015, it retained back with an area coverage of 7.99 km^2 (Fig. 5c). However, the overall percentage contribution of water to class cover has remained approximately constant throughout a quarter of a century (Fig. 3). It may be inferred that the built-up has increased over the years but its contribution to overall area has increased at minimal rate. Representing 2.32 km^2 in 1990, 6.83 km^2 in 2003 and 7.8 km^2 in 2015, built-up had a relative change of 5.48 km^2 ever since (Fig. 5e).With an area coverage of 198.11 km^2 in 1990, the barren area increased up to 233.6 km^2 in 2003; this was mainly because of decrease in water cover, which exposed the bare soil at the bed of lakes. Nevertheless loss of barren area has led to an area coverage of 195.95 km^2 in 2015 (Fig. 5d).

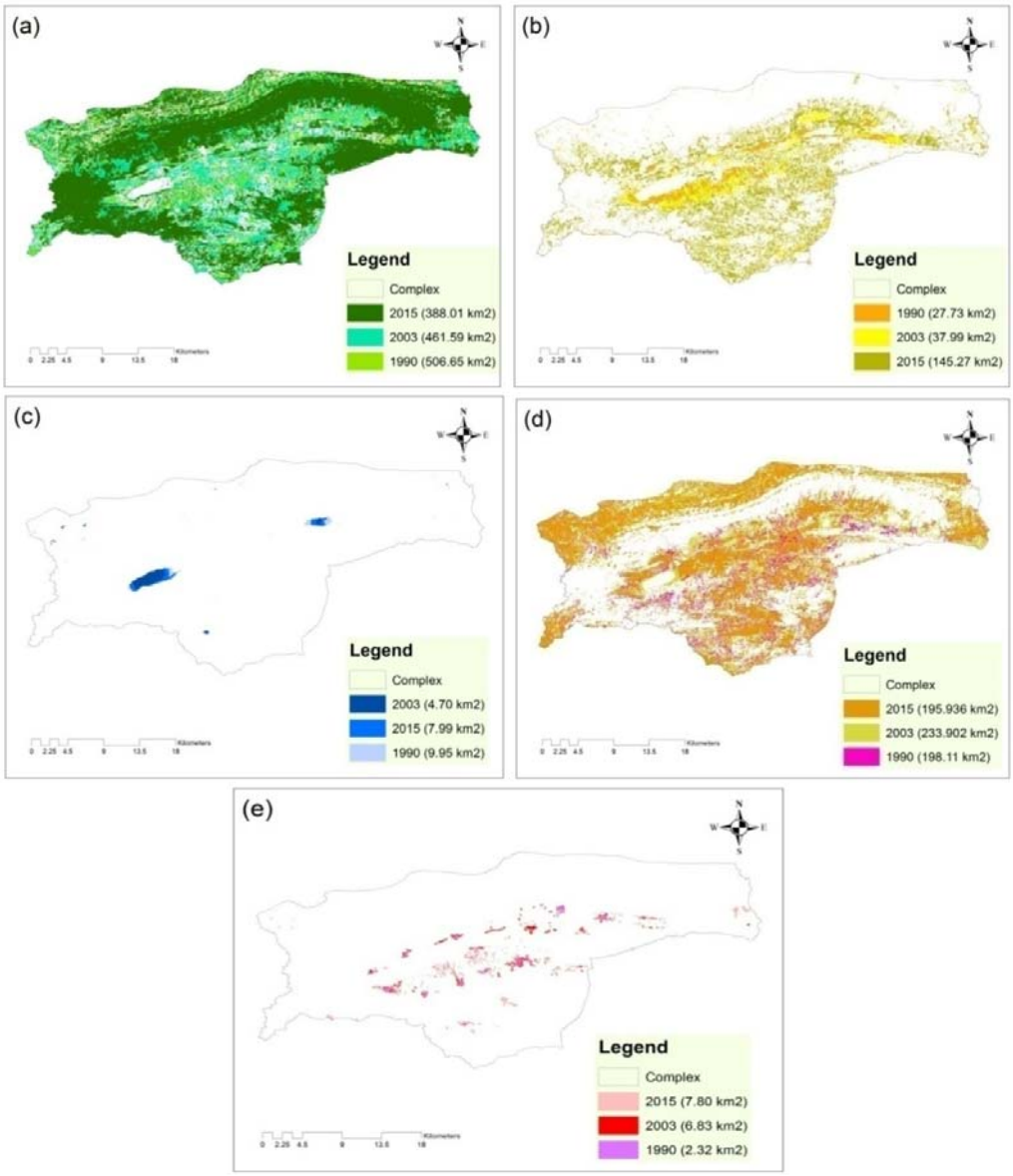

Fig. 5: Land use change map of (a) Forest (b) Agriculture (c) Water (d) Barren (e) Built-up from 1990-2015.

