A Computational Algorithm Using Wilcoxon-Based Statistical Significance and Magnitude Assessment in Regional Land Use Studies

Karan Veerbhan
Department of Geography, Meerut College, Meerut (U.P.) 250001- India

Abstract

Understanding land use dynamics requires a nuanced approach that considers both statistical significance and the magnitude of change. This study investigates land use changes across development blocks between 2013-14 and 2022-23, focusing on four key categories: forest, current fallow, barren and uncultivable land and area sown more than once. The study proposes a dual-framework analysis that integrates the Wilcoxon Signed-Rank Test with percentage change metrics to evaluate the performance of each block.

While the Wilcoxon test captures whether changes in land categories are statistically significant over time, percentage change reflects the practical and operational magnitude of that change. This combination enables a more comprehensive assessment, distinguishing between blocks with statistically meaningful shifts and those with large, but potentially inconsistent, variations. The results reveal that several blocks with high percentage changes did not pass the significance threshold ($p < 0.05$), indicating volatile but statistically unreliable shifts. Conversely, some blocks demonstrated consistent, statistically significant transformations with moderate percentage gains, highlighting stable performance.

The analysis also includes clustering of development blocks using K-means based on percentage change vectors, revealing spatial and structural similarities in land use evolution. By mapping significance against magnitude, the study provides a policy-relevant framework for prioritizing interventions. Developmental blocks that exhibit both high statistical significance and large magnitude of change emerge as critical targets for land management strategies. This combined approach bridges the gap between statistical rigor and practical interpretation, offering a robust tool for regional planning and sustainable land resource governance.

Keywords: Land Use Change; Wilcoxon Signed-Rank Test; Percentage Change; Development Block Analysis; Statistical Significance

Introduction

1. Background and Rationale

In order to meet their requirements, humans have always attempted to use the land in various ways, such as for transportation, housing, and food production. However, human needs are limitless, while the land base is finite. This requirement has become more pressing due to the world's population growth, particularly in the past 50 years (Degife et al., 2019; Firozjaei et al., 2019a). Future planning, employment as a tool for policymakers, sustainable land resource management, and sustainable use of the natural resource all depend on the assessment and quantification of spatiotemporal land use change (Berihun et al., 2019; Duveiller et al., 2020; Firozjaei et al., 2019b; Kanianska et al., 2014; Ma et al., 2022; Mungai et al., 2022; Spiegal et al., 2022).

In addition to being the fundamental geographical unit that unites humans and the natural world, land is the most fundamental natural resource for guaranteeing and sustaining human survival and progress (Wu 1991; Liu 1997). "Land is closely related to the field of human activity and carries the development of human civilization through various historical stages" (Wang et al. 2002). However, land use and land cover change (LUCC) has an explicit and implicit binary structure (Dai and Ma 2018; Cai et al. 2020) and is caused by human activity, the environment, and socioeconomic circumstances (Mooney et al. 2013). Yi-Fu Tuan, a scholar, thought that LUCC is a two-way mirror of human society. In the meanwhile, it plays a significant role in ecological preservation, regional sustainable development, and global environmental change. But in 1995, the IGBP and IHDP plans jointly implemented the "LUCC Cross Scientific Research Plan" and offered the "International Global Environmental Change: Man and Environment Plan," which is the scientific forecast of LUCC (Turner et al. 1995). As a result, LUCC has steadily developed to the point where numerous nations have conducted studies on sustainable development and global environmental change (Turner et al. 2007). The IIASA began doing research on "land cover change in land use in Europe and North Asia" in 1995. The IGBP project introduced the idea of the "Anthropocene" in 2000 (Ruddiman 2013), which holds that changes in the earth's surface are largely due to human activity. Additionally, according to Xu et al. (2013), the United States' ESSC suggested that "human activities are the third driving factor affecting changes in the geographical and natural environment." LUCC will become a significant material spatial structure for achieving the sustainable development of humans in the future, according to Houghton et al. (2000). On all temporal and spatial scales, changes in land-use and land-cover (LULC) are the primary human-caused drivers of ecological change (Lambin et al., 2003; N¨aschen et al., 2019). These modifications are intricate and brought on by a variety of elements, including human and physical ones (Huang et al., 2008). They also cover ecological concerns including climate change, biodiversity loss, and pollution of natural resources like soils, water, and air (Slingenberg et al., 2009; Twisa et al., 2020). On a local and global level, LULC change has given rise to particular issues about sustainable development and the management of natural resources (Foley et al., 2005; Wei et al., 2015; Yirsaw et al., 2017). Land is a finite resource and the foundation of agriculture, forestry, habitation, and ecological balance. Over the past few decades, the pressure on land has grown due to expanding population, urbanization, and climate variability. As a result, changes in land use and land cover (LULC) have emerged as critical indicators of environmental sustainability and policy effectiveness. Tracking these changes over time is not only essential for documenting ecological transformation but also for assessing the effectiveness of developmental schemes and agricultural interventions at the micro-level, particularly in rural development blocks where local administration plays a direct role. Conventional assessments of LULC often focus either on magnitude-based changes measuring how much a land use type has increased or decreased over time or on statistical tests to verify the significance of such changes. However, these two approaches rarely intersect in analytical frameworks, resulting in incomplete or one-sided evaluations. A large change in land use area may seem impactful, but if it lacks statistical consistency across categories or observations, it may be misleading for policy-making. On the other hand, statistically significant changes that involve only minor percentage shifts may not always carry practical relevance. Therefore, a balanced framework that considers both the magnitude of change and its statistical significance is necessary to comprehensively assess land transformation at the block level. This study proposes such a dual-framework by combining percentage change and the Wilcoxon Signed-Rank Test to evaluate block-wise performance in land use transformation between the years 2013-2014 and 2022-2023. This approach ensures that both practical implications and statistical robustness are considered, offering deeper insights for targeted land use policies. This non-parametric test is particularly suitable when the data consist of definite, paired scores. Unlike the sign test which is appropriate for qualitative observations (e.g., “more” vs. “less”) the Wilcoxon test is used when the direction and extent of change can be meaningfully assessed in paired datasets (Scheff, 2016).

