Impacts of Land Use and Climate Variability on Groundwater Storage in the Cauvery River Basin Using GRACE and Empirical Orthogonal Function Analysis

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Abstract

Groundwater storage (GWS) within the Cauvery River Basin is facing increasing stress due to the combined effects of climate variability and land use/land cover (LULC) changes. This study provides a comprehensive assessment of the spatial and temporal variations in GWS and examines the influence of LULC and climatic factors using data from the Gravity Recovery and Climate Experiment (GRACE) satellite mission, supplemented by Empirical Orthogonal Function (EOF) analysis and Spearman correlation. GRACE-derived terrestrial water storage anomalies (TWSA) were utilized to estimate GWS variations, while EOF analysis was employed to extract the dominant spatial and temporal patterns of groundwater fluctuations, LULC changes, and precipitation variability. The analysis identified distinct seasonal and interannual GWS variations, which are primarily influenced by monsoonal rainfall patterns and increasing anthropogenic groundwater extraction. While the study observed a statistical link between certain precipitation modes and groundwater dynamics, the correlations between dominant LULC patterns and GWS were found to be more consistently significant and of greater magnitude. These findings indicate that rapid urbanization and agricultural expansion are more robustly associated with groundwater stress in the basin compared to the measured climatic variability. The results underscore the critical need for sustainable water resource management strategies that specifically address the landscape changes driven by human activities to mitigate the adverse effects on groundwater availability in the Cauvery River Basin.

Keywords: EOF analysis, Giovanni, GRACE, TWSA

1 Introduction

1.1. Background and Context

Groundwater constitutes a critical component of the global water cycle and serves as a vital resource for human consumption, agriculture, and industry, particularly in

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arid and semi-arid regions. As the world's most extracted raw material, its availability and sustainability are of paramount importance. In India, groundwater is the primary source for irrigation and domestic use, supporting millions of livelihoods. The Cauvery River Basin, spanning approximately 81,155 km^2 across the states of Tamil Nadu, Karnataka, and Kerala, is a hydro-ecologically significant region and a major agricultural hub, making its groundwater resources particularly susceptible to stress. The long-term stability of this resource is not merely a scientific concern but is inextricably linked to regional food security, economic stability, and environmental sustainability. Understanding the complex dynamics of groundwater storage in such a critical basin is a prerequisite for informed water resource governance and policy formulation.

1.2. The Research Problem

The Cauvery River Basin is a prime example of a region facing a dual threat to its water security: the increasing pressures of human activity and the effects of climate variability. Over the past decade, the basin has experienced rapid urbanization, agricultural intensification, and extensive infrastructural development, all of which have significantly altered the natural land use and land cover (LULC) patterns. These transformations, such as the expansion of impervious surfaces and the conversion of forests to farmlands, have directly impacted natural groundwater recharge. Concurrently, changes in climatic patterns, notably the variability of monsoonal rainfall, have introduced additional stress by altering the primary mechanism of aquifer replenishment. The central problem, therefore, is to accurately quantify and attribute the changes in groundwater storage to these competing influences. This requires a robust, data-driven approach that can effectively separate the dominant drivers of change in a complex, multi-variable system.

1.3. Review of Existing Literature and Research Gap

Satellite-based remote sensing has emerged as an invaluable tool for monitoring large-scale terrestrial hydrological changes. The Gravity Recovery and Climate Experiment (GRACE) and its successor, GRACE-FO, have been widely adopted for this purpose. Studies such as those by Dasgupta et al. (2022) and Satishkumar et al. (2023) have demonstrated the effectiveness of GRACE data in tracking groundwater storage changes globally and in specific regions of India, highlighting significant depletion trends. Likewise, the impact of LULC changes on groundwater has been documented by Saraskanroud et al. (2022), who used GRACE data to monitor how aquifer levels respond to land cover transformations.

The statistical technique of Empirical Orthogonal Function (EOF) analysis has proven to be a powerful method for decomposing complex environmental datasets into dominant spatial and temporal patterns. Its application in hydrology has allowed researchers to identify key modes of variability in datasets such as rainfall and groundwater storage. For instance, Kumar et al. (2015) applied EOF analysis to assess rainfall variability in the Cauvery Basin, while Zhang et al. (2020) used it to analyze groundwater storage variations in the North China Plain. More recently, Mohasseb et al. (2024) demonstrated the utility of EOF analysis in linking groundwater storage variations to climate parameters, noting a significant spatio-temporal agreement between specific modes of precipitation and groundwater storage in African river basins.

While prior research has established the individual impacts of LULC and climate variability on water resources, a critical gap remains in the quantitative integration of all three factors—LULC, precipitation, and groundwater storage—to identify their primary interactive effects and relative contributions to GWS changes within the Cauvery Basin. This study uniquely addresses this gap by leveraging EOF analysis to decouple the complex signals of each dataset and then using statistical correlation to determine the strength of the relationship between their dominant modes of variability. This approach allows for a more nuanced understanding of the specific mechanisms driving groundwater stress, moving beyond simple, direct correlations to investigate the interplay of systemic patterns.

1.4. Objectives

The primary objective of this study is to assess the influence of land use dynamics and climate variability on groundwater storage in the Cauvery River Basin using a combination of GRACE satellite data and EOF analysis.