Post classification comparison: Shift maps from 1990-2003 (Fig. 6) and 2003-2015 (Fig. 7) were produced for post classification comparison to comprehend 'from-to' class shift information. Apart from spatiotemporal map, statistical cross tabulation was also conducted to depict the class shift areas in km^2 during the respective time period.

During the first half of the study period (1990-2003), a major class shift from forest to barren class has taken place, which is 118 km^2, whereas certain barren land has also been shifted to forest class, i.e., 79.66 km^2. The shift of forest to agriculture was 17.4 km^2, whereas from agriculture to forest, it was 12.21 km^2, which almost negates the shift. Besides, there was also a prominent shift of 10.5 km^2 from barren to agriculture and vice versa, i.e., 5.5 km^2. The quantification of LULC shift for the analyzed categories is given in Table 4.

During the second half of the studied period (2003-2015), a major class shift pertained from forest to barren and forest to agriculture. Other major shifts pertaining to the area were barren to forest and barren to agriculture. The rest comparatively minor class shifts are tabulated in Table 5.

Table 4: Cross tabulation of LULC from 1990 to 2003.

1990	**2003**				
	Forest	**Agriculture**	**Water**	**Barren**	**Built-up**
Forest	**368.6**	17.4	0.1	118	1.4
Agriculture	12.21	**10.1**	0	5.5	0.5
Water	1.756	0.03	**4.6**	3.5	0.2
Barren	79.66	10.5	0	**106**	2.7
Built-up	0.063	0.05	0	0	**2.2**

Table 5: Cross tabulation of LULC from 2003 to 2015.

2003	2015				
	Forest	**Agriculture**	**Water**	**Barren**	**Built-up**
Forest	**306**	72	1	81	0.8
Agriculture	5.3	**16**	0	17	0.2
Water	0	0.1	**4.7**	0	0
Barren	76	57	2.3	**97**	0.8
Built-up	0.1	0.3	0	0.4	**6**

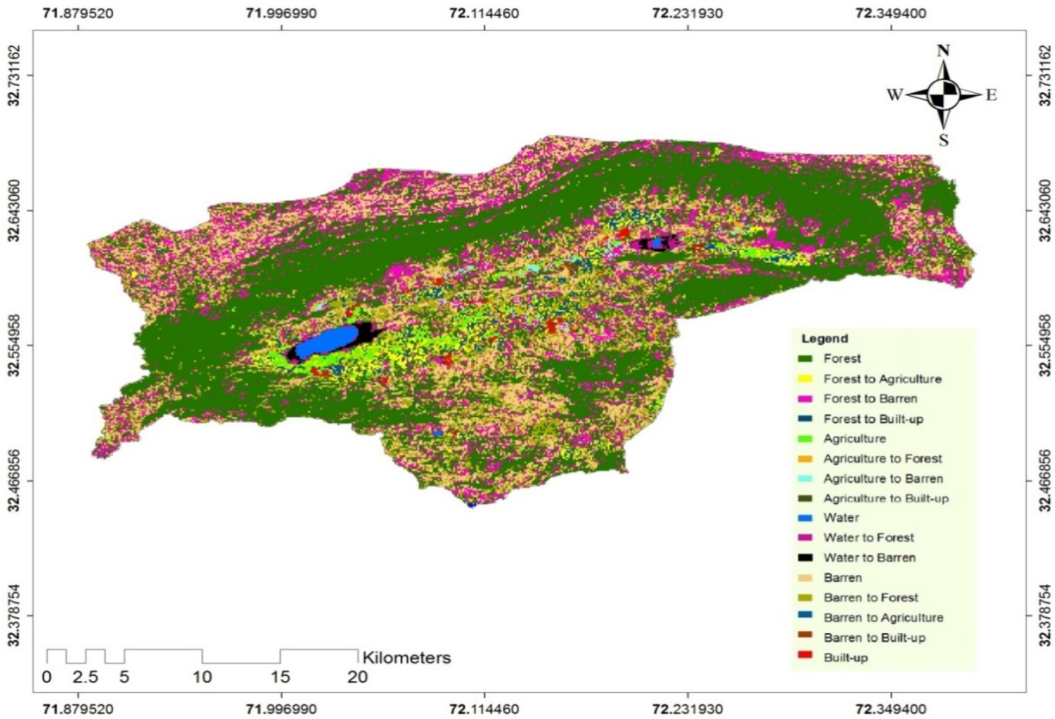

Fig. 6: Area shifting map (1990-2003).