1.2. Objectives and Research Questions

The primary objective of this study is to examine land use changes across development blocks using a combination of quantitative and statistical techniques. The research focuses on four major land use categories: Forest area Current fallow land Barren and uncultivable land Area sown more than once. The goal is to identify which blocks have undergone statistically consistent transformations and whether those changes are significant in magnitude. To achieve this, the study integrates two analytical methods: the Wilcoxon Signed-Rank Test, a non-parametric test that measures the statistical difference between paired observations, and percentage change analysis, which quantifies the extent of increase or decrease in each land category over the study period.

The study is guided by the following research questions:

1. Which development blocks show significant land use change across selected categories between 2013-2014 and 2022-2023?

2. Do blocks with large percentage changes also exhibit statistically significant transformations?

3. Can a dual framework of significance (Wilcoxon test) and magnitude (percentage change) offer better decision-making tools than either approach alone?

4. How can cluster analysis based on percentage changes further aid in classifying blocks with similar land use transition patterns?

These questions are particularly relevant in the context of agricultural land governance, resource optimization, and localized development planning. By answering them, this research provides a diagnostic model that integrates practical and statistical lenses for analysing land use performance.

2. Methodology

This section outlines the step-by-step procedures used to evaluate land use changes across development blocks by integrating both statistical significance and magnitude of change. The approach comprises four analytical stages: data acquisition and pre-processing, computation of absolute and percentage change, significance testing using the Wilcoxon Signed-Rank Test and spatial clustering based on land use dynamics.

2.1. Data Acquisition and Pre-processing

The analysis utilizes secondary data on land use/land cover (LULC) across development blocks of the study area for two different time periods: 2013-2014 and 2022-2023. The categories include forest, fallow land, barren land, and multi-sown areas. Each land use category's area (in hectares) per block is extracted from official government reports.

Steps taken:

CSV files representing each year's land use distribution are merged based on block and category.

Data files are checked for missing values and consistency.

2.2. Absolute and Percentage Change Calculation

To assess temporal dynamics, both absolute change and percentage change are computed for each block and category.

- Absolute Change = Area in (2022–23) – Area in (2013–14)
- Percentage Change = (Absolute Change / Area in (2013–14) × 100)

This dual approach offers a comprehensive view of magnitude: absolute change emphasizes raw area changes, while percentage change contextualizes growth or decline relative to baseline levels.

2.3. Statistical Significance Testing:

Wilcoxon Signed-Rank Test

To determine whether the observed changes are statistically significant across the land use categories considered, the Wilcoxon Signed-Rank Test is applied on land use categories for two time periods. It is a non-parametric test ideal for comparing paired samples. The test is performed per category, using block-level data as pairs. The null hypothesis assumes no median difference between the two time periods. A significance threshold of $p < 0.05$ is considered to reject the null hypothesis. This method provides insight into whether observed changes are consistent and statistically robust rather than due to random variation.

2.4. Clustering of Blocks Based on Land Use Change

To explore patterns and group similar blocks, unsupervised clustering is performed using K-means or Hierarchical Clustering based on normalized values of change across all land use categories. Input features: percentage change in Forest, Fallow, Barren, and Multi-Sown areas per block. The optimal number of clusters are identified using silhouette scores and dendrograms. Cluster membership is visualized through maps and plots, offering insights into regional land use trends.

2.5. Software and Visualization

Python is used for all computations and statistical analysis. Libraries included pandas, numpy, scipy, matplotlib, and seaborn. Also, artificial intelligence is solely employed for data cleaning and organization, while all interpretations and analyses are conducted manually by the author.

