

Land Use and Water Storage Dynamics in the Krishna River Basin: Insights from Satellite Observations and Machine Learning

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Abstract

Water scarcity and recurrent droughts threaten agricultural productivity and water security in the semi-arid Krishna River Basin of southern India. This study integrates satellite observations and machine learning techniques to assess long-term terrestrial water storage (TWS) and drought dynamics from 1992 to 2022. The Extreme Gradient Boosting (XGBoost) algorithm was employed to reconstruct GRACE-based Terrestrial Water Storage Anomalies (TWSA) using precipitation, temperature, evapotranspiration, and soil moisture as predictors. The reconstructed TWSA showed strong consistency with GRACE/GRACE-FO data ($R^2 = 0.92$, $RMSE = 43.18$ mm), extending the GRACE record to earlier decades. The GRACE Drought Severity Index (GRACE-DSI), applied at a 3-month scale, identified 15 major drought events during 1992–2022, with the most severe occurring in 2015–2017 (minimum DSI = -2.0) and 2018–2019 (minimum DSI = -2.63). Droughts typically recurred every 5–7 years, showing increased intensity after 2010. Land use and land cover (LULC) analysis from ESA-CCI data revealed declining agricultural areas and shrublands, alongside expansion of forests and urban land. Correlation between LULC changes and TWSA was weak, indicating stronger climatic control on basin water storage. The study underscores the value of fusing remote sensing, statistical tools, and hydrological indices to support better monitoring and governance of land and water systems in drought-prone basins.

1. Introduction

Water scarcity and droughts are among the most critical challenges affecting soil moisture, agricultural productivity, ecosystem stability, and socio-economic development in semi-arid regions of India and around the world (Kang and Sridhar, 2020). Management of the water resources in the basin requires an integrated understanding of water availability and multi-sectoral water needs (Hoekema and Sridhar, 2013) through modeling and satellite-based soil moisture storage data analysis (Sridhar et al., 2013). The Krishna river basin, one of the largest and most water-stressed basins in southern India, has experienced recurring droughts over the past few decades due to erratic rainfall, rapid urbanization, intensive irrigation, and changing land use patterns (Kumar et al., 2020). Understanding the long-term variability of terrestrial water storage (TWS) and its linkage with land cover changes is therefore essential for sustainable water resource management in the Krishna river basin.

Traditional drought indices such as the Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI) rely primarily on precipitation and temperature data, which may not fully represent subsurface hydrological conditions (Mishra and Singh 2010; Wang et al. 2015). The advent of satellite

gravimetry missions, particularly the Gravity Recovery and Climate Experiment (GRACE) and its successor GRACE Follow-On (GRACE-FO), has revolutionized large-scale drought monitoring by providing direct observations of time-variable Terrestrial Water Storage Anomalies (TWSA). GRACE-derived TWS reflects the combined effects of surface water, soil moisture, and groundwater variations, offering a holistic view of hydrological drought conditions (Vishwakarma, 2020).

In recent years, the GRACE Drought Severity Index (GRACE-DSI) has emerged as a robust, observation-based metric for assessing drought intensity and duration using only GRACE TWS data (Zhao et al., 2017). Unlike traditional model-dependent indices, GRACE-DSI effectively captures the spatiotemporal variability of water storage without requiring additional model assimilation, making it particularly suitable for data-scarce regions such as the Krishna Basin. However, the GRACE mission provides data only from 2002 onward, limiting its application for long-term drought trend analysis.

To overcome this limitation, machine learning approaches offer promising solutions to reconstruct GRACE-like TWSA using hydroclimatic variables such as precipitation, temperature, evapotranspiration, and soil moisture (Kumar et al., 2023). In this study, the Extreme

Gradient Boosting (XGBoost) algorithm was used to reconstruct continuous TWSA from 1992 to 2022, extending the GRACE record backward in time. The reconstructed TWSA was then used to compute GRACE-DSI and to evaluate the basin's long-term drought characteristics.

Additionally, land use and land cover change significantly influence hydrological systems, especially in regions exposed to climatic stress including the river basins in South India (Loukika et al., 2025; Buri et al., 2024). The Krishna River Basin is one of the most critical basins in peninsular India, supporting dense populations, agricultural economies, and rapidly urbanizing landscapes. However, rising water demand, irregular monsoons, and infrastructure pressures have led to increased drought frequency and land degradation (Kumar et al., 2020; Kumar et al., 2021a). Given the limitations of ground-based monitoring networks, this study leverages satellite-based datasets and advanced machine learning approaches to evaluate the relationship between LULC changes and water storage variations from 1992 to 2022.