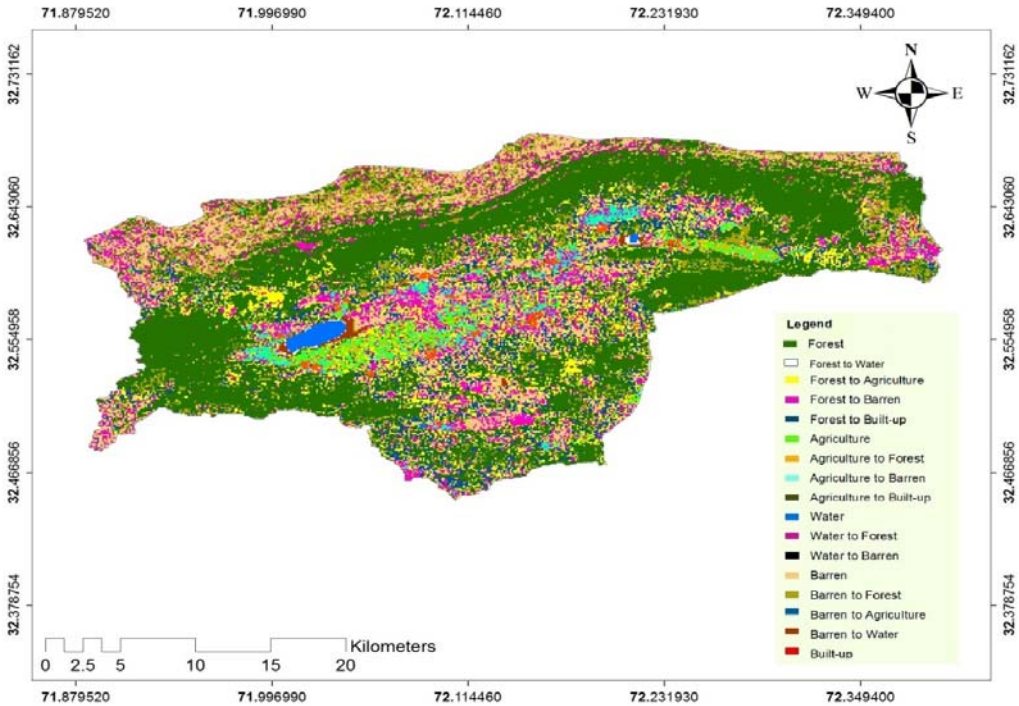

Fig. 7: Area shifting map (2003-2015).

LULC detection and analysis: While performing LULC change analysis few limitations were also encountered. Due to relatively low spatial resolution of landsat imageries, land cover classification was

possible only upto level-I of Anderson system (Anderson, 1976). Therefore, only broad classes were delineated from the study area, i.e., forest, agriculture, water, barren and built-up. Moreover, the area had complex terrain with rugged mountainous topography, which made land cover classification difficult because of difference in surface illumination. LULC classification in complex wetland and mountainous topography presents several complexities, due to topographic shadowing, high slope angles, complex LULC patterns and large spatial diversity. This influences the interpretation of spectral signatures and land cover classification accuracy gets affected (Wundram and Loffler, 2008; Weiss and Walsh, 2009; Qasim *et al.*, 2011; Mwita *et al.*, 2013; Iqbal and Khan, 2014; Nagel *et al.*, 2014).

LULC changes, occurring from 1990 to 2015, were due to the result of various natural and human induced factors. Over the study period, the decrease in forest and water class has taken place, while the agriculture, built-up and barren classes have faced immense increase. Forest cover category includes naturally growing vegetation with dense canopy as well as patchy herbaceous and shrubby vegetation. By visual interpretation, this class was easily distinguishable through haze removal of satellite images. Forest, the most vulnerable class, occupied 68% of the area in 1990 and accounted for 506.65 km^2, while declined to 62% (461.59 km^2) and 52% (388.01 km^2) in 2003 and 2015, respectively, with the total relative change of –118.64 km^2 (Fig. 8a). Prevailing habitat in the area is dry sub-tropical semi-evergreen scrub forest (Roberts, 1992). Various natural and artificial driving factors may be held responsible for causing a significant change in the area (Zhang *et al.*, 2011). Climatic conditions, such as, less rainfall (Fig. 11) in the area to some extent would have been a limiting factor for the abundant growth of natural vegetation in the area. Locals are fully dependant on this natural resource for their survival and the area is though vulnerable to natural disasters. The area has previously suffered from the worst drought conditions during 1990-2003, followed by devastating floods (Arshad, 2011). Forests serve as a source of timber, fuel wood for cooking and heating purposes and fodder for animals in the region. The communities in the vicinity of the area do not have gas supply, so they are fully dependent on fuel wood. People of the adjacent villages graze their animals in the forest. Moreover, much of the forests have also been cleared up to export out of the region and meet the wood requirements for other parts of the country. And, in return, locals are paid good financial incentives from outsiders for cutting of forests of the region. Illegitimate cutting of forests has affected the catchment area as well as contributing mainly in damaging habitat and natural ecosystem. Most of the range ecology and productivity has also been degraded by heavy grazing of domestic livestock. Even the traditional approaches of forest conservation and rotational grazing are not being followed by the local community. Furthermore, the increase in population compels dwellers to extend residential area onto the forested land. Illicit cutting of forests and overgrazing have led to soil erosion in the region. These findings are in concurrence with patterns of deforestation observed by several other researchers (Qasim *et al.*, 2011; Butt *et al.*, 2015).