3. Results and Discussion

3.1. Absolute and Percentage Change

Table 1: Absolute and Percentage Change in Four Categories of Land use Per Developmental Block in Meerut District with Area in Hectares.

Development Block	Category	2013-14	2022-23	Change	% Change
Daurala	Area sown more than once	4802	6662	1860	38.73386089
Daurala	Barren and uncultivable land	197	393	196	99.49238579
Daurala	Current Fallow	404	62	-342	-84.65346535
Daurala	Forest	330	303	-27	-8.181818182
Hastinapur	Area sown more than once	7078	10126	3048	43.06301215
Hastinapur	Barren and uncultivable land	87	207	120	137.9310345
Hastinapur	Current Fallow	975	68	-907	-93.02564103
Hastinapur	Forest	3762	3460	-302	-8.02764487
Janikhurd	Area sown more than once	6438	8825	2387	37.0767319
Janikhurd	Barren and uncultivable land	97	225	128	131.9587629
Janikhurd	Current Fallow	145	60	-85	-58.62068966
Janikhurd	Forest	799	735	-64	-8.010012516
Kharkhoda	Area sown more than once	8001	11172	3171	39.63254593
Kharkhoda	Barren and uncultivable land	141	313	172	121.9858156
Kharkhoda	Current Fallow	225	56	-169	-75.11111111
Kharkhoda	Forest	279	256	-23	-8.243727599
Machhra	Area sown more than once	6882	9712	2830	41.12176693
Machhra	Barren and uncultivable land	42	168	126	300
Machhra	Current Fallow	69	51	-18	-26.08695652
Machhra	Forest	633	582	-51	-8.056872038
Mawana Fort	Area sown more than once	6027	8239	2212	36.70150987

Mawana Fort	Barren and uncultivable land	76	186	110	144.7368421
Mawana Fort	Current Fallow	199	65	-134	-67.33668342
Mawana Fort	Forest	951	875	-76	-7.991587802
Meerut	Area sown more than once	6157	8614	2457	39.90579828
Meerut	Barren and uncultivable land	204	407	203	99.50980392
Meerut	Current Fallow	393	57	-336	-85.49618321
Meerut	Forest	938	863	-75	-7.995735608
Parikshitgarh	Area sown more than once	7459	10395	2936	39.36184475
Parikshitgarh	Barren and uncultivable land	667	781	114	17.09145427
Parikshitgarh	Current Fallow	474	82	-392	-82.70042194
Parikshitgarh	Forest	10072	9264	-808	-8.022239873
Rajpura	Area sown more than once	6031	6182	151	2.503730725
Rajpura	Barren and uncultivable land	124	273	149	120.1612903
Rajpura	Current Fallow	224	57	-167	-74.55357143
Rajpura	Forest	680	625	-55	-8.088235294
Rohta	Area sown more than once	5548	8680	3132	56.45277578
Rohta	Barren and uncultivable land	140	297	157	112.1428571
Rohta	Current Fallow	271	62	-209	-77.12177122
Rohta	Forest	533	490	-43	-8.067542214
Sardhana	Area sown more than once	4865	6731	1866	38.35560123
Sardhana	Barren and uncultivable land	83	198	115	138.5542169
Sardhana	Current Fallow	638	82	-556	-87.14733542
Sardhana	Forest	460	423	-37	-8.043478261
Sarurpur Khurd	Area sown more than once	6333	6598	265	4.18443076
Sarurpur Khurd	Barren and uncultivable land	126	273	147	116.6666667
Sarurpur Khurd	Current Fallow	411	78	-333	-81.02189781
Sarurpur Khurd	Forest	520	478	-42	-8.076923077

Four types of land are compared in the analysis: forest, current fallow, barren and uncultivable land, and area that has been sown more than once. Deeper understandings of agricultural intensity, land degradation, and potential land recovery are revealed by the distinct land transformation trajectory that each block offers.

