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Statistical Model based decadal Land Use/ Land Cover Change identification and Prediction in & around West Bengal Dry-Land area

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Abstract: Under the climate risk study, historical land use/ land cover (LU/LC) change identification is very relevant; because earth surface cover depends on climatic condition; hence good soil zone appears as a fallow land in LU/LC classification not only in dry-land area but also all over the world. Once the LU/LC is an important factor in the regional economy, it is also closely related to population growth. LU/LC dynamic in the West Bengal dry-land area was assessed by analyzing four Multi-temporal Landsat images from Landsat 5 Thematic Mapper (TM) land use map in 1985, 1995, 2005, & 2015 by using Erdas 2014 & Arc GIS 10.6 software, while 2015 was used to validate the predictions of model using the ground-based land cover image. The linear regression model is a statistical model about the trends forecast, and if current artificial factors continued, the results would gradually change along with a certain trend; and tend to stabilize in a long time and reach a balanced state at last. After validating the model (84.85%), future LU/LC changes for 2025 & 2035 were predicted by the model. The result shows that crop land and fallow land gradually decrease. On the other hand, built-up land, water bodies, shrub land increase significantly. The predicted LU/LC scenario would provide useful inputs for effective, pragmatic management of the districts and a direction for an effective land use policy making also help in biodiversity conservation, and for mitigating climate change.

Key-Words: Decadal, LU/LC, Rarh, Prediction, Gain/Loss

1. **Introduction:** Land is the green carpet of the Earth, which is change by the rapid worldwide population growth accompanied by economic activities (Yirsaw et al., 2017, Guan et al., 2011; Halmy et al., 2015; Zheng et al., 2015 23; Parker et al., 2003). The land use and land-cover change also known as land change is a term for the human modification of Earth's terrestrial surface (Mishra et al., 2014). Land use term usually defined more strictly and refers to the way in which, and the purposes for which, humans employ the land and its resources (William 2000, Mishra et al., 2014). Land cover refers to the habitat or vegetation type presents, such as forest and agriculture area. Land Use / Land Cover (LU/LC) have an important effect on both the functioning of the Earth's systems as a whole (Lambin et al. 1999) and the majority of ecosystems (Hansen et al. 2001; Millennium, 2005; Fischlin et al. 2007, Mishra et al., 2014). Land use and land cover change have been recognized as an important driver of environmental change on all spatial and temporal scales (Adepoju et al., 2006, Mishra et al., 2014), in addition to emerging as a key environmental issue and on a regional scale, leading to one of the major research endeavours in global change studies. These changes encompass the greatest environmental concerns of human populations today,

including climate change, biodiversity loss (Roy et al., 2015, Yamaura et al., 2009, Koning et al., 2007) and the pollution of water, soils (Islam and Weil 2000, Tolba et al., 1992) and air Dixon et al., 1994, Mishra et al., 2014). Therefore in recent years, researchers academician those who favour modelling (Yirsaw et al., 2017, Fische & Sun 2001, Han et al., 2015, Santé et al., 2010), causes and consequences of LU/LC dynamics (Yirsaw et al., 2017, Gautam et al., 2003 Porter et al., 2007); have been greatly attached to the issues of LU/LC changes. Numerous kind of models such as statistical model, cellular Automata (Yirsaw et al., 2017, Araya & Cabral 2010), Markov chain (Yirsaw et al., 2017, Guan et al., 2011, Paegelow and Olmedo, 2005; Sun et al., 2007; Courage et al., 2009; Guan et al., 2011; Tong et al., 2012), Agent-based (Yirsaw et al., 2017, Xie et al., 2007) and CLUE (Han et al., 2015), have been developed for the prediction of LU/LC change. In this context, for the purpose, it is much needed to current LU/LC management practices (Yirsaw et al., 2017) as well as estimate the land use changes over time (Mishra et al., 2014) and predicts the future scenario of Bengal dry-land, its can export by by spatial information technology (Myint and Wang, 2006; Courage et al., 2009; Tong et al., 2012, Mishra et al., 2014, Sang et al., 2011, Yu, F 2009, Roy et al., 2015) based statistical model (Linear Regression) (Sahsuvaroglu et al., 2006). This model form can be used to assess the changes in the area covered by a given land use type for specified changes in one or more of the predictor variables (Colenut 1968, Lee 1973) by substituting their values in the equation. Early applications were made by Chapin and Weiss (1968), Chapin (1965), Chapin and Kaiser (1979).