The main objectives of this study are to:

1. Reconstruct long-term terrestrial water storage anomalies (TWSA) for the Krishna River Basin using the XGBoost model.
2. Assess spatiotemporal drought variability using the GRACE Drought Severity Index (GRACE-DSI) at a 3-month scale.
3. Analyze long-term land use and land cover changes and their correlation with basin-scale water storage variations.

2. Material and Methods

2.1 Study Area

The Krishna River Basin spans approximately 258,948 km² and flows through four Indian states: Karnataka, Maharashtra, Andhra Pradesh, and Telangana (Figure 1). It comprises key tributaries like the Bhima, Tungabhadra, and Musi rivers, and is divided into seven hydrological subbasins. The region's tropical climate features annual rainfall of about 960 mm and temperatures ranging from 20.7°C to 32.2°C. The basin's population exceeds 74 million, with over 77% of land under cultivation, highlighting the reliance on agriculture.

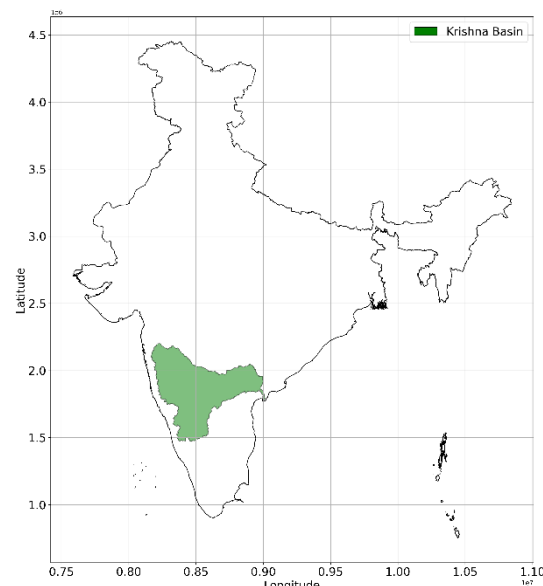


Figure 1. Study area: The Krishna River basin

2.2 Data

2.2.1 European Space Agency (ESA) Climate Change Initiative (CCI) Land Cover product

The European Space Agency (ESA) Climate Change Initiative (CCI) project provides consistent global land cover maps at 300-meter resolution on annual basis. In this study, the annual land cover maps are considered from 1992 to 2022. The product provides more specific information about land cover/use change in the context of the IPCC land categories (for example: forest, agriculture, grassland, settlement, wetland, water etc.).

2.2.2 Gravity Recovery And Climate Experiment (GRACE) Terrestrial Water Storage Anomalies (TWSA)

The GRACE twin satellites, launched on 17th March 2002, measure changes in the Earth's gravity field. The GRACE mission is a collaboration between United States (NASA) and German (DLR) space agencies. The mission ended up in 2017 providing more than 13 years of continuous measurements. Then a successor mission is launched on 22nd May 2018 named as GRACE Follow On (GRACE-FO) which continues to track Earth's water movement. GRACE and GRACE-Fo missions help to monitor changes in the water storage in large lakes, rivers, soil moisture, groundwater, ice sheets, and glaciers etc from 2002 to present with some data gaps. In the present study, Jet Propulsion Laboratory (JPL) mass concentrations (mascons) GRACE level 3 product is used from 2002 to 2022. The level 3 data provide monthly TWSA at 3° × 3° spatial resolution.

2.2.3 India Meteorological Department (IMD) rainfall and temperature

IMD provides high spatial resolution (0.25° × 0.25°) daily gridded rainfall dataset from 1901 to 2024 covering India (Pai et al., 2014). In this study, daily rainfall data

were aggregated into monthly totals by summing the daily values for the period 1992–2022. IMD also provides gridded daily maximum and minimum temperature from 1951 to 2024 at a spatial resolution of $1^\circ \times 1^\circ$ (Srivastava et al., 2009). In this study, daily maximum and minimum temperatures were averaged to obtain monthly mean maximum and minimum temperatures for the period 1992–2022.