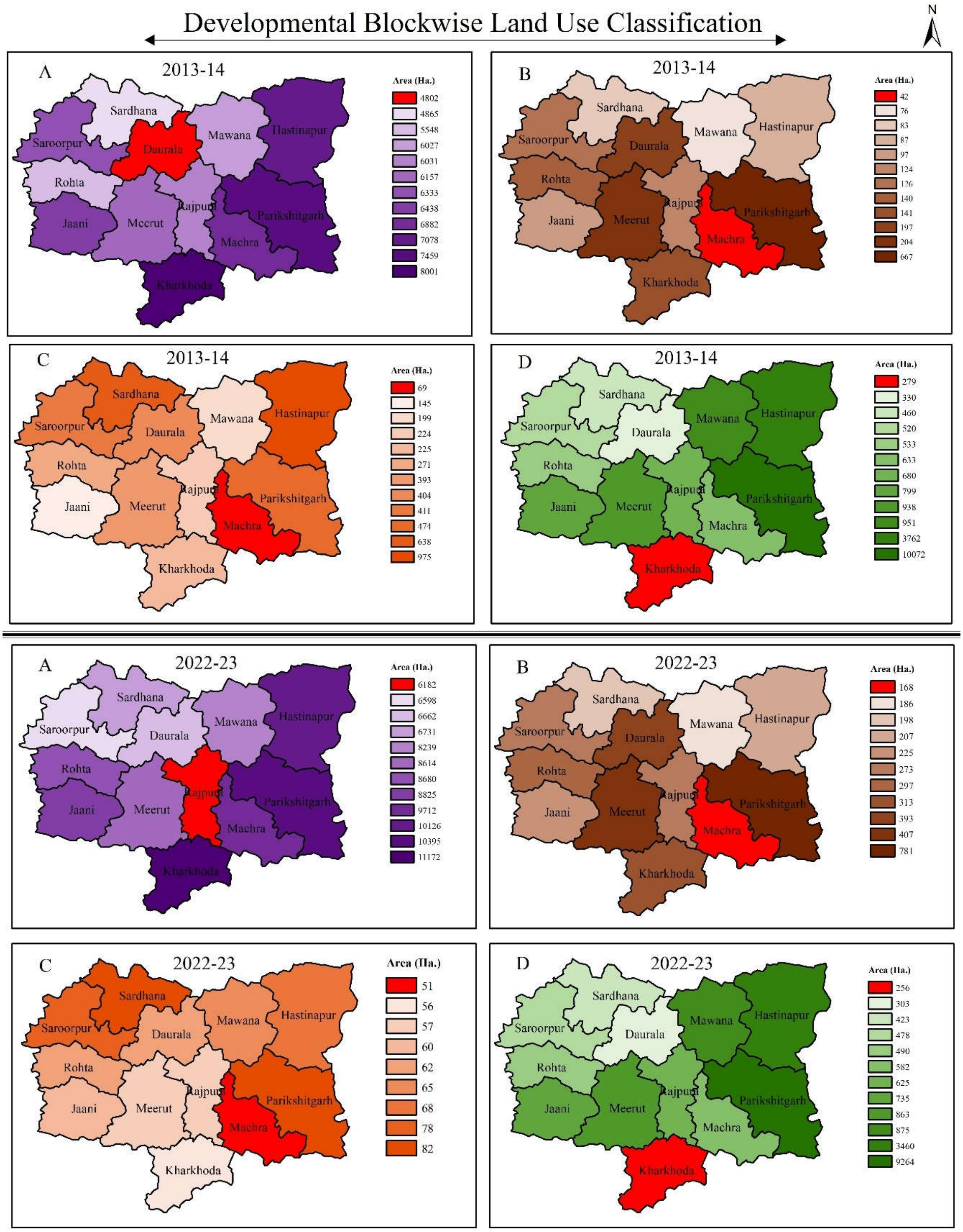

Fig. 1: A: denotes the area sown more than once, B: denotes barren land, C: denotes current fallow land, and D: denotes forest area for the two time periods, 2013-14 and 2022-23, in Meerut district at the developmental block level. In each map, red colour represents the lowest value for the respective land use category.

1. Rise in Cultivated Intensity with a Sharp Decline in Fallow Land

One of the most consistent trends across nearly all development blocks is the significant increase in area sown more than once, suggesting intensified cropping practices. Developmental blocks like Machhra, Parikshitgarh, Rohta, and Hastinapur saw increases exceeding 2800 hectares each, indicating greater land productivity and improved irrigation. These gains range from 36% to over 56%, with Rohta leading with a 56.4% increase. There's a near-universal and steep reduction in Current Fallow land across all blocks. In blocks like Meerut, Parikshitgarh and Sardhana, fallow lands dropped by more than 80%, suggesting that land previously left to rest is now under regular cultivation.

2. Barren Land Sees Massive Percentage Increases but Interpretation Requires Caution

While the absolute increases in Barren and uncultivable land are smaller than multi-sown land, the percentage increases are extraordinarily high in blocks like Machhra (300%), Mawana Fort (144.7%), Hastinapur (137.9%), and Sardhana (138.5%). These drastic rises likely reflect localized land degradation or encroachment. Interestingly, while overall area gains may be modest (e.g., 83 to 198 hectares in Sardhana), the percentage change signals potential degradation hotspots that warrant investigation. Yet these numbers could also be affected by reclassification or better reporting, hence the context and field validation are essential before drawing firm conclusions.

3. Forest Areas Are Declining Steadily but Not Drastically

Across all 13 development blocks, forest area shows a relatively uniform decline, typically between 7% and 8%. For example, Parikshitgarh lost 808 hectares (a −8.02% drop), the highest in absolute terms, while Janikhurd, Meerut and Rohta also followed this downward trend. Although the declines appear modest in percentage, they reflect a consistent negative trajectory. This uniform shrinkage suggests systemic pressure on forest lands likely due to encroachment, urban expansion and shifting cultivation. Unlike barren or fallow land, forest loss is more irreversible, making this trend alarming from an ecological standpoint.