Hence, it is important to conduct research to identify the extent and rate of LU/LC change for the future and to detect the impacts on sustainable economy and ecological value of the area. This study is designed with the objectives of (1) based on past trend (from 1985-2015) of land use changes, (2) the future land use prediction in and around the Bengals dry-land for the year 2025 and 2035. The predicted LU/LC scenario further decrease or loss of area 45 & 97 km^2 of crop land, 210 & 122 km^2 Fallow land 2025 & 2035 respectively and 50.5 km^2 forest land in 2035 on the other hand forest increase or gain the area in 53 km^2 by 2025 also other remain LU/LC are gain the area gradually. This kind of analytical study can be remarkable in sustainable development.

2. About Study Area: The study area West Bengal dry-land approximate area of 28,697 km^2 (25.47 % of the total area of West Bengal state) is located by the Orissa and Jharkhand state in the west and north by Malda district east & south covered by Murshidabad, Barddhaman (E), Hugli, Howrah, Medinipur (E) district accordingly. Dry-land area between longitudes 85° 40' E to 88° 15' E and latitudes 21° 45' N to 24° 45' N (Fig. 1). The western portion of the study area under plateau and highlands forms by eastern fringes of the Chota-Nagpur Plateau with some hills and other than this area under 'Rarh' (the region that intervenes between the Vajjabhumi and the Ganges Delta). Elevation and slope are directed by the west to east. Relatively, high rates of precipitation and humidity in all seasons, especially in the monsoon period (annual precipitation of about 1,250 mm and relative humidity of about 80 %), the minor difference between day and night temperatures (autumn) and extensive vegetation coverage are among the most important characteristics of this region. The total population in the study area is around 17101395 (according to official Census 2011 district wise detail). Most of the people involved in the agricultural sector, i.e., agriculture, hunting, forestry, and fisheries, limited villagers are occupied from industries mining.

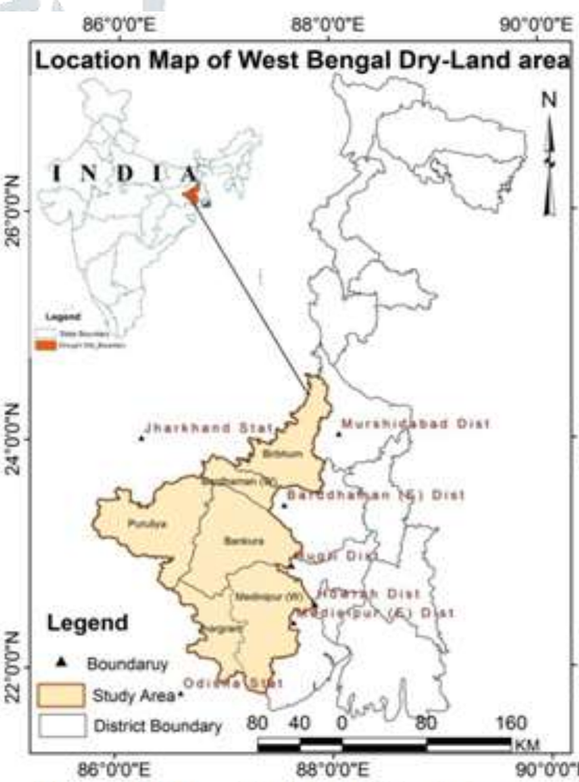

Figure: 01, Location Map of Study Area

3. Data & Method used:

3.1 Data Used: To study the dynamic changes in land use in the dry-land area used multi-temporal data from different satellite images. Landsat ETM satellite image downloaded from the United States Geological Survey (USGS) portal. Images are geometrically co-registered Landsat MSS/TM, IRS 1C–LISS III, and Resourcesat1 data for three seasons, viz. winter (January to March); pre-monsoon (April to May) and post-monsoon (mid-October to December) form the main data for analysis. Landsat MSS/TM images were when cloud free Landsat data was unavailable, IRS 1C–LISS III for 1994–1995 and Resourcesat 1 for 2004–2005 (Roy et al. 2015). The details of data from different satellite sensors used in the present study are given in Table 1.