2.2.4 Global Land Evaporation Amsterdam Model (GLEAM) evapotranspiration

Global Land Evaporation Amsterdam Model (GLEAM) used Penman equation to calculate potential evaporation using observations of surface net radiation, near-surface air temperature, wind speed, leaf area index, and vapor pressure deficit (<https://www.gleam.eu/>). GLEAM does not directly provide total evapotranspiration data. Instead, it is derived by summing individual components, including transpiration, interception loss, soil evaporation, open-water evaporation, and snow sublimation. The monthly evapotranspiration is calculated from 1992 to 2022 at a spatial resolution of $1^\circ \times 1^\circ$ for Indian river basins.

2.2.5 Global Land Data Assimilation System (GLDAS) soil moisture

The GLDAS framework produces high-quality global fields of land surface states and fluxes by integrating satellite and ground-based observations with advanced modelling and data assimilation techniques (Rodell et al., 2004). In this study, root zone soil moisture data from the GLDAS Noah Land Surface Model (LSM) are utilized for the period 1992–2022 at a spatial resolution of $1^\circ \times 1^\circ$. The Noah model represents soil moisture in four vertical layers (0–10 cm, 10–40 cm, 40–100 cm, and 100–200 cm). For grassland vegetation, the root zone soil moisture includes the top three layers, whereas for forest vegetation, it encompasses all four layers. The Noah version 2.0 dataset (GLDAS_NOAH10_M_2.0) is used for the period 1980–1999, and the Noah version 2.1 dataset (GLDAS_NOAH025_M_2.1) is used for 2000–2023. The root zone soil moisture values are expressed in kilograms per square meter (kg/m^2), which is equivalent to millimeters (mm) of water depth.

2.3 Methodology

2.3.1 Land Use and Land Cover (LULC) Data Processing and Classification for the Krishna River Basin

To examine the long-term land use and land cover (LULC) dynamics over the Krishna river basin, the ESA CCI land cover dataset (300 m spatial resolution) for the period 1992–2022 was systematically processed. The original annual NetCDF files were first converted into GeoTIFF format and georeferenced to the WGS 84 coordinate reference system (EPSG:4326). Each raster was then projected to the UTM Zone 43N system (EPSG:32643) to enable accurate spatial analysis and area estimation. The reprojected rasters were clipped to the Krishna river basin boundary to extract basin-specific land cover data. For each year, the areal extent of individual land cover classes was computed by multiplying the

number of pixels of each class by the corresponding pixel area (0.09 km^2). To facilitate consistent interpretation and reduce classification complexity, the detailed ESA CCI LCCS classes were aggregated into nine major categories following the Intergovernmental Panel on Climate Change (IPCC) classification framework: Agriculture, Forest, Grassland, Wetland, Settlement, Shrubland, Sparse Vegetation, Bare Area, Water Body. The resulting annual land cover maps and area statistics provided a consistent temporal record of LULC distribution across the Krishna River Basin from 1992 to 2022.

2.3.2 Reconstruction of GRACE TWSA using Extreme Gradient Boosting (XGBoost) Algorithm

In this study, we employed a machine learning approach to reconstruct GRACE-derived TWSA over Krishna river basin. The reconstruction aims to capture the GRACE signal using multiple hydro-climatic variables (input variables) such as precipitation, maximum temperature, minimum temperature, evapotranspiration, and root zone soil moisture. We first compiled a dataset of these hydro-meteorological variables for the basin studied from 1992 to 2022. The GRACE TWSA data from the JPL product was used as the target variable. To focus on inter-annual variability and remove long-term mean seasonal cycles, anomalies of each input variable were calculated by subtracting their 2004–2009 baseline mean. This anomaly computation ensures that the input variables and GRACE TWSA are on a comparable anomaly scale.

Next, we applied the XGBoost regression model, a robust ensemble learning method. For Krishna basin, a separate model was developed using data from 2002 to 2022, corresponding to the period of GRACE/GRACE-FO data availability. The dataset was split into training and testing sets in an 80:20 ratio, and hyperparameter optimization was performed using Optuna, a Bayesian optimization framework. The model was tuned using 5-fold cross-validation, and the Kling-Gupta Efficiency (KGE) was used as the primary scoring metric to ensure hydrologically relevant performance. Once the best hyperparameters were selected, the final XGBoost model was trained and evaluated on the test set using performance metrics including KGE, coefficient of determination (R^2), and root mean square error (RMSE). The optimized model was then used to predict GRACE TWSA over the entire time period i.e., 1992–2022.