4. Divergence Between Area Gains and Ecological Trade-Offs

The data reveals a clear trade-off: as agricultural intensification increases through expansion of multi-cropping areas the ecological buffers such as forest, fallow and even marginal lands are being compressed. This trend is most evident in blocks like Hastinapur and Meerut, where aggressive increases in multi-sown areas (over 2400 ha) correspond with significant losses in fallow and forest land. The narrative of 'more agriculture equals more development' needs careful balancing, especially considering long-term sustainability, groundwater usage, and soil fertility, which are often compromised under intensive agriculture.

5. Moderate Performers and Stable Blocks

Developmental blocks like Rajpura and Sarurpur Khurd exhibit relatively stable patterns. Rajpura's area sown more than once increased only by 151 hectares (just 2.5%), and Sarurpur Khurd by 265 hectares (4.1%). Interestingly, despite lower gains in cultivation, Sarurpur Khurd recorded a significant 116.6% increase in barren land, pointing to potential land degradation rather than agricultural progress. This may represent regions where development has plateaued or where more targeted interventions are required.

6. Implications for Land Use Planning and Policy

The contrasting trends of intensified cultivation and shrinking fallow and forest lands signal the urgent need for block-specific land management strategies. While blocks like Rohta and Parikshitgarh show promising agricultural expansion, it may come at environmental costs. Meanwhile, blocks showing alarming increases in barren land, such as Machhra, Sardhana, and Mawana Fort, should be prioritized for land reclamation or soil restoration programs. Importantly, the steady loss of forests across all blocks though small in annual terms represents a long-term environmental threat that demands urgent conservation planning.