Table: 1 Details of Satellite Images

Sl. no	Satellite	Sensor	Spatial Resolution	Data acquired
1	Landsat	MSS	80 (resample 60 m*	1984-1985
2	Landsat & IRS 1B	TM, LISS-I	30 and 72 m resample 56m*	1994-1995
3	Landsat & Resourcesat 1	TM, LISS-III	30 m and 23.5 m*	2004-2005
4	Landsat	ETM	30 m	2014-2015

*All images were resample to 30 m by using nearest neighbor technique

3.2.1 Images correction method: To study LU/LC data needs to be geo-rectification mainly geometric correction. For geometric rectification of images, used first polynomial order equation with allowable Root Mean Square (RMS) error of less than one pixel (default). According to Roy et al. 2015, RMS error was found to be 0.4 pixels (less than 9.2 m) in the case of LISS-III satellite images, with the minimum of 15 Ground Control Points (GCPs) in each scene having a range of 0.35 to 0.60 pixels (*i.e.*, 8 to 15 m).

3.2.2 Image classification method: The hierarchical classification scheme has been applied in the study area followed by Anderson classification guidelines. Supervised classification (2015) techniques with Maximum Likelihood algorithm (highest probability) applied for (Label III) LU/LC categorization in the study area. The level of classification can be presented at a wider range of scales. Level I category is further classified into Level II classes. Similarly, Level II categories are further refined using satellite images for detailed mapping in Level III. Level III classification scheme has been aggregated to Level II by Natural Resource Census for LU/LC mapping (Table 2).

Table: 2 Land use/land covers (LU/LC) classification scheme and description of classes.

LU/LC Type	Description
Crop Land (CL)	Temporarily cropped area followed by harvest and a bare soil period (e.g. single and multiple cropping systems).
Fallow Land (FL)	Land taken up for cultivation temporarily allowed remaining uncultivated for one or more seasons.
Deciduous Forest (DF)	Woody vegetation with a percent cover >60% and height exceeding 2 m. It consists of broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
Mixed Forests (MF)	Trees with a percent cover >60% and height exceeding 2 m. It consists of trees communities with interspersed mixtures or mosaics of the other four forest types. None of the forest types exceeds 60% of landscape
Plantations (P)	Commercial horticulture plantations, orchards and tree cash crops
Built-up (Bu)	Land covered by buildings and other man-made structures.
Barren Land (BL)	Exposed soil, sand, rocks, or snow and never have more than 10% vegetation cover during any time of the year.
Waste Land (WL)	Sparsely vegetated land with signs of erosion and land deformation that could be attributed to lack of appropriate water and soil management, or natural causes. Degraded forest (<10% tree cover) with signs of erosion is classified under wasteland.
Wetland (WL)	Land with permanent mixture of water and herbaceous or woody vegetation. The vegetation can be present either in salt, brackish, or fresh water.
Shrub Land (SL)	Land with woody vegetation less than 2 m in height and with greater than 10% shrub canopy cover.
Water Bodies (WB)	Areas with surface water, either impounded in the form of ponds, reservoirs or flowing as streams, rivers, etc. Can be either fresh or salt-water bodies.

3.2.3: Statistical model for LU/ LCC and Prediction & Validation:

The modeling literature suggests several numbers and various models of land use change where land use and its change are treated explicitly and are the direct object of the modeling exercise. The linear regression model is one of the statistical and econometric models, whose direct object of analysis is land use change date since the 1960s (Briassoulis, H. 2020). In a statistical model Linear Regression model of land use change, the study area is usually subdivided into a number of zones (or, LU/LC class) the size and shape of each cell depending on the aggregation level chosen as well as the availability of data. In the continuous case, for each zone, the distribution of land use types (the dependent variables) as well as the values of other environmental and socio-economic predictor variables. A multiple regression equation for each land use type fits these data (usually referring to a given year) Briassoulis, H. (2020). The general form of the equation is:

$$LUTi = a + \beta_1 X_1 + B_2 X_2 + \ldots \ldots \ldots \ldots \beta n X n + \varepsilon \qquad (Eq.\ 1)$$

Where: LUT: is the area of land occupied by land use type i (in each class) and X_1, X_2, . . .X_n the predictor variables used. The term "ε" is the error term of the statistical model.

