Impact of El Niño on Groundwater Levels in Chennai: Analysis and Identification of Recharge Potential Areas Using Satellite Imagery and Temporal Data

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***Abstract*—Chennai, a coastal city in the southern Indian state of Tamil Nadu, is rapidly urbanising, and its groundwater is increasingly under stress from erratic monsoonal patterns that El Niño exacerbates. Using satellite imagery and temporal data to determine the potential zones for recharge, this study analyses the relationship of El Niño events with the variations in the groundwater level in Chennai. Based on the study of historical groundwater levels (2021–2024), rainfall trends, and remote sensing indices (NDWI, NDMI), wards showing a substantial post-monsoon recharge were segregated. Groundwater trends under El Niño scenarios were predicted using machine learning models (LSTM, Random Forest), using spatial analysis within GIS of the data noted intervention areas that should take priority. Results also indicate declining groundwater levels in urban wards and high groundwater potential recharge in peri-urban areas with favourable topography. The study warns of El Niño-induced scarcity of groundwater and proposes actionable strategies for sustainable water management, including the delamination of artificial recharge structures in prioritized zones.**

***Index Terms*—El Niño, Groundwater Recharge, LSTM, NDWI, NDMI, Urban Water Management.**

I. Introduction

Climate variability is one of the driving forces of regional weather phenomena, which is particularly crucial for the management of water (resource) systems. One such climatic occurrence, El Niño, features the abnormal heating of ocean surface waters in the central and eastern Pacific Ocean. This warming upsets atmospheric circulation and modifies global weather patterns, including the Indian monsoon. In the Indian context, El Niño events are typically associated with suppressed southwest monsoons, resulting in below-normal rain and drought conditions. But they can also intensify northeast monsoon activity to bring about more rainfall in South India and Tamil Nadu. This dual influence positions El Niño as a key driver in the precipitation variability equation that relates to water availability effects.

Tamil Nadu has also seen extensive urbanization and thus has faced issues of water resource management in most of its large metros, including Chennai, which solely relies on the monsoon season's precipitation. Approximately 60 per cent of

the State capital's drinking water requirements, are fulfilled via groundwater, which is replenished during the northeast monsoon. Yet El Niño can have a massive impact on precipitation patterns worldwide, leading to both extremes of overabundance of rainfall and prolonged spells of drought. This volatility causes extreme difficulty in managing water, leading either to desperate water shortages or catastrophic flooding. One of the major examples of El Niño impacts on Indian rainfall includes the 2015 Chennai floods, in which an overactive northeast monsoon was impacted fully, which possibly might have been influenced by El Niño conditions, leading to disastrous floods. Again, the 2023 Chennai floods focused the limelight on the susceptibility of the city to weather extremes. Citywide flooding due to catastrophic rains during the northeast monsoon and poor stormwater drainage, halted day-to-day life while incurring enormous economic losses. These flooding events highlight the necessity of better understanding climatic impacts on urban hydrology.

Knowledge of how El Niño events influence monsoonal rainfall patterns is vital, given that variations in the level of groundwater in Chennai can be high. The purpose of this research is to examine the relationship between El Niño and monsoonal variability and its application to groundwater recharge and availability. The purpose of this research is to evaluate the consequences of El Niño variability on the monsoonal rainfall pattern in the Chennai area, and also to investigate the existence of a relationship between occurrences of El Niño.

This study provides a better understanding of the nexus between climate variability and urban water security through an array of diverse methods, leveraging features of meteorological data, groundwater level measurements and remote sensing techniques. It is essential to have proper management of water resources, hence, understanding groundwater recharge potentialities using satellite and temporal data will be an admirable study for Chennai. Ultimately, such results could inform policy decision-making and urban planning to reduce water scarcity and strengthen climate resilience to water cycle changes.

II. LITERATURE REVIEW

Groundwater level prediction is an important issue in sustainable water management and has attracted much attention. An abundance of studies have used deep learning or machine learning methods to improve predictive accuracy. The ST-Att-LSTM proposed by [1] combines a graph-based spatial attention mechanism and LSTM-based temporal attention mechanism with a sequence-to-sequence LSTM to enhance groundwater level predictions. Their model exceeds the performance of traditional numerical models, such as MODFLOW, and baseline machine learning methods, such as SVR and FNN.

For example, [2] compared several models including LSTM, GRU, Random Forest, and XGBoost, and showed that LSTM performs better than others in capturing temporal dependencies and achieving optimal accuracy. In another study, [3] introduced a straightforward linear regression model, which, although computationally lightweight and easily interpretable, struggled with complex environmental interactions. Building on this, [4] investigated the use of GRU-based models for groundwater forecasting, showing that GRU not only successfully captured temporal dynamics but also used fewer computational resources compared to LSTM, presenting an alternative for applications with limited resources. Lastly, [5] used a ConvLSTM model with transfer learning to predict El Niño events and found that training on synthetic climate model data enhanced the accuracy of forecasting El Niño events, despite still showing difficulties in predicting Central-Pacific events. These studies highlight the utility of deep learning models for groundwater forecasting, as evidenced by the performance of LSTM-based architectures. Nevertheless, challenges remain, including the incorporation of more environmental conditions, computational limits, and model interpretability. In summary, future studies should include the use of attention mechanisms, domain knowledge, applicable meteorological features, and hybrid models to enhance the prediction accuracy and applicability of methods for groundwater management.

Forecasting and monitoring of climate phenomena is a complex problem, with challenging phenomena including El Niño-Southern Oscillation (ENSO), droughts, and trends in groundwater storage requiring advanced data-driven computational techniques in order to derive actionable information. [6] proposed a Graph-based Spatial-Temporal Convolutional Network (GSTCN), which combined graph learning with deep learning for ENSO forecasting. With such a design, the Graph Convolution Module can fully exploit both spatial relationships from SST and long-term temporal dependencies, and the Transformer-based Informer Module also fully models long sequences, achieving better performance against existing deep learning models.

Using MODIS NDVI, [7] investigated the MODIS NDVI variation in Java during both El Niño and La Niña events and found that during El Niño, decreased precipitation led to a decline in vegetation health. However, in La Niña conditions, a rapid return of vegetation or recovery could be observed. They highlight the importance of regional adaptation strategies to alleviate ENSO-driven agricultural consequences. In a separate study, [8] predicted groundwater storage (GWS) variations in the Amazon River Basin using downscaling methods based on machine learning applied to GRACE/GRACE-FO satellites. Their findings illustrated the efficiency of machine learning in hydrological studies, as Adaptive Boosting (AB) and Random Forest (RF) models increased spatial resolution and revealed climate-caused changes in GWS from 2002 to 2021 of global significance.

[9] summarized the use of ML models for drought predictions, concluding that hybrid models such as wavelet-ANNs and long-short-term memory Gaussian Process Regression (GPR) are more effective in improving predictive accuracy. They highlighted the challenges of data availability, model interpretability, and computational costs, and argued for multi-source dataset integration and explainable AI for enhancing the assessment of agricultural drought risk. [10] utilized multiple machine