Agriculture class includes human induced cultivation. Agriculture land occupied 4% (27.73 ha) of area in 1990 and underwent great expansion of up to 20% (145.26 ha) in 2015, leading to a massive temporal change of 117.53 km^2 from 1990-2015, as shown in Fig. 8b. The decrease in forest class has resulted in a substantial increase of agricultural land. The area has undergone extensive cultivation of crops and offseason vegetables that require high intake of water. Locals from around the village have their major dependency on agriculture and livestock for their livelihood. Principal crops, grown in the region, are vegetables during the summer season and wheat in the winter. Even though, when the water level in lakes is low, the bed of the lakes is used for agricultural practices. For the sake of pursuing economic benefits, lots of cash crops (i.e., Cauli flower, potato and onions, etc.) are grown on agricultural land around the three lakes. Substantial natural and semi natural area in the complex has been reclaimed for agricultural intensification, which stemmed mainly from population growth, economic pressure and market forces. This apart from affecting the quantity of water, the quality of water has also been deteriorated, due to heavy use of fertilizers and pesticides. The same condition prevailed in Hanshiqiao wetland Nature Reserve China, Donana marshes Spain and Driefontein Grasslands Zimbabwae, where apart from natural climate and precipitation conditions, a large part of wetland was converted to agricultural land to obtain maximum yield (Zhang *et al.*, 2011; Zorrilla *et al.*, 2014; Fakarayi *et al.*, 2015).

Water covered 9.95 km^2 area in 1990, reduced to 4.7 km^2 in 2003 and appeared to have increased back to 7.99 in 2015 (Fig. 8c). The overall percentage contribution of water to the entire area though had faced no significant change. In wetland landscape change, precipitation has been regarded as a key element in altering the spatial distribution and ecological function (Mwita *et al.*, 2013). In 2003, an extreme decline in water was due to climatic pressure, such as, less rainfall mentioned earlier. The reduced precipitation and runoff bring conversion in wetland to other terrestrial land use types, such as, forests, agricultural land and barren area (Starr *et al.*, 2016). Butt *et al.* (2015) study in Rawal watershed acknowledged that water serves as a limiting factor and there exists a consistent practice of cultivating crops near water resource to achieve maximum yield. These findings are consistent with the patterns of land use change observed over past few decades (Ashraf *et al.*, 2007 and Qasim *et al.*, 2011). Due to increased

domestic usage and extensive agricultural practices in the region, there is a constant pressure on groundwater resource. Ground water in the vicinity is extracted by several means, which include hand pumps, dug wells and tube-wells. The total groundwater consumption in the valley was reported to be 24.134 million cubic meter and extracted through 2072 irrigation and 173 municipal tube-wells (Arshad, 2011). The diversion of water at various points for domestic supply and to meet the demand for increasing agriculture resulted in lesser runoff reaching the lakes. Deforestation has also been regarded to decrease the infiltration rate and reduce groundwater recharge (Butt *et al.*, 2015). Consequently, these all scenarios contribute to lower the ground water-table and exert additional pressure on lakes. Additionally, various chemical fertilizers used to enhance crop growth degrade water quality by leaching down through the soil.

The built-up class covers artificially surfaced areas, such as, concrete roads, rural settlements and urban development. Due to conflict in spectral signatures, it was difficult to isolate bare soil from rural settlements, as most of them were non concrete and had fragmented structures. However, this confusion was later overcome by cross verification and raster recoding in Erdas imagine (Mwita *et al.*, 2013; Iqbal and Khan, 2014). The built-up occupied 2.32, 6.83 and 7.8 km^2 of area in the respective years of 1990, 2003 and 2015, and had a relative temporal increase in area of 5.48 km^2 since 1990 (Fig. 8d). A similar trend of built-up was observed in a previous study conducted on Kalar Kahar wetland, which lies in the same area of salt range region (Qazi *et al.*, 2012; Ahmad and Erum, 2012). The built-up of any scale has great impact and manipulates the natural system of the earth everywhere in the world. In 1990, 2% of earth covered urban area and upto 60% has been expected by the year 2025. This will result in precarious increase in urban ecological footprint.