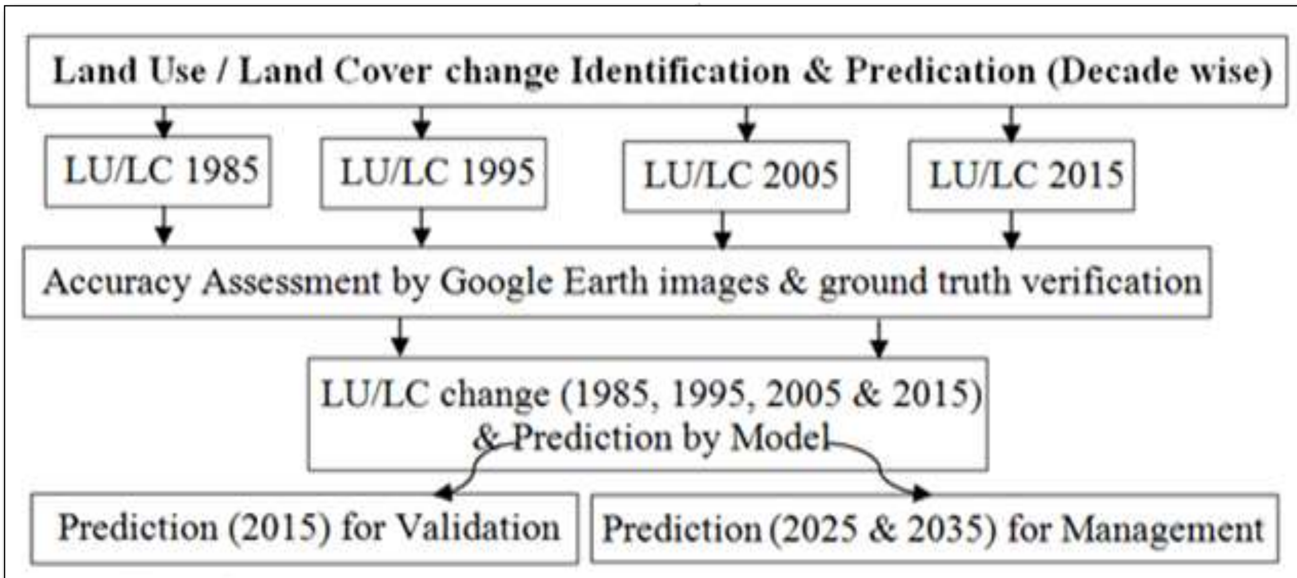

Fig 2, Work Flowchart

A work flow diagram for LCC and prediction as well as accuracy assessment and validation of model data, point out step by step shown in figure 2.

4. Analysis and Result:

4.1 Decadal LU/LC Mapping: Decadal wise (1985, 1995, 2005 & 2015), satellite image's (Table 1) was classified, and a map (Figure 3, 4, 5, and 6) of land use/ land cover was reproduced. The classification was categorized into six major classes i.e Crop Land, Fallow Land, Forest (Deciduous, Mixed, & Plantations), Built-up, Shrub Land (Barren, Waste, and Wet) Water Bodies; (Table 3).