The specific objectives are as follows:

- To assess LULC changes in the Cauvery River Basin using remote sensing data and GIS techniques.
- To analyze GRACE and GRACE-FO satellite data to estimate groundwater storage variations in the basin over the past decade.
- To identify the dominant spatial and temporal patterns of groundwater storage, LULC, and precipitation variations using EOF analysis.
- To investigate the effects of land use changes and climate variability on groundwater storage dynamics through correlation analysis.

2. Literature Review

2.1. GRACE Satellite Mission and Groundwater Monitoring

The GRACE mission, launched in 2002, provides a revolutionary method for monitoring changes in terrestrial water storage (TWS) by measuring variations in Earth's gravitational field. TWS encompasses all water on and below the land surface, including soil moisture, surface water, snow, and groundwater. By subtracting the contributions of other water components from the total TWS signal, GRACE data can be used to estimate changes in groundwater storage (GWS). This approach provides a spatially comprehensive view of hydrological changes at regional scales, which is difficult and costly to achieve using conventional ground-based monitoring networks.

A number of studies have validated GRACE's utility in hydrological research. Asoka et al. (2017) demonstrated the effectiveness of combining GRACE-derived TWS anomalies with ground-based well data to confirm severe groundwater depletion in several Indian regions, particularly due to agricultural over-extraction. Similarly, Satishkumar et al. (2023) reviewed TWS trends using GRACE and GRACE-FO data and confirmed significant groundwater depletion in northwestern India, while also noting the limitations of GRACE's coarse spatial resolution. These studies collectively affirm the value of GRACE as a long-term monitoring tool, especially when integrated with other data sources to enhance accuracy and resolution.

2.2. Empirical Orthogonal Function (EOF) Analysis in Hydrology

EOF analysis is a multivariate statistical technique used to decompose a time series of spatial data into a set of orthogonal spatial patterns (EOFs) and their corresponding temporal coefficients (Principal Components, or PCs). This method is particularly well-suited for hydrological and climatic research because it can efficiently capture the most significant modes of variability in large datasets.

The technique identifies the dominant, coherent spatial patterns that explain the maximum variance in the data, thereby simplifying the analysis of complex systems. For instance, a study by Kumar et al. (2015) applied EOF to assess rainfall variability in the Cauvery River Basin, revealing spatial heterogeneity and declining monsoonal rainfall trends that directly affect groundwater recharge. Similarly, Zhang et al. (2020) used EOF to analyze GRACE-derived GWS variations in the North China Plain, successfully detecting seasonal and long-term depletion patterns linked to both human extraction and climatic influences.

More contemporary research, such as that by Mohasseb et al. (2024), has used EOF analysis to investigate the relationship between climate parameters and groundwater changes, finding a significant spatio-temporal agreement between specific modes of precipitation and groundwater storage in African river basins.

This body of work establishes EOF analysis not just as a descriptive tool but as a critical technique for decoupling the complex, multi-factor influences on GWS into a few dominant, interpretable modes.

2.3. The Influence of Land Use and Land Cover Changes

LULC changes are a major driver of groundwater dynamics. Human activities such as urbanization, deforestation, and agricultural expansion fundamentally alter the surface water balance, thereby impacting groundwater recharge and discharge. Urbanization, for example, increases the extent of impervious surfaces, which reduces infiltration and increases surface runoff, leading to lower recharge rates and, consequently, groundwater depletion. In contrast, agricultural expansion often leads to increased groundwater extraction for irrigation, further straining aquifers.

Dasgupta et al. (2022) investigated the global relationship between LULC changes and groundwater storage using remote sensing and GRACE data, concluding that urbanization and agricultural expansion are strongly associated with groundwater depletion. Similarly, Saraskanroud et al. (2022) demonstrated the utility of GRACE data in monitoring the effects of LULC on aquifer levels, highlighting spatial variability in depletion patterns. These studies underscore the critical role of land use practices in shaping groundwater trends and provide a compelling case for integrating sustainable land use planning into water resource management strategies.

3. Materials and Methods

3.1. Study Area

The Cauvery River Basin is situated between 75° 27' to 79° 54' E and 10° 9' to 13° 30' N, encompassing an area of approximately 81,155 km². It is an ecologically and hydrologically significant region, making it an ideal location for a detailed hydrological assessment. The basin is shared by the states of Tamil Nadu, Karnataka, and Kerala, as well as the union territory of Puducherry. Over the study period (2005–2023), the region has experienced significant socio-economic development, leading to notable shifts in LULC patterns and increased water resource utilization. The basin's geographical context and digital elevation model (DEM) are depicted in Fig.1.

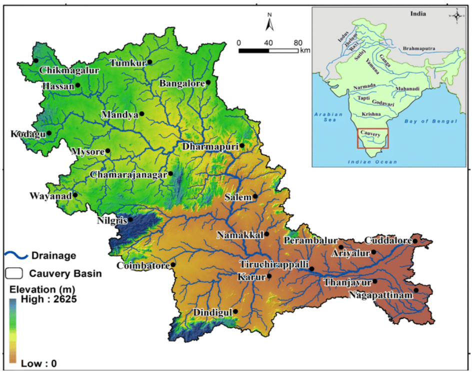


Fig. 1 Location and DEM of Cauvery Basin

3.2. Data Collection

The study employed a multi-source data collection approach to ensure a comprehensive analysis of the hydrological system. The datasets were collected for the period 2005 to 2023 to capture long-term trends and interannual variability. Table 1 summarizes the data products used in the analysis.