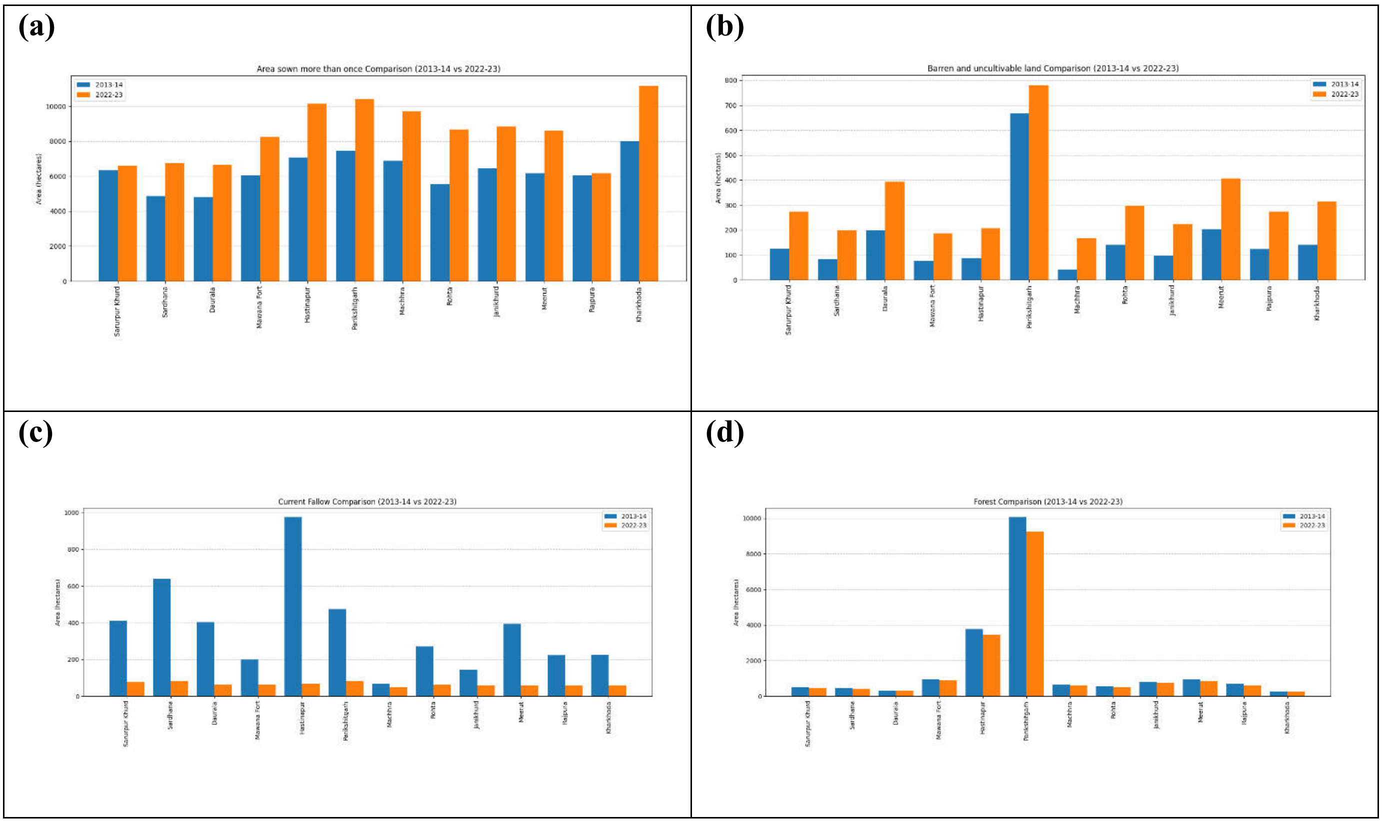

Fig. 2: Absolute Change represented by orange colour for 2022-2023 and by blue colour for 2013-2014, on X-axis we have developmental blocks and on Y-axis we have absolute change count for (a) area sown more than once, (b) Barren land, (c) Current fallow land and (d) Forest area.

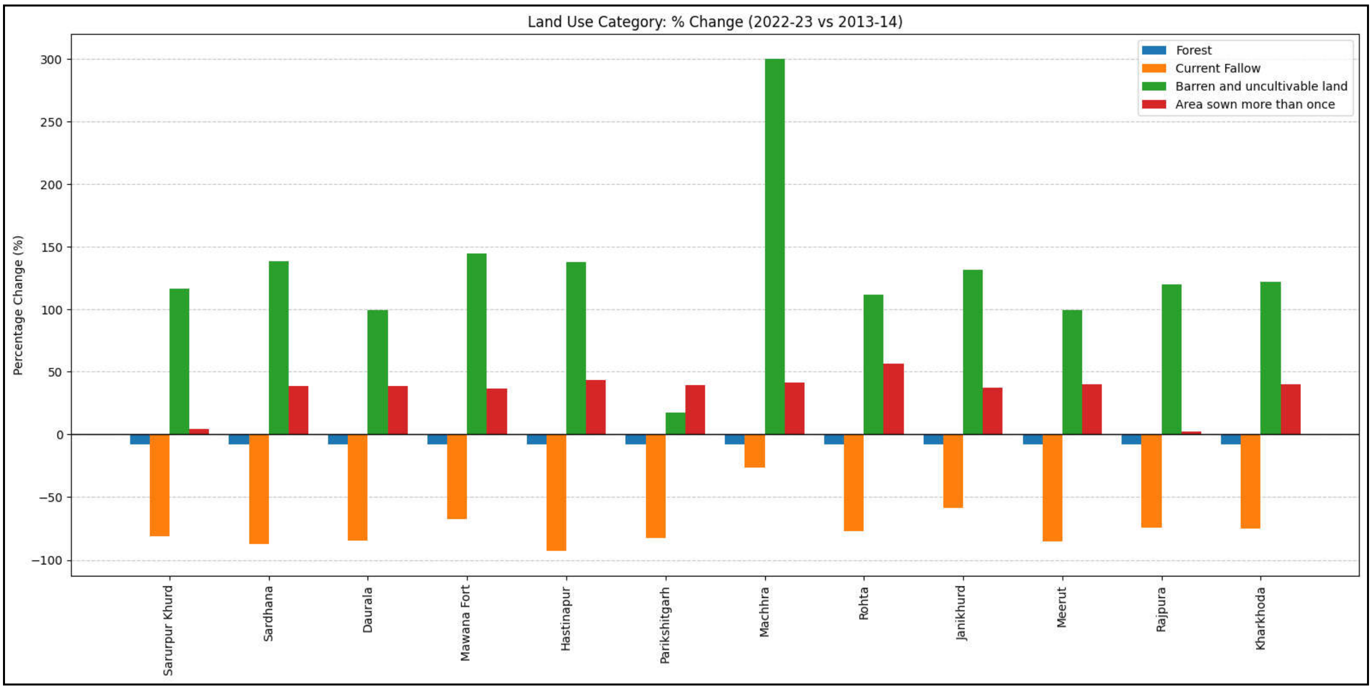

Fig. 3: Percentage change per developmental block in Meerut district for four categories of land use.

3.2. Wilcoxon Signed-Rank Test

The Wilcoxon Signed-Rank Test is applied separately to each of the four land use categories of the study region to assess whether the changes observed between 2013-2014 and 2022-2023 are statistically significant. This non-parametric test helps determine if the median differences in land use over time are not due to random variation, but reflect meaningful and consistent shifts in land use patterns.