Decadal wise (1985, 1995, 2005 & 2015) Land Use/ Land Cover map

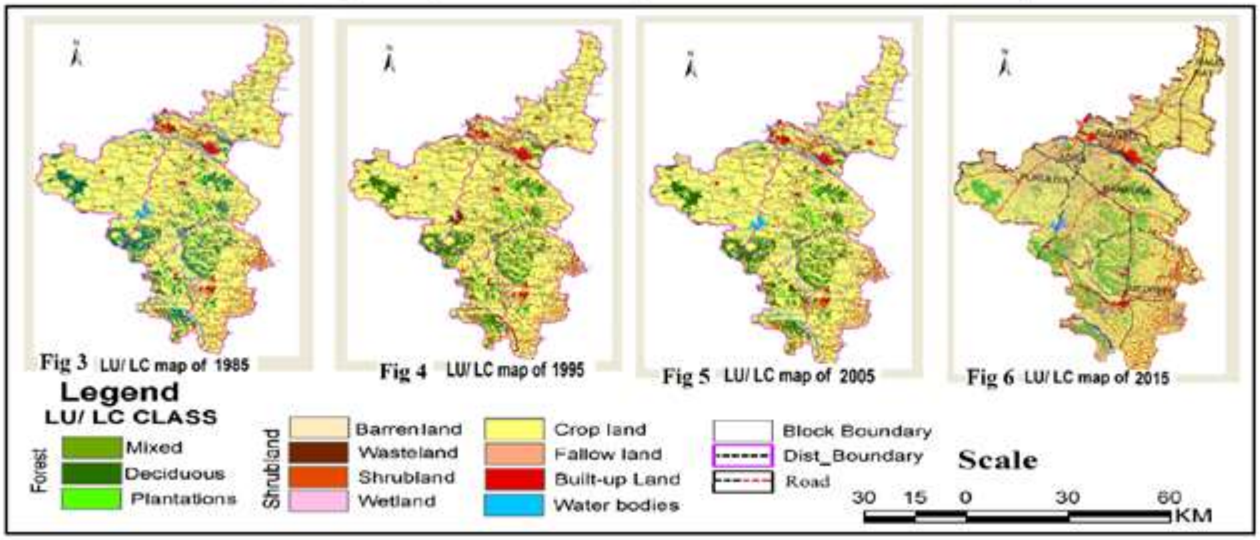

Table 03	Decade wise Land Use / Land Cover (1985, 1995, 2005, and 2015)							
Land Use / Land Cover Type	LU/LC area cover (km^2) and				Parentage (%) of area cover			
	1985	1995	2005	2015	% (1985)	% (1995)	%(2005)	%(2015)
Crop land	21674	21654	21584	21460	75.53	75.46	75.21	74.78
Fallow land	610	380	189	136	2.13	1.32	0.66	0.47
Forest land	3593	3705	3699	3604	12.52	12.91	12.89	12.56
Built-up land	1381	1422	1508	1627	4.81	4.95	5.26	5.67
Shrub land	713	797	956	1087	2.48	2.78	3.33	3.79
Water bodies	726	739	761	783	2.53	2.58	2.65	2.73

4.1.1 Accuracy assessment: On completion of the classification accuracy was performed. The basic idea is to compare the predicted classification of each pixel with the actual classification. The accuracy of the data was evaluated using pre-determined field sample points. Stratified random samples are selected to assess the accuracy of the classification with the help of ground truth data (Biodiversity Information System, 2014; Roy et al., 2012) and Google Earth images. The confusion error matrix was created with the mapped and ground reference points to determine the users' accuracy and Cohen's kappa accuracy. Most of the LULC classes showed accuracies of more than 90%. An overall mapping accuracy of classification was achieved of 90.17%, and overall Kappa Statistic (index of agreement) is 0.88 (Table 04).

Table 04	Accuracy Assessment of Land Use / Land Cover map								
LU/LC Type	Crop land	Fallow land	Forest land	Built-up land	Shrub land	Water bodies	Row Total	User Accuracy **(%)**	Kappa Statistic
Crop land	**93**	2	0	5	0	0	100	93	0.92
Fallow land	0	**90**	10	0	0	0	100	90	0.88
Forest land	1	10	**89**	0	0	0	100	89	0.87
Built-up land	0	2	5	**84**	9	0	100	84	0.81
Shrub land	7	0	0	2	**88**	3	100	88	0.85
Water bodies	0	1	2	0	0	**97**	100	97	0.96
Column Total	101	105	106	91	97	100	600		

Producer Accuracy (%)	92.08	85.71	83.96	92.31	90.72	97	**Overall classification Accuracy (%)= 90.17** **Overall Kappa Statistic = 0.88**

4.2 Decadal wise land use/land cover change: The decadal wise land use/ land cover were evaluated by gains and losses experienced by using LU/LC maps of 1985, 1995, 2005, and 2015. Table 05 shows the gains and losses in LU/LC area in different time periods (1985-1995, 1995-2005, and 2005-2015). Different colors (blue, red, and green) indicate the gain or loss per class in km^2. The crop land has lost gradually in the first decade (1985-1995) 20 km^2, in the second decade (1995-2005) 70 km^2, and in the third decade (2005-2015) 124 km^2. Simultaneously the Fallow land remarkably lost 230km^2 in1985-1995, 191km^2 in 1995-2005, and 53 km^2 in 2005-2015. Forest in 1985-1995 is gain the area 112 km^2 due to the huge plantation after that 1995-2005, and 2005-2015 13 km^2, 6 km^2, and 95 km^2 lose respectively. On the other hand built-up land gradually gains 41 km^2, 86 km^2, and 119 km^2 in 1985-1995, 1995-2005, and 2005-2015 respectively. Mixed forest gain 14 km^2in 1985-1995, 35 km^2 in 1995-2005, and 23 km^2 in 2005-2015. Shrub land gain 84 km^2 1985-1995, 159 km^2 in 1995-2005, and 131 km^2 2005-2015. Decade wise water body's increases (gain) 13, 22, & 22 km^2 in 1985-1995, 1995-2005, and 2005-2015 respectively (Figure 7).