2.3.3 GRACE Drought Severity Index (GRACE-DSI)

Drought indices are useful tools for assessing drought conditions, understanding their social and ecological impacts, and supporting decision-making for drought prevention and mitigation. TWS estimates from the GRACE mission have been widely used to study regional-scale droughts across the world (Leblanc et al., 2009; Long et al., 2013). Recently, Zhao et al. (2017) developed the GRACE-DSI, which relies solely on GRACE TWS data. Unlike previous approaches, GRACE-DSI does not

require model assimilation and effectively captures the spatial and temporal variability of local hydroclimatic conditions. In this study, the GRACE-DSI is applied at 3-month scale to evaluate drought patterns in the Krishna River Basin for the period 1992–2022.

GRACE DSI is a satellite-based drought index derived solely using satellite observed time-variable TWSA from GRACE (Zhao et al., 2017). The GRACE-DSI is defined as the standardized anomalies of GRACE TWS as given in Eq.1.

$$GRACE - DSI_{i,j} = \frac{TWS_{i,j} - \overline{TWS_j}}{\sigma_j} \quad (1)$$

where i = year ranging from 1992 to 2022, j = month ranging from Jan to Dec, $\overline{TWS_j}$ and σ_j are the mean and standard deviation of TWSA in month j , respectively. The GRACE-DSI is a dimensionless quantity that detects both drought and wet events. The GRACE-DSI categories are provided in table 1.

Table 1: GRACE-DSI drought categories related to dry (D) and wet (W) conditions

Categor y	Description of drought	Criterion
W4	Exceptionally wet	2.0 or greater
W3	Extremely wet	1.60 to 1.99
W2	Very wet	1.30 to 1.59
W1	Moderately wet	0.80 to 1.29
W0	Slightly wet	0.50 to 0.79
WD	Near normal	0.49 to -0.49
D0	Abnormally dry	-0.50 to -0.79
D1	Moderate drought	-0.80 to -1.29
D2	Severe drought	-1.30 to -1.59
D3	Extreme drought	-1.60 to -1.99
D4	Exceptional drought	-2.0 or less

2.3.4 Correlation analysis

In this study, the Pearson correlation coefficient (r) is used to calculate the relationship between GRACE TWSA and land cover changes over the period 1992–2022. The ' r ' measures the strength and direction of the linear association between two variables, ranging from -1 (perfect negative correlation) to $+1$ (perfect positive correlation). The Pearson correlation coefficient is computed as given in Eq. 2.

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (2)$$

where, x_i and y_i represent observations of land cover change and TWSA respectively. \bar{x} and \bar{y} represents the mean values. n is the total number of observations.

3. Results

3.1 Land use land cover variations over Krishna river basin

Between 1992 and 2022, the Krishna River Basin underwent significant land use transitions (Kumar et al., 2021b). Agricultural land declined steadily, while forest cover increased, possibly due to afforestation or classification changes (Figure 2). Grasslands initially shrank but recovered moderately in recent years. Shrublands showed a consistent downward trend. Urban areas expanded rapidly, particularly around cities like Pune and Vijayawada, intensifying land use pressures. Sparse vegetation increased later in the study period, and wetlands slightly declined. Water bodies remained relatively stable. These changes reflect a broad shift from rural/agricultural dominance to a more urbanized and forested landscape. This transformation is prevalent in many river basins in South India (Naga Sowjanya et al., 2022, Loukika et al., 2021; Loukika et al., 2023). The percentage of change in area covered by 9 different classes named as agriculture, forest, grassland, wetland, settlement/urban, shrubland, sparse vegetation, bare areas, and water are given in Table 2.

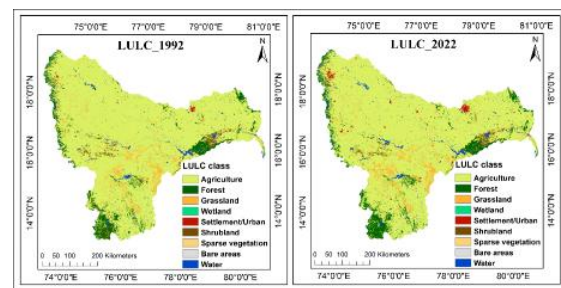


Figure 2: land cover maps of 1992 and 2022.