Table 1 Summary of Data Products

Data Type	Source	Time Period	Spatial Resolution	Extracted Layers
Groundwater Storage (GWS)	GRACE (GIOVANNI GLDAS)	2005-2023 (monthly)	Coarse (approx. 150 km)	Daily GWS Data
Land Use/Land Cover (LULC)	Landsat, MODIS, ESA CCI	2005-2023 (yearly)	Varies (e.g., 30m, 500m)	LULC Maps
Precipitation Data	GIOVANNI (CHIRPS, GPCP)	2005-2023 (daily)	Varies (e.g., 0.05°, 0.25°)	Daily Rainfall Data
Digital Elevation Model (DEM)	Bhuvan/USGS Earth Explorer	N/A	Varies	Shape file

3.3. Methodological Workflow

The methodology follows a structured sequence designed to integrate data from multiple sources to analyze how land use and climate changes impact groundwater storage in the Cauvery River Basin using GRACE satellite data and Empirical Orthogonal Function (EOF) analysis. The overall workflow is outlined in Fig.2.

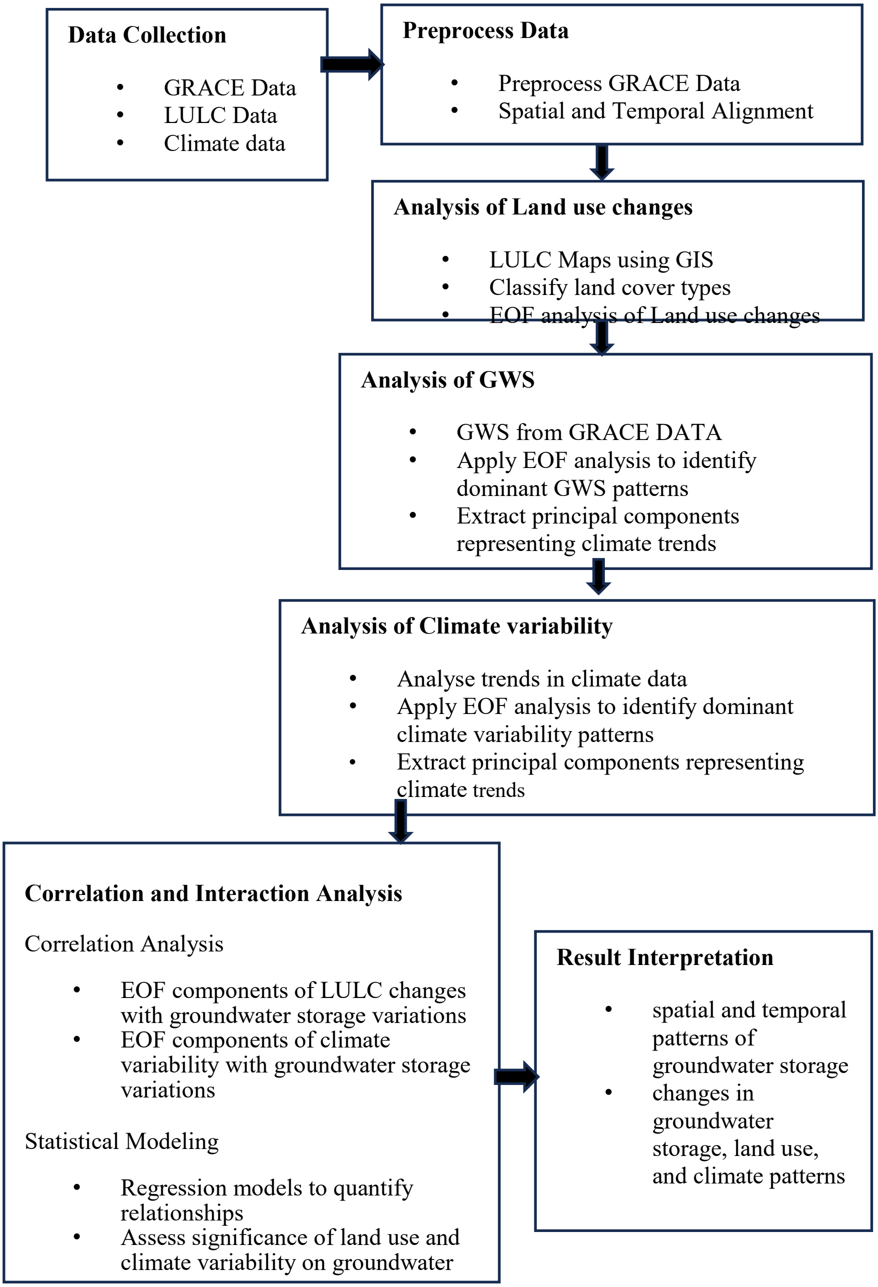


Fig. 2 General methodology flowcha

Data Preprocessing

The raw datasets were subjected to a series of preprocessing steps to ensure they were suitable for analysis. GRACE data, obtained from the GIOVANNI platform, was processed to estimate groundwater storage anomalies (GWS) by accounting for other terrestrial water components. Remote sensing imagery from Landsat and other sources was used to classify LULC into categories such as urban, forest, agriculture, and water bodies using GIS methods. To prepare the LULC data for EOF analysis, which requires continuous rather than categorical input, the LULC maps were transformed into a quantitative fractional cover format, representing the proportion of each land cover type within a given grid cell. All datasets were then spatially and temporally aligned to a consistent resolution and time frame.