Barren category includes bare or sparsely vegetated areas mainly exposed soil or rock and dry lake beds. A barren area showed total opposite magnitude and trend of change to water over the two periods, increasing from 1991 to 2003 and decreasing from 2003 to 2015. In 1990, the barren area made up 27% of the area and increased to contribute 31% of the area in 2003. Conversely, in 2015, the area has again shrunken to 26% share in the total area. Due to climatic conditions and less rainfall (Fig. 11) received during first half of the study period (1990-2003), there was a great increase in bare soil. The level of water dried up to the extension of exposing the bare lake bed. This was clearly noticed in Khabeki Lake because of its shallow surface water. However, the condition had greatly reversed during second half of the study (2003-2015), which is also the main reason behind the noticed decrease in barren area. Besides comparing the area coverage of 1990 and 2015, the barren area has almost stayed constant coving 198.11 and 195.93 km^2, respectively (Fig. 8e).

Correlation between temporal climatic change and land cover: Wetlands are predominantly sensitive to climate change (Wan *et al.*, 2015). The change may affect their hydrology, plant communities, biogeochemical processes and ecosystem function. In this study, temperature, precipitation, humidity and wind speed were selected to investigate relationship between wetland change and climatic conditions. The change in LULC patterns also led to a change in climatic conditions and vice versa. The monthly trends of these climatic parameters for studied time period of 1990, 2003 and 2015, are presented in Figs. 9, 10, 11, 12 and 13.

The Pearson correlation analysis of land use features relative to climatic variables assisted in strengthening the results of the study by giving a clear representation of variations in terms of positive and negative change.

There exists a negative correlation of –0.961 between forest and wind speed. Since, forest and trees act as environmental buffers, an increase in the number of trees will decrease the wind speed by playing a role of windbreaker. They act as a shelter to nearby areas by reducing erosion, decreasing noise, improving irrigation and protecting structures and wildlife from troublesome winds. Various well managed farming practices involve planting large trees to act as shelter belts to protect the growing crops. As discussed earlier, the increase load of sediments, reported into the lakes, might have been contributed to a greater extent because of a decrease in forest cover and an increase in wind speed (Fig. 13) in the area. Forests also play a key role in water cycle by absorbing and evapo-transpiring. If trees are cleared to a large extent the rain pattern alters. As role of carbon sinks forest and temperature have a negative correlation. The decrease in forest cover results in drier and warmer climate and, hence, increase in minimum temperature of the region as shown in Table 6.

Agricultural crops have positive correlation with local rainfall patterns. Increase precipitation and better irrigation practices tend to produce better crop yield. Kang *et al.* (2009) reported that the crops are more sensitive to precipitation fluctuations than temperature alteration, which is in concurrence with the results of Table 6. However, a reverse intensity of rain has been observed to ruin the crops (Rosenzweig *et al.*, 2002). The results of Pearson correlation (Table 6) have illustrated a positive correlation between agriculture and wind speed. However, single factor cannot be entirely linked to a single variable. All climatic factors are interlinked and are a result of overall LULC change. However, the Pearson correlation analysis helps to mark out the most significant correlation.