Table 2: Statistical values of Wilcoxon Signed-Rank Test for four land use categories

Land Use Type	Wilcoxon Stat	p-value	Significant at 5%	Significant at 1%
Forest	0	0.000488	Yes	Yes
Current Fallow	0	0.000488	Yes	Yes
Barren and uncultivable land	0	0.000488	Yes	Yes
Area sown more than once	0	0.000488	Yes	Yes

All land use types show statistically significant changes over time. The p-value for each is 0.000488, which is well below both the 5% and 1% significance thresholds. This means that the observed differences in land area between the two years are not due to random variation. Wilcoxon Statistic = 0, this indicates that all paired differences (i.e., per block for each category) are either all positive or all negative (or the differences are strongly directional). Such a result suggests a highly consistent shift across development blocks in each land use type.

3.4. Clustering Blocks Based on Land Use Change

Table 3: Developmental Block-wise Clustering with PC1 and PC2 Statistical Values

Development Block	Area sown more than once	Barren and uncultivable land	Current Fallow	Forest	Cluster	PC1	PC2
Daurala	38.73386	99.49239	-84.6535	-8.18182	2	-0.87843	-0.82377
Hastinapur	43.06301	137.931	-93.0256	-8.02764	1	-0.53695	0.850899
Janikhurd	37.07673	131.9588	-58.6207	-8.01001	1	0.785238	0.573289
Kharkhoda	39.63255	121.9858	-75.1111	-8.24373	2	-0.30706	-1.48297
Machhra	41.12177	300	-26.087	-8.05687	0	4.013181	-0.20642
Mawana Fort	36.70151	144.7368	-67.3367	-7.99159	1	0.596419	0.757371
Meerut	39.9058	99.5098	-85.4962	-7.99574	1	-0.6486	1.052532
Parikshitgarh	39.36184	17.09145	-82.7004	-8.02224	1	-1.51911	0.917315
Rajpura	2.503731	120.1613	-74.5536	-8.08824	2	-0.37434	-1.67994
Rohta	56.45278	112.1429	-77.1218	-8.06754	1	-0.13268	1.045944
Sardhana	38.3556	138.5542	-87.1473	-8.04348	1	-0.34611	0.445779
Sarurpur Khurd	4.184431	116.6667	-81.0219	-8.07692	2	-0.65156	-1.45002

Based on K-means clustering, the blocks are grouped into three distinct clusters (0, 1 and 2)

Cluster 0 (only Machhra) is an outlier with extreme values, especially +300% increase in barren land and the smallest fall in fallow land (−26.08%). It's very high PC1 value (4.01) confirms it as a unique block, likely facing unusual land transformation pressures.

Cluster 1 includes blocks like Hastinapur, Janikhurd, Mawana Fort, Meerut, Parikshitgarh, Rohta, and Sardhana. These share moderate to high increases in multi-sown land, substantial fall in fallow land and similar trends in forest reduction. They are agriculturally active zones undergoing intensification and marginal forest loss.

Cluster 2 contains Daurala, Kharkhoda, Rajpura, and Sarurpur Khurd, showing more balanced or modest shifts, with some having unusually low gains in agriculture (e.g., Rajpura: +2.5%) or large increases in barren land. These blocks might be experiencing either stagnation or uneven development.

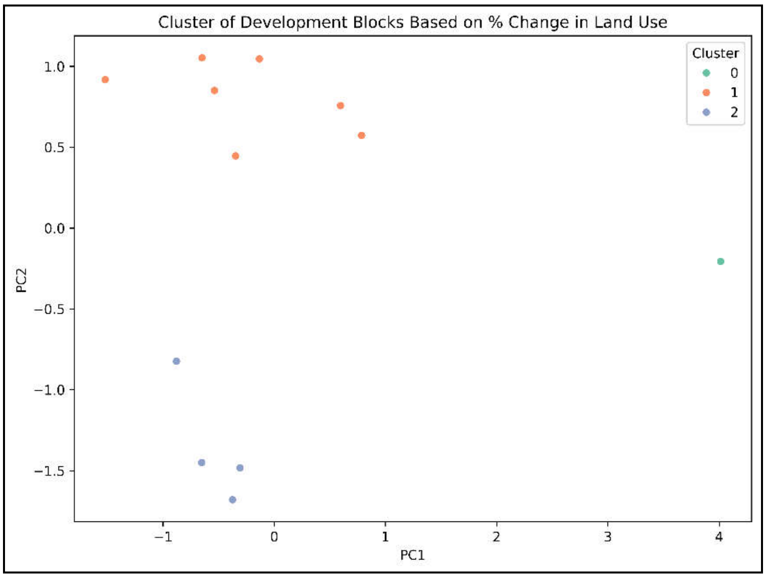

Fig. 4: Each developmental block has been Clustered by k means clustering and plotted by PCA (Principal Component Analysis)

Dimensions of Variation the PC1 (Principal Component 1) axis captures the overall intensity of land use change, where higher values (e.g., Machhra +4.01) signify more extreme transformations, while negative scores indicate lower impact. Most blocks have negative PC1 values, suggesting moderate overall changes. PC2, on the other hand, appears to distinguish between fallow loss and barren increase. Parikshitgarh and Rohta have high PC2 values (≈ +0.9 to +1.04), reflecting strong fallow-to-agriculture shifts, while Kharkhoda and Rajpura show highly negative PC2 values, due to more barren land expansion.