Empirical Orthogonal Function (EOF) Analysis

EOF analysis was performed separately on the pre-processed LULC, GWS, and precipitation datasets to identify their dominant patterns of variability. This powerful technique allows for the decoupling of the complex, multi-factor influences on groundwater storage into a few primary, interpretable modes. The process involved constructing a covariance matrix for each dataset, performing an eigenvalue decomposition to find the principal components, and identifying the dominant spatial and temporal patterns.

The EOF method applied on a given data field Z(s,t) decomposes the signal into different orthogonal modes:

$$Z(s,t) = \Sigma \quad (t). \quad (s)\ldots\ldots\ldots\ldots (1)$$

where *s* represents the geographic grid points, *t* is the monthly time tag, and *M* is the number of modes. The vectors $u_k(s)$ are the orthogonal spatial functions, and $c\ (t)$are the corresponding time-dependent coefficients. This analysis was conducted using Python programming language, which provides libraries such as NumPy and scikit-learn to automate the decomposition process.

Spearman Correlation Methodology

To investigate the quantitative relationships between the dominant modes of variability, Spearman's rank correlation coefficient was employed. This non-parametric statistical method is suitable for the study's environmental data, which may exhibit non-linear relationships or may not be normally distributed, making it a more robust alternative to methods like Pearson correlation.

The methodology involved ranking the values of the principal components from the EOF analysis for each dataset. The differences between the ranks (di) of corresponding pairs of LULC and GWS values, and precipitation and GWS values, were calculated and used to compute the Spearman correlation coefficient (ρ). The formula for the Spearman correlation coefficient is given by :

$$\frac{6\sum d}{n(n \quad 1)} \text{........} \quad (1)$$

where di is the difference between the ranks of each pair of observations, and n is the number of observations. A corresponding p-value was calculated to determine the statistical significance of each correlation. Python was used to streamline these calculations.

4. Results

4.1. Land Use/Land Cover Change Analysis

The EOF analysis of LULC data for the Cauvery River Basin from 2005 to 2023 revealed a dominant pattern of change captured by the first EOF mode. As illustrated in Fig.3, this mode accounted for approximately 95% of the total variance, indicating that a single, consistent trend governed most of the landscape transformation across the study period. The remaining modes (EOF 2, EOF 3, etc.) explained a negligible amount of the total variance.

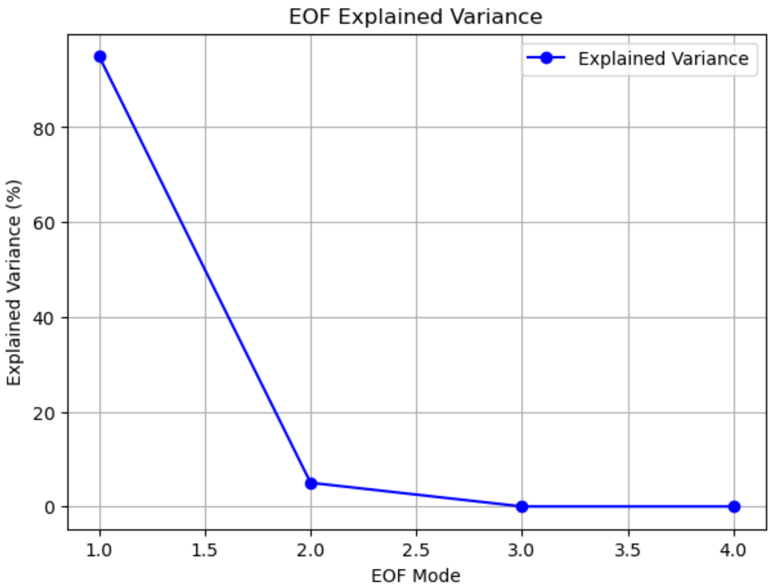


Fig. 3 Explained variance of LULC

Table 2 Fractional cover LULC

Year	Trees	Crops	Built up	Rangeland	Barren land	Water	Flooded
2005	0.3327	0.5663	0.025	0.0407	0.0032	0.0267	0.0054
2006	0.3187	0.564	0.0312	0.0529	0.0031	0.0252	0.0049
2007	0.3047	0.5617	0.0374	0.065	0.003	0.0237	0.0044
2008	0.2907	0.5595	0.0436	0.0771	0.0029	0.0223	0.0039
2009	0.2767	0.5572	0.0498	0.0893	0.0028	0.0208	0.0035
2010	0.2627	0.5549	0.056	0.1014	0.0026	0.0193	0.003
2011	0.2487	0.5526	0.0622	0.1136	0.0025	0.0178	0.0025
2012	0.2348	0.5504	0.0684	0.1257	0.0024	0.0164	0.002
2013	0.2208	0.5481	0.0746	0.1378	0.0023	0.0149	0.0015
2014	0.2069	0.5458	0.0809	0.15	0.002	0.0134	0.001
2015	0.1928	0.5436	0.087	0.1621	0.0021	0.0119	0.0005
2016	0.1898	0.5411	0.0906	0.1632	0.0019	0.0128	0.0005
2017	0.1868	0.5387	0.0942	0.1643	0.0018	0.0137	0.0005
2018	0.1838	0.5363	0.0979	0.1654	0.0016	0.0146	0.0005
2019	0.1808	0.5339	0.1015	0.1665	0.0014	0.0154	0.0004
2020	0.1954	0.5257	0.1069	0.153	0.0014	0.017	0.0006
2021	0.2099	0.5174	0.1123	0.1396	0.0014	0.0186	0.0007
2022	0.2245	0.5092	0.1176	0.1261	0.0014	0.0202	0.0009
2023	0.2391	0.5009	0.123	0.1127	0.0014	0.0218	0.001