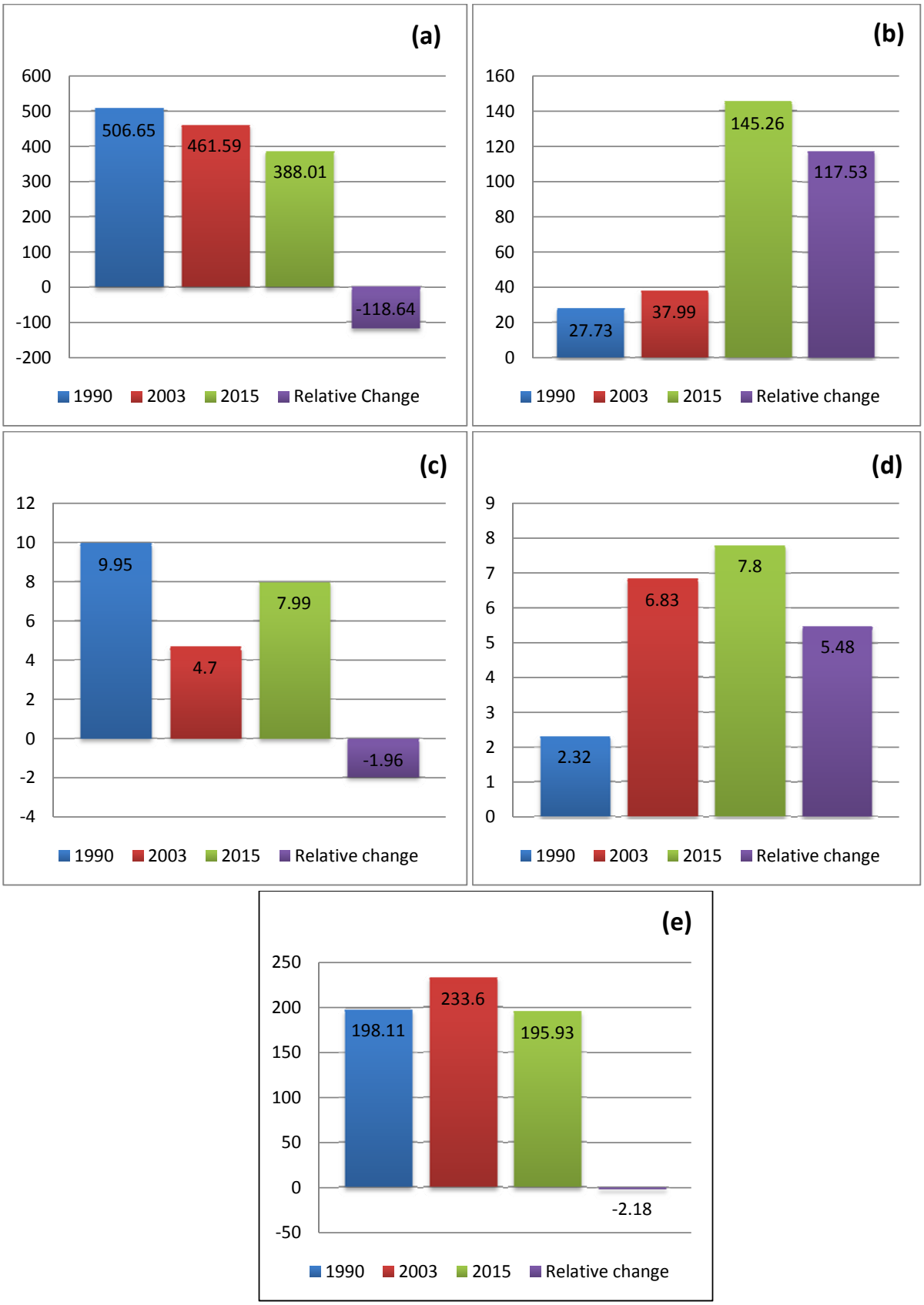

Fig. 8: Relative change of (a) Forest (b) Agriculture (c) Water (d) Built-up (e) Barren area from 1990-2015.

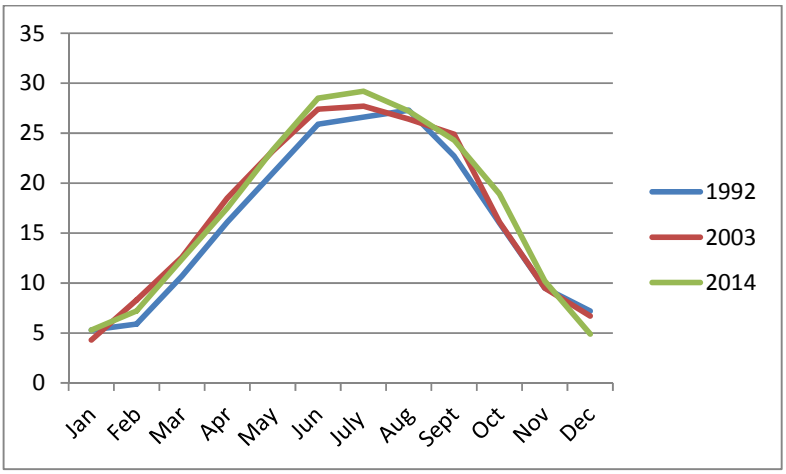

Fig. 9: Mean monthly minimumtemperature (Mean daily minimum temperature) (˚C).

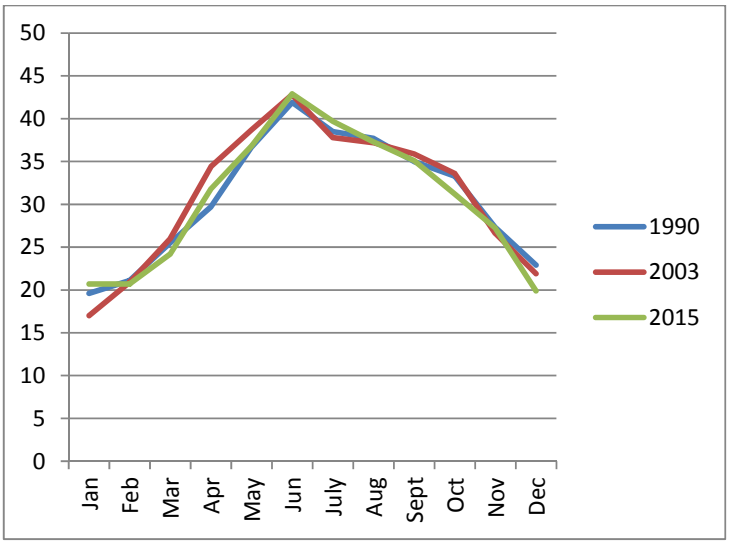

Fig.10: Mean monthly maximum temperature (Mean daily maximum temperature) (˚C).