This two-dimensional PCA view gives a compressed yet interpretable structure to understand how different blocks vary. It also explains why certain blocks end up in the same cluster due to shared direction and magnitude of change across these four variables.

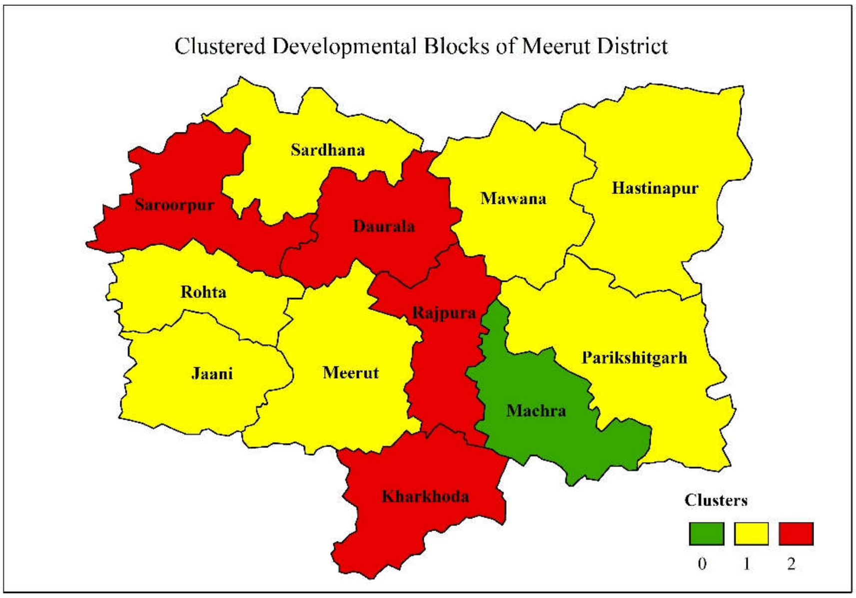

Fig. 5: The map of Meerut district depicts developmental blocks clustered using the k-means algorithm

Conclusion

Based on the two tables, a clear trend emerges in land use dynamics across the study region between 2013-14 and 2022-23. The Wilcoxon Signed-Rank Test results for four land use categories Forest, Current Fallow, Barren and Uncultivable Land, and Area Sown More Than Once indicate statistically significant changes over the years. With p-values of 0.000488 for all categories and W-statistics of 0, these results suggest consistent and significant shifts across the entire region. Notably, forest and fallow lands have experienced significant declines, while barren land and multi-sown areas have increased implying a transformation from ecological or unused lands toward more intensive or expanding cultivation practices.

The clustering and principal component analysis reveal distinct patterns of land use transformation across development blocks. Blocks like Rohta, Hastinapur, and Machhra show exceptionally high changes, with Machhra notably forming a unique cluster due to extreme increase in barren land. Most blocks exhibit increased multi-sown and barren land and decreased forest and fallow areas. The PCA scores further distinguish these blocks based on the intensity and direction of change, indicating spatial heterogeneity in land use practices across the region.

Suggestions

1. Promote Sustainable Multi-Cropping

As "Area sown more than once" has significantly increased across all blocks, policies should encourage efficient water use, crop rotation, and soil fertility management to maintain productivity without degrading resources.

2. Control Barren Land Expansion

The sharp rise in barren and uncultivable land especially in blocks like Machhra and Mawana Fort calls for reclamation initiatives, including afforestation, soil health restoration, and bunding to reduce degradation.

3. Revive Current Fallow Land

With a consistent decline in fallow land, targeted programs should be launched to support smallholders through credit access, irrigation support, and input subsidies to utilize these lands sustainably.

4. Protect Declining Forest Areas

Even though forest area reduction appears modest, its uniform decline across all blocks signals the need for community-driven forest management and stricter enforcement of land use regulations.

5. Block-Specific Land Management Plans

Wilcoxon results show significant change only at the land use category level but not at the block level, micro-level interventions tailored to each block’s context would be more effective than one-size-fits-all solutions.

6. Monitor High-Risk Clusters (Cluster 0 and 2)

Cluster analysis revealed anomalies like Machhra in a separate group due to extreme change. These should be treated as priority zones for environmental risk assessments and corrective actions.

7. Use PCA for Planning and Targeting

Principal component scores (PC1 and PC2) offer a statistical basis to identify blocks undergoing similar patterns of land use change. Planning resource allocation based on these components can ensure targeted and efficient intervention.

Compliance with ethical standards

This study adheres to ethical research standards, ensuring integrity, transparency, and accountability throughout the analysis. No human or animal subjects are involved, and all data used are secondary and publicly available.

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Disclosure

Author declares no conflict of interest.

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