The spatial pattern of the first EOF mode, shown in Fig. 4 and Table 3 indicates a clear trend of natural land types decreasing while developed areas expand. This is supported by the corresponding time series of the principal component (PC1) for

LULC, which shows a steady and consistent decrease over time (Fig.5). The fractional cover data in Table 2 further confirms this pattern, revealing a decline in the proportion of 'Trees' and 'Crops' over the study period, while the proportion of 'Built-up' areas consistently increases from 2005 to 2023. This dominant trend represents the widespread and consistent process of urbanization and agricultural intensification throughout the basin.

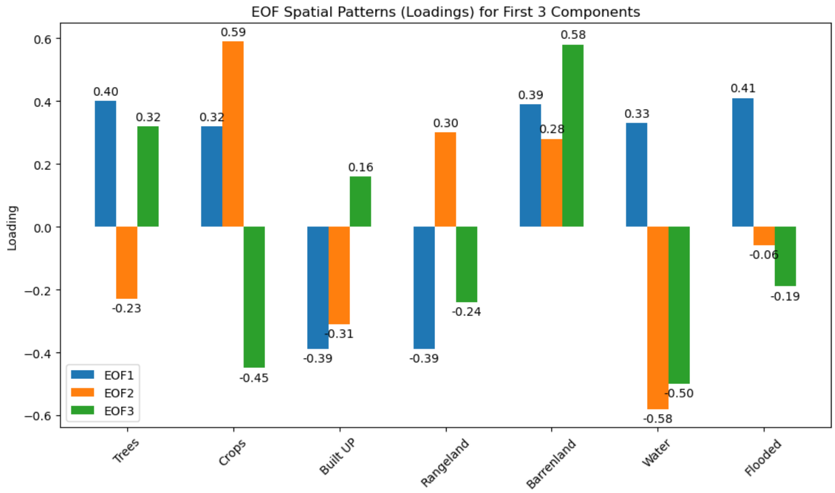


Fig. 4 EOF Spatial pattern of LULC

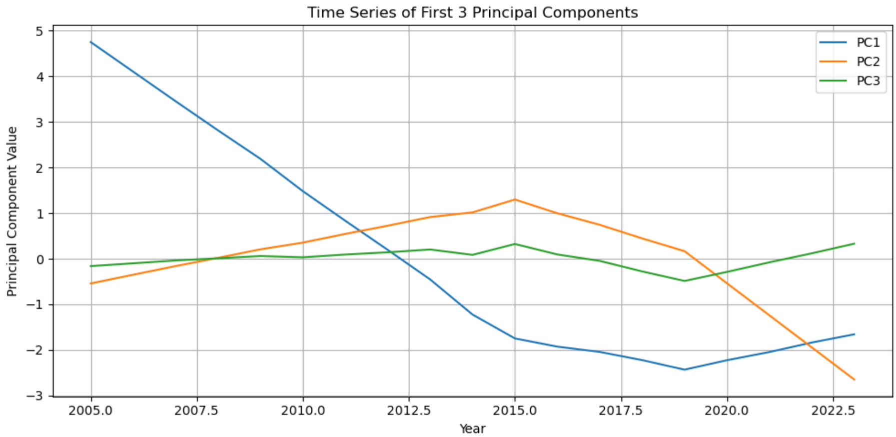


Fig. 5 Time series of LULC

Table 3 LULC spatial pattern explanation

Feature	EOF1	EOF2	EOF3	Interpretation
Trees	0.40	-0.23	0.32	Trees show a strong positive loading on EOF1, indicating they are the dominant land cover change in this mode. EOF2 shows a slight decline, while EOF3 indicates moderate increase.
Crops	0.32	0.59	-0.45	Croplands contribute strongly to EOF2. They are also slightly favoured in EOF1 but show a clear decline in EOF3.
Built-up	-0.39	-0.31	0.16	Strong negative loadings on EOF1 and EOF2 suggest urban (built-up) areas are reducing in these patterns. Slight positive loading in EOF3 shows minimal variation.
Rangeland	-0.39	0.30	-0.24	Rangeland decreases significantly under EOF1, shows slight growth in EOF2, and declines again in EOF3.
Barren land	0.39	0.28	0.58	Barren land increases across all three EOFs, most notably in EOF3, indicating a strong expansion trend.
Water	0.33	-0.58	-0.50	Water bodies show notable variation in EOF1. The strong negative loadings in EOF2 and EOF3 suggest reduction in water extent under these patterns.
Flooded	0.41	-0.06	-0.19	Flooded areas increase significantly under EOF1. Slightly negative loadings in EOF2 and EOF3 indicate minor declines.

4.2. Groundwater Storage Dynamics

The EOF analysis of GRACE-derived GWS data revealed a highly concentrated pattern of variability, with the first EOF mode (EOF 1) accounting for nearly 99% of the total variance (Fig. 6). This finding confirms that the majority of the changes in groundwater storage across the basin were captured by a single, dominant spatio-temporal trend.