Table 2: Area covered by each land cover class (%)

	Area covered by each class (%)	
IPCC class	1992	2022
Agriculture	86.24	84.74
Forest	5.32	6.10
Grassland	4.00	4.30
Wetland	0.00	0.00
Settlement/Urban	0.25	1.05
Shrubland	2.09	1.51
Sparse vegetation	0.20	0.22
Bare areas	0.00	0.00
Water	1.90	2.07

3.2 Reconstruction of Total Water Storage Anomalies over the Krishna River Basin from 1992 to 2022

The XGBoost-based reconstruction of TWSA over the Krishna river basin exhibited strong consistency with the observed GRACE and GRACE-FO TWSA data (Figure 3). The reconstructed TWSA (blue line) closely followed the temporal evolution of the GRACE-derived anomalies

(red dashed line), successfully replicating both seasonal fluctuations and interannual variations in basin water storage. The XGBoost model achieved satisfactory performance during training and testing, with KGE = 0.68, $R^2 = 0.66$, and RMSE = 85.39 mm. When evaluated against the actual GRACE and GRACE-FO TWSA, the reconstructed estimates showed a very strong correlation ($R^2 = 0.92$), a NSE of 0.92, and a considerably reduced RMSE of 43.18 mm, demonstrating the robustness and reliability of the model. The close alignment of reconstructed and satellite-based TWSA signals indicates that the XGBoost algorithm effectively captured the dominant hydro-climatic controls on terrestrial water storage variations. Moreover, extending the model to the pre-GRACE era (1992–2001) enabled the generation of a long-term continuous TWSA record, providing valuable insights into multi-decadal water storage dynamics across the Krishna river basin.

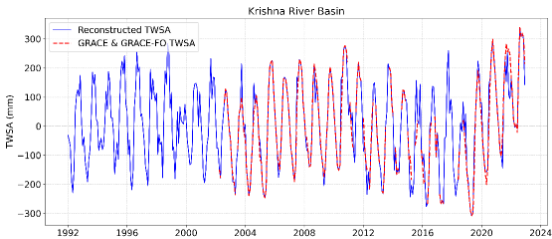


Figure 3: Time series of TWSA for the Krishna River Basin from 1992 to 2022. The blue line represents the reconstructed TWSA, while the red dashed line represents the GRACE and GRACE-FO TWSA time series.

3.3 Drought Assessment Using GRACE DSI

The GRACE-DSI time series for the Krishna river basin (1992–2022) (Figure 4) captures diverse episodes of hydrological variability, alternating between wet and dry conditions. Based on the 3-month averaged GRACE-DSI values, a total of 15 drought events were identified during the study period (Table 3). These events varied considerably in duration, severity, and intensity, indicating the basin’s sensitivity to hydroclimatic fluctuations.

Among the major droughts, the 2002–2003, 2003–2005, 2012–2013, 2015–2017, and 2018–2019 events stand out as the most significant. The 2015–2017 drought was particularly severe, lasting 28 months with a cumulative severity of 36.74 and a minimum GRACE-DSI of -2.00 , classifying it as an exceptional drought (D4). This was followed by the 2018–2019 drought, which persisted for 19 months, recording the lowest GRACE-DSI value (-2.63) across the entire record. Earlier droughts such as those in 1999 (-1.84) and 2003–2005 (-1.41) also reached

severe to extreme levels (D2–D3 categories), but with shorter or more moderate intensities. Periods of recovery are evident between these major events, marked by positive GRACE-DSI values that indicate improved total water storage (wet conditions). For instance, significant wet anomalies occurred around 1994–1998, 2010–2011, and especially after 2020, when the GRACE-DSI rose steadily above $+2$, suggesting an exceptionally wet phase (W4). The average inter-drought period ranged between 5 and 35 months.

The GRACE-DSI analysis reveals that the Krishna basin experienced recurring droughts approximately every 5–7 years, with increasing drought severity observed after 2010. The long-term pattern suggests a shift toward more intense but less frequent droughts, followed by strong wet recoveries. These results highlight the basin’s dynamic water storage behavior and the usefulness of GRACE-DSI for tracking spatiotemporal drought variations.

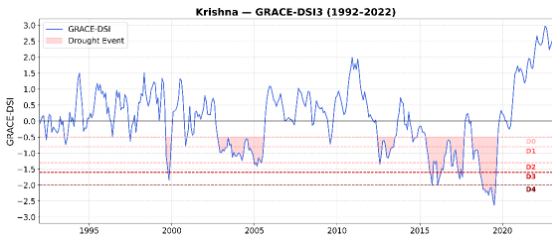


Figure 4: GRACE-DSI3 timeseries for Krishna river basin from 1992 to 2022. Red horizontal dashed line represents drought categories. Red shaded part represents drought events.