Table 05 Decadal wise LU/LC gain or lose in km^2

LU/LC Type	1985-1995	1995-2005	2005-2015
Cl	-20	-70	-124
Fal	-230	-191	-53
Fol	112	-6	-95
Bl	41	86	119
Sl	84	159	131
Wb	13	22	22

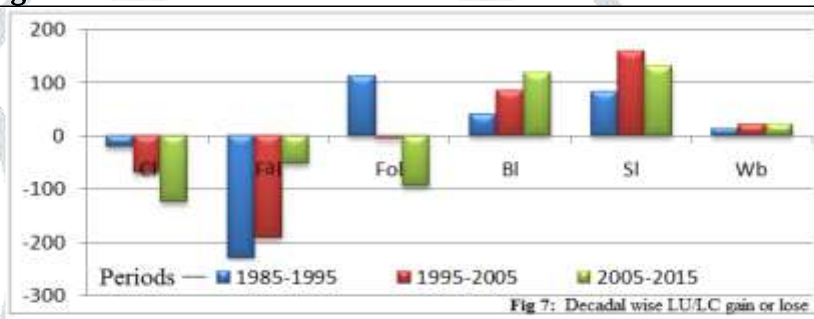

Fig 7: Decadal wise LU/LC gain or lose

Cl= Crop land, Fal= Fallow land, Fol= Forest land, Bl= Built-up land, Sl= Shrub land, & Wb=Water bodies

4.3 LU/LC prediction by statistical model and validation: The modeling is incomplete without validating the model with actual data (Kumar et al. 2014). So the model validation and based on the comparison of predicted land use/land cover area of 2015 with the actual area of the 2015 classification map. The validation (%) of each LU/LC type calculated in table 6. The lowest validation value, 20.59%, occurs in fallow land due to the negative value of prediction. Other than all land use/land cover class validation percent above 90. Crop land area is 99.6%, Forest land 95.55%, Built-up land 96.13% Shrub land 97.98%; and Water bodies 99.23% validate in relation to the prediction area. Over-all validation is 84.85%; these findings show no significant errors between prediction value (area) and actual area value (Mishra et al., 2010, Eastman, J.R 2006). Therefore, the model can be used in LU/LC forecast in the West Bengal dry-land area for the upcoming two decades 2025 and 2035.

Table 06 Model data validation (2015)

LU/LC Type	Crop land	Fallow land	Forest land	Built-up Land	Shrub land	Water bodies
Classification	21460	136	3604	1627	1087	783
Predicted	21547	-28	3777	1564	1065	777
Validation (%)	99.6	20.59	95.55	96.13	97.98	99.23
			Overall Validation 84.85%			

Table 07 Predicated LU/LC of 2025 & 2035					Gain / Lose	
LU/LC Type	Area (km2) &		% of area		2015-2025	2025-2035
	2025	2035	2025	2035		
Crop land	21415	21318	74.62	74.29	-45	-97
Fallow land	-74.5	-196.5	-0.26	-0.68	-210.5	-122
Forest land	3657	3606.5	12.74	12.57	53	-50.5
Built-up land	1690.5	1793	5.89	6.25	63.5	102.5
Shrub land	1208.5	1353.5	4.22	4.7	121.5	145
Water bodies	800.5	822.5	2.79	2.87	17.5	22
Total	**28697**	**28697**	**100**	**100**	**- Value = Lose**	

Prediction: Considering the accuracy challenges that might appear from using different potentials, a statistical model (1985, 1995, 2005, and 2015) was used for forecasting LU/LC area change in 2025 and 2035 (Temesgen et al., 2021). The prediction model of LU/LC area changes provides an answer to the research question of where LU/LC area changes are expected to occurs under six land use and land cover classes. The statistical model-based changes of LU/LC area and percentage (%) distribution in table 7 for the future two decades (2015 to 2025 and 2025 to 2035). Through time and space (1985-2035) each LU/LC area change is explained in the discussion section (5).