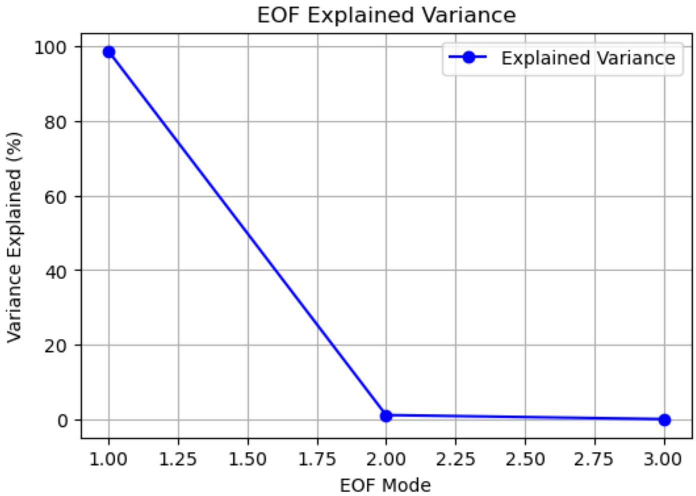


Fig 6. Explained variance of GWS

The time series of the GWS principal component (PC1) shows significant fluctuations over the study period, with periods of severe decline and subsequent recovery (Fig.7). The spatial pattern of the first EOF mode, as depicted in Fig.8,Fig.9 and Fig.10 shows a distinct east-west separation, with higher positive amplitudes (indicating areas of more change) concentrated in the eastern and northern regions of the basin. These regions, which correspond to the basin's most agriculturally intensive and urbanized zones, were identified as areas of significant groundwater depletion.

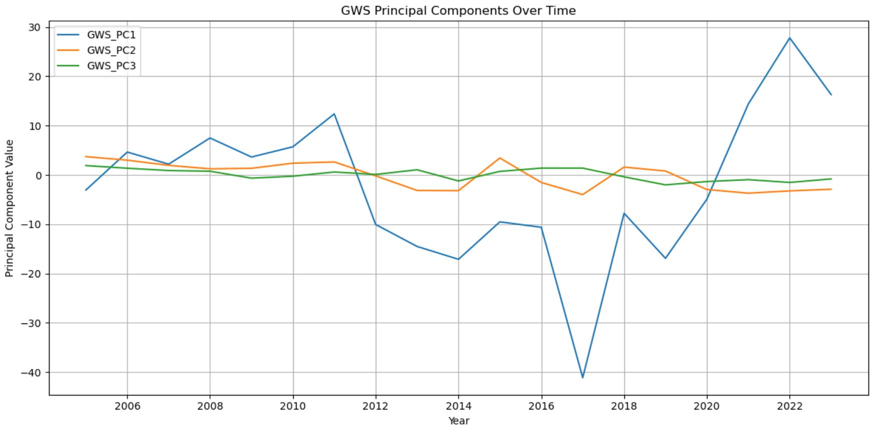
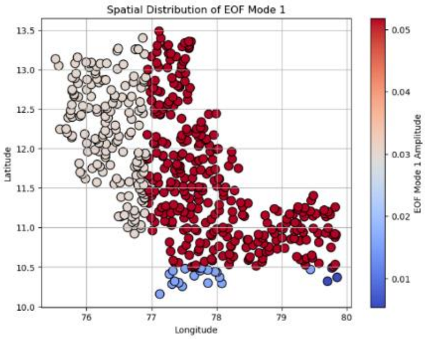


Fig.7. Time series of GWS



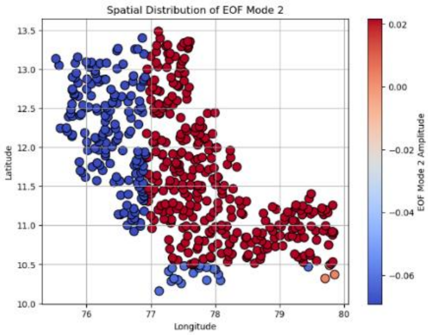


Fig. 8 EOF mode 1 GWS

Fig. 9 EOF mode 2 GWS

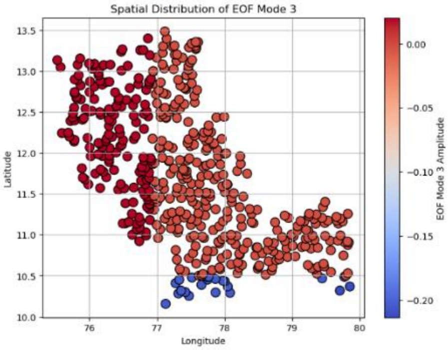


Fig.10 EOF mode 3

4.3. Precipitation Variability

The EOF analysis of precipitation data for the study area also identified a clear dominant mode. The first EOF mode (EOF 1) explained approximately 76% of the total variance (Fig.11). This mode represents the most significant pattern of rainfall variability across the basin.