Table 3: Summary of GRACE-DSI3 derived drought events in the Krishna River Basin (1992–2022)

Event ID	Onset	Termination	Duration months	Severity	Min GRACE-DSI3
1	2/1/1981	8/1/1981	7	7.37	-1.44
2	9/1/1982	12/1/1982	4	3.21	-1.31
3	9/1/1984	1/1/1986	17	19.02	-1.69
4	6/1/1986	1/1/1987	8	7.45	-1.47
5	7/1/1987	12/1/1987	6	6.14	-1.44

6	3/1/ 198 9	5/1/1 989	3	2.0 6	-0.77
7	1/1/ 199 0	5/1/1 990	5	4.5 7	-1.31
8	10/1/ 199 0	12/1/ 1990	3	2.3 7	-0.84
9	9/1/ 199 9	12/1/ 1999	4	5.6 3	-1.84
10	11/1/ 200 2	5/1/2 003	7	6.1 6	-0.98
11	7/1/ 200 3	8/1/2 005	26	26. 12	-1.41
12	7/1/ 201 2	6/1/2 013	12	11. 09	-1.35
13	8/1/ 201 4	11/1/ 2014	4	2.2 2	-0.65
14	6/1/ 201 5	9/1/2 017	28	36. 74	-2.00
15	3/1/ 201 8	9/1/2 019	19	32. 83	-2.63

3.4. Correlation Analysis Between LULC and Water Storage

To explore statistical relationships between land cover changes and groundwater storage between 1992 to 2022, the study used the Kendall correlation test (Hipel and McLeod, 2005). The correlation between LULC classes and reconstructed GTWSA for the Krishna basin showed generally weak associations (Figure 5). This analysis illustrates spatial and temporal relationships between major land cover transitions—such as expansion of agriculture or urban areas—and variations in groundwater storage anomalies, highlighting areas of significant positive or negative correlation. This analysis provides insights into how land use dynamics influence subsurface water resources across the basin. This method is robust for detecting monotonic trends and less sensitive to outliers compared to Spearman's correlation.

The Kendall Tau values were as follows: agriculture (−0.143), forest (0.008), grassland (−0.024), wetland (0.071), settlement/urban (0.153), shrubland (−0.199), barren (0.030), and water (0.143). None of these correlations were statistically significant, suggesting that over the study period, the direct influence of individual land cover classes on GTWSA may be limited or masked by other dominant factors like climate variability, groundwater extraction, or policy interventions. Nonetheless, these relationships can inform exploratory modeling and future hypothesis-driven studies.

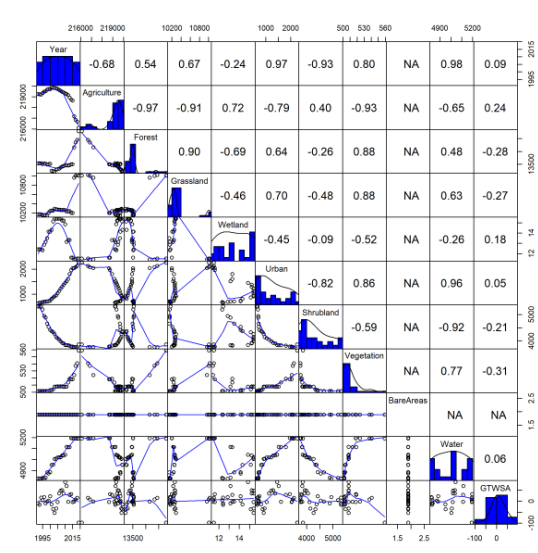


Figure 5: Correlation analysis between land cover changes and groundwater storage in the Krishna River basin

4. Conclusion

This study integrated multi-source satellite and ground-based datasets to analyze long-term hydrological and land surface dynamics over the Krishna river basin from 1992 to 2022. The reconstructed GRACE TWSA using the XGBoost model effectively extended the GRACE record, capturing both seasonal and interannual variations in basin water storage. The GRACE-DSI revealed 15 major drought events during the study period, with particularly severe and prolonged droughts occurring in 2015–2017 and 2018–2019. These findings indicate that droughts in the basin typically recur every 5–7 years, with a tendency toward higher severity in recent decades. Land use and land cover analysis showed significant shifts from agricultural dominance toward increased forest and urban areas, while correlation analysis suggested only weak relationships between LULC changes and water storage anomalies. The combination of long-term datasets, robust analytics, and drought indicators presents a powerful framework for advancing drought resilience and water sustainability strategies within the Krishna river basin.

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