5. Discussion: The historical LU/LC of dry-land area change was observed decade-wise from 1985 to 2015 in Table 4, and models based future data of 2025 and 2035 discussed in Table 7. The spatial patterns of the predicted and classification LU/LC map indicate that in study area crop land trend (Fig 8) would be a decrease and an increase of the built-up land (Fig 11) from 1985 to 2025, which represents a period of economic conflict in the form of a comprehensive set of section (Headey and Jayne 2014).The fallow land would decrease (Fig 9), simultaneously shrub land (Fig 12) would be increased gradually include future data. LU/LC classes of forest land (deciduous and mixed) are decrying decade wise due to plantation class area varied from time to time (Fig 10). Moreover, a slight increase can be observed in water bodies between 1985 and 2035 (Fig 13).

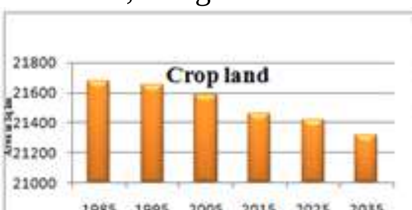

Fig 8: Crop Land 1985-2035

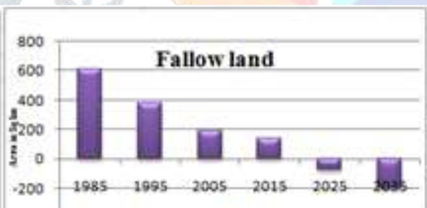

Fig 9: Fallow Land 1985-2035

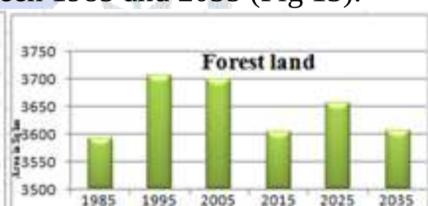

Fig 10: Forest Land 1985-2035

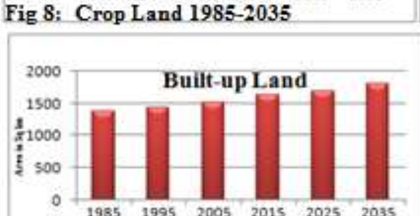

Fig 11: Built-up Land 1985-2035

Fig 12: Shrub Land 1985-2035

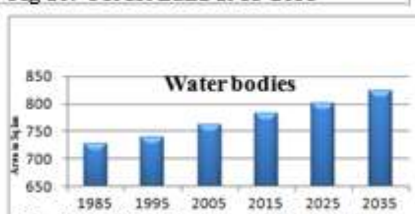

Fig 13: Water bodies 1985-2035

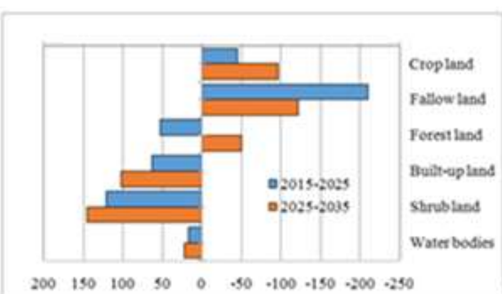

Figure 14 Predicted LU/LC area gain / lose (km²)

Conclusion: This study explored future LU/LC change perdition by a statistical model in combination with remote sensing and GIS technology by using satellite images and ground data. The study revealed that there are changes in many land use/cover categories over the year (1985- 2015). The validation of our model with the actual data of the base year 2015 shows an overall satisfactory result (84.85%), revealing that linear regression models can apply for predicting future LU/LC change. Results clearly confirm significant changes in LU/LC from the start of expansion to the current area in 2015 to 2035. Significant increases in built-up areas (5.89% & 6.25%) were associated with parallel loss of important land cover types such as crop (74.62% & 74.29%) and fallow land (-0.26% & -0.68%). The study also show that spatial information technology (remote sensing, GIS, and GNNS) are an effective platform for simulating LU/LC changes, useful for guiding planning and management. The findings of this study are useful to policy makers, planners, and the public to adopt better environmental management practices, including adaptation and mitigation strategies for the dry-land and its surrounding areas. The studies recommend ecosystem-based adaptation policies and other legal frameworks should be developed and practically implemented to protect the current crop cover as well as rehabilitate and improve the existing green spaces in and around the dry-land.

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