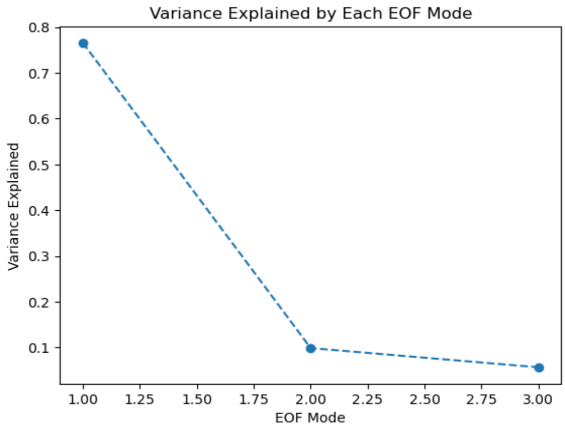


Fig.11. Explained variance of precipitation

The spatial pattern of precipitation EOF 1 (Fig.13, Fig.14 and Fig.15) reveals a strong east-west contrast. This suggests that precipitation anomalies tend to have opposite signs in the western and eastern parts of the basin, representing a dominant pattern of coherent but opposing behaviour across the region. The time series of the first principal component (PC1) of precipitation shows pronounced fluctuations with notable peaks and troughs over the years (Fig. 12), reflecting significant regional rainfall anomalies.

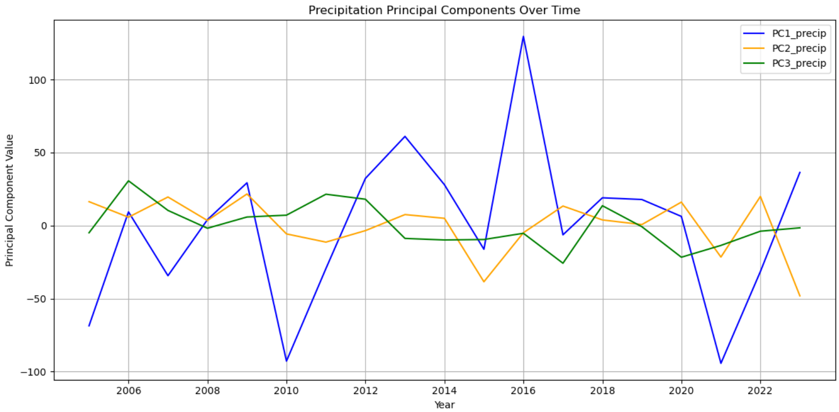
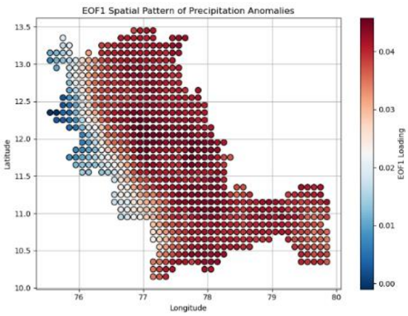


Fig. 12. Time series of precipitation



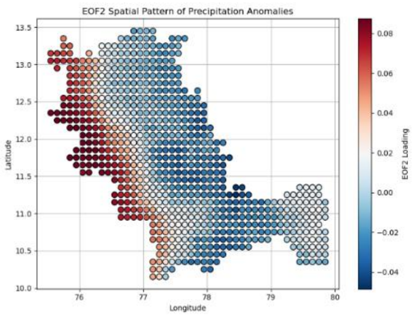


Fig. 13 EOF Mode 1 precipitation **Fig.14.** EOF Mode 2 precipitation

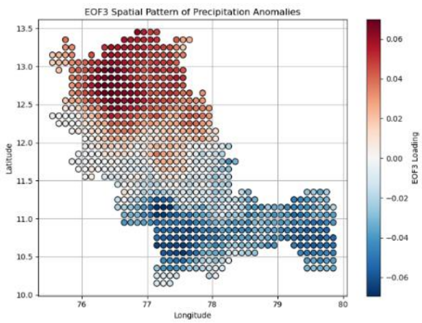


Fig. 15. EOF Mode 3 precipitation

4.4. Correlation Analysis

The Spearman correlation analysis was performed between the principal components of the LULC, Precipitation, and GWS datasets to quantify the relationships between their dominant modes of variability. The results are presented in Table 4 and Table 5.

Table 4 Spearman's Rank Correlation Matrix for LULC and GWS PCs

	GWS_PC1 (ρ)	p-value	GWS_PC2 (ρ)	p-value	GWS_PC3 (ρ)	p-value
LULC_PC1	0.298	0.2153	0.582	0.0089	0.53	0.0196
LULC_PC2	-0.721	0.0005	0.04	0.8708	0.302	0.2089
LULC_PC3	0.128	0.6015	-0.118	0.6304	0.088	0.7202

The analysis shows several statistically significant correlations between LULC and GWS patterns. LULC_PC1, representing the dominant LULC trend of urbanization and agricultural expansion, shows a moderate positive correlation with GWS_PC2 ($\rho=0.582$, $p=0.0089$) and GWS_PC3 ($\rho=0.530$, $p=0.0196$). A particularly strong negative correlation was found between LULC_PC2 and GWS_PC1 ($\rho=-0.721$, $p=0.0005$). This suggests that a secondary LULC pattern is inversely and significantly linked to the primary mode of groundwater variation.