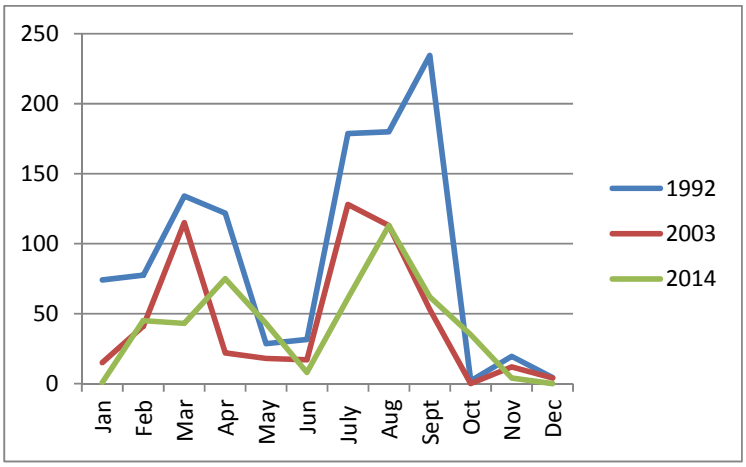

Fig. 11: Monthly Amount of Precipitation (Mm).

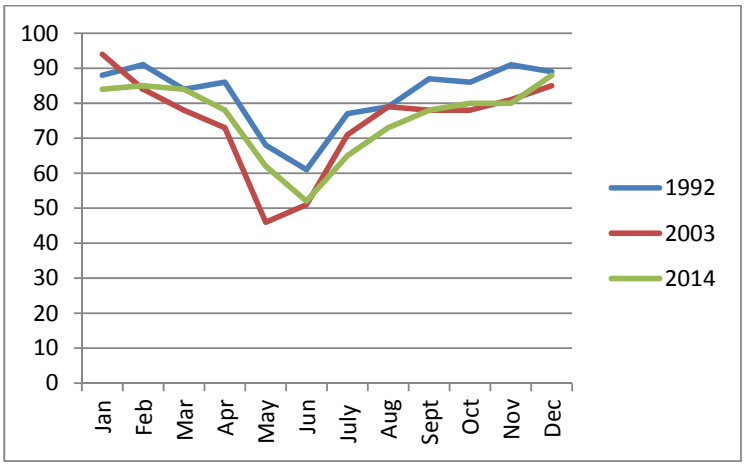

Fig. 12: Mean monthly relative humidity (Mean) at 0000 UTC (%).

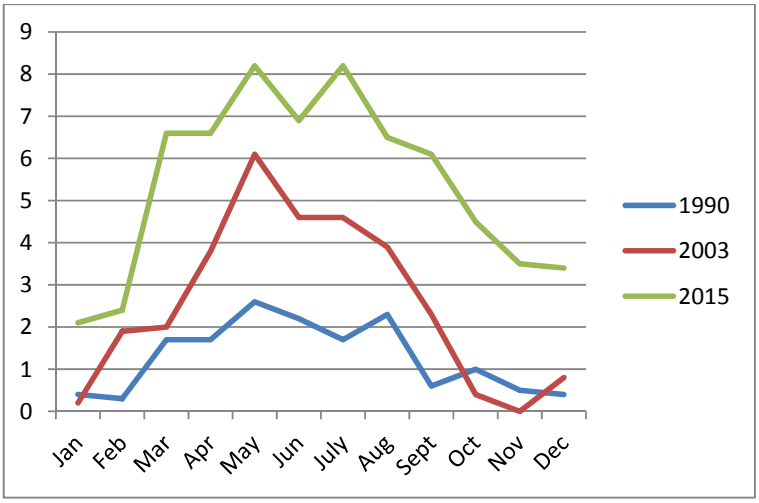

Fig. 13: Mean monthly wind speed at 0 UTC (Knots).

Water has illustrated a negative correlation with maximum temperature while a strong positive correlation with humidity. The increase in surface water will ultimately lead to increase humid conditions and this will, in turn, cause evaporative cooling and hence lower the maximum temperature and vice versa (Fall *et al.*, 2010). It has been observed in the lakes of Ucchali wetlands complex, that low rainfall has resulted in decrease in water level and the same positive correlation between two parameters is also illustrated by Pearson correlation (Table 6).

A very high significant positive Pearson correlation value of 0.992 exists between the built-up and temperature. Urbanization increases pollution, which ultimately results in global warming. Moreover, built surfaces are water resistant and reflect sun radiations, which tend to be released as heat and trapped in the lower atmosphere, as compared to natural surfaces, such as, vegetation and soil, which trap moisture and release vapors, which contribute to humidity and consequently have a cooling effect.

Barren area has shown a strong positive correlation with maximum temperature and negative correlation with precipitation and humidity. The forests act as carbon sink and the removal of carbon store house eventually results in global warming and elevated temperature conditions. It has been reported by previous researches that forest cover returns ten times more moisture than a barren land and twice as much as herbaceous and shrubby vegetation (Brooks, 1928; Marin *et al.*, 2000; Andréassian, 2004; Fall *et al.*, 2010; Cinar, 2015). Concludinga barren area significantly affects the local weather patterns and a very significant change in cover pattern does influence the precipitation pattern (Cinar, 2015).

All these are the indications of impact of changing climatic patterns on the land cover. The challenges that climatic alterations bring planning authorities need to tackle them and keep them in mind while initiating or planning developmental activities in the area. They, along with local stakeholders, need to evaluate the effects of climatic change and anthropogenic activities on natural resources and take adaptations to exercise better sustainable efforts and effective strategies for protection and management of Ucchali wetlands complex.

Table 6: Pearson's correlation analysis of land use parameters and climatic variables.

		Contents									
		Forest	Agriculture	Water	Urban	Barren	Max_temp	Min_temp	Precipitation	Humidity	Wind_speed
Forest	Pearson correlation	1	–.953	.238	–.880	.188	.093	–.812	–.684	.129	–.961
	Sig. (1-tailed)		.098	.423	.158	.440	.470	.198	.260	.459	.090
	N	3	3	3	3	3	3	3	3	3	3
Agriculture	Pearson correlation	–.953	1	.066	.695	–.476	–.390	.598	.873	.177	.832
	Sig. (1-tailed)	.098		.479	.255	.342	.373	.296	.162	.443	.187
	N	3	3	3	3	3	3	3	3	3	3
Water	Pearson correlation	.238	.066	1	.671	–.909	–.945	–.760	.545	.994*	–.498
	Sig. (1-tailed)	.423	.479		.266	.137	.106	.225	.316	.035	.334
	N	3	3	3	3	3	3	3	3	3	3
Urban	Pearson correlation	–.880	.695	–.671	1	.301	.391	.992*	.256	–.584	.977
	Sig. (1-tailed)	.158	.255	.266		.403	.372	.041	.418	.301	.068
	N	3	3	3	3	3	3	3	3	3	3
Barren	Pearson correlation	.188	–.476	–.909	.301	1	.995*	.420	–.845	–.950	.092
	Sig. (1-tailed)	.440	.342	.137	.403		.031	.362	.180	.101	.471
	N	3	3	3	3	3	3	3	3	3	3
Max_temp	Pearson correlation	.093	–.390	–.945	.391	.995*	1	.505	–.790	–.975	.187
	Sig. (1-tailed)	.470	.373	.106	.372	.031		.331	.210	.071	.440
	N	3	3	3	3	3	3	3	3	3	3
Min_temp	Pearson correlation	–.812	.598	–.760	.992*	.420	.505	1	.130	–.683	.942
	Sig. (1-tailed)	.198	.296	.225	.041	.362	.331		.458	.261	.109
	N	3	3	3	3	3	3	3	3	3	3
Precipitation	Pearson correlation	–.684	.873	.545	.256	–.845	–.790	.130	1	.635	.455
	Sig. (1-tailed)	.260	.162	.316	.418	.180	.210	.458		.281	.350
	N	3	3	3	3	3	3	3	3	3	3
Humidity	Pearson correlation	.129	.177	.994*	–.584	–.950	–.975	–.683	.635	1	–.399
	Sig. (1-tailed)	.459	.443	.035	.301	.101	.071	.261	.281		.369
	N	3	3	3	3	3	3	3	3	3	3
Wind_speed	Pearson correlation	–.961	.832	–.498	.977	.092	.187	.942	.455	–.399	1
	Sig. (1-tailed)	.090	.187	.334	.068	.471	.440	.109	.350	.369	
	N	3	3	3	3	3	3	3	3	3	3

*Correlation is significant at the 0.05 level (1-tailed).

CONCLUSION

The study area has observed massive LULC changes in the past 25 years. With the passage of time,the rate of change has accelerated. Primarily, the pattern of change is more dynamic to vegetation as the forest cover has decreased, whereas agricultural area has increased predominantly. Lack of proper management and land use planning has also subjected to alter the water and barren class. Moreover, a very significant change in climatic conditions is also responsible for altering the LULC cover and vice versa. Over the years, it may be observed that the extent of wetlands is dependent on climatic and anthropogenic factors acting on them. The extent increases in good rains and following drought conditions and human pressure they are squeezed. Apart from promoting sustainable use of natural resource around the complex; ecological integrity of the Ramsar site must be maintained and improved through ecological interventions related to illicit cutting of forest, unsustainable utilization of water resource, domestic induced pollution, agricultural intensification, etc.

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