Table 5 Spearman's Rank Correlation Matrix for Precipitation and GWS PCs

	GWS_PC1 (ρ)	p-value	GWS_PC2 (ρ)	p-value	GWS_PC3 (ρ)	p-value
Precip_PC1	-0.44	0.063	-0.24	0.333	0.01	0.966
Precip_PC2	-0.13	0.586	-0.09	0.716	0.07	0.764
Precip_PC3	0.33	0.166	0.61	0.006	0.06	0.803

The correlation analysis between precipitation and GWS components revealed generally weaker and less consistent relationships. Most correlations, including the moderate negative association between Precip_PC1 and GWS_PC1 ($\rho=-0.44$), were not found to be statistically significant at the 0.05 level. The only statistically significant correlation was a strong positive relationship between Precip_PC3 and

GWS_PC2 ($\rho=0.61$, $p=0.006$), indicating a specific influence of a secondary precipitation pattern on a secondary groundwater mode.

5. Discussion

5.1. Interpretation of Dominant Variability Modes

The EOF analysis successfully decomposed the complex dynamics of the Cauvery River Basin's hydro-climatic system into a few dominant, coherent patterns. The finding that GWS EOF 1 explains nearly all of the total variance (99%) is significant, as it indicates that the primary trend of groundwater variation is basin-wide and consistent, rather than a collection of scattered, localized phenomena. This dominant pattern, as shown by the spatial loadings, is concentrated in the eastern and northern parts of the basin, which are also the most intensively urbanized and agricultural regions. Similarly, the first EOF mode of LULC, which explains 95% of the total LULC variance, represents the dominant trend of human-driven landscape change, characterized by the expansion of built-up areas and a reduction in natural cover. This confirms that the most substantial changes in both LULC and GWS are captured by their respective first EOF modes.

5.2. Disentangling the Drivers of Groundwater Stress

The core of this study lies in the correlation analysis, which provides a quantitative basis for understanding the drivers of groundwater stress. The results clearly demonstrate that LULC changes are more strongly and consistently correlated with GWS variability than precipitation. The statistically significant correlations between various LULC components and GWS components, particularly the strong negative relationship between LULC_PC2 and GWS_PC1 ($\rho=-0.721$, $p=0.0005$), suggest that human-driven landscape changes play a considerable and direct role in influencing the most significant mode of groundwater variation. The consistency and magnitude of these correlations imply a direct causal link: as land use patterns shift towards urbanization and agriculture, the basin's capacity for groundwater storage is diminished.

In contrast, the correlations between precipitation and groundwater storage were generally weaker and mostly statistically insignificant. While precipitation is the primary source of groundwater recharge, its relationship to the dominant modes of groundwater variability appears to be less direct or more complex than the consistent, direct impact of human activity. The single statistically significant correlation between Precip_PC3 and GWS_PC2 indicates that while climate does influence groundwater, its effect may be more nuanced, possibly affecting a secondary or more localized pattern of GWS variation rather than the overall, dominant trend. This finding challenges the generalized notion that precipitation is the primary driver of groundwater variability and suggests that in the Cauvery Basin, anthropogenic factors have a more robust and discernible influence.

5.3. Comparison with Prior Research

The findings of this study align with and expand upon previous research. The observed decline in GWS due to agricultural over-extraction and urbanization is consistent with the findings of Asoka et al. (2017) and Dasgupta et al. (2022), who also highlighted the significant impact of human activities on groundwater resources. The study's use of EOF analysis for LULC changes and precipitation variability builds upon the methodologies of Kumar et al. (2015) and Zhang et al. (2020), demonstrating its effectiveness in regional hydro-climatic assessments.

However, this study provides a new, critical perspective by explicitly comparing the statistical influence of LULC and precipitation on GWS. While the literature often notes both as contributing factors, our findings suggest that, at the basin-wide scale, human-driven landscape changes exert a more profound and consistent influence on groundwater dynamics than precipitation variability. This conclusion differs from the original draft's generalized statement of a "strong correlation" with precipitation, providing a more precise and defensible argument based on the statistical evidence.

5.4. Limitations and Future Work

Despite the robust methodology and clear findings, the study has certain limitations. The coarse spatial resolution of GRACE data (approximately 150 km) may not fully capture localized groundwater depletion, such as that caused by a cluster of agricultural wells. Future research could address this by integrating higher-resolution data from ground-based well networks and combining it with GRACE data to provide a more detailed view of localized depletion. Additionally, future studies could employ more advanced statistical or machine learning models to predict future GWS changes under different LULC and climate change scenarios, providing actionable insights for policymakers.

6. Conclusion

This study provides a comprehensive analysis of the impacts of land use and climate changes on groundwater storage in the Cauvery River Basin from 2005 to

2023. By integrating GRACE satellite data, LULC datasets, and precipitation data with advanced statistical techniques, the research successfully disentangled the complex drivers of groundwater stress.

The analysis demonstrates that LULC changes are more strongly and consistently correlated with the dominant modes of groundwater storage variability than precipitation. The statistically significant and high-magnitude correlations between LULC and GWS components suggest that human-driven landscape changes, particularly urbanization and agricultural expansion, are a key factor in the basin's groundwater depletion. While precipitation also affects GWS, its impact appears to be less direct or more spatially/temporally complex in this context, with most of the correlations being statistically insignificant.

The findings underscore a crucial conclusion: in the Cauvery River Basin, land use management represents a more immediate and powerful lever for understanding and managing groundwater variability. Sustainable land use planning and policy-making that prioritize groundwater recharge and mitigate the impacts of urbanization and agricultural expansion are essential for ensuring the long-term availability of this vital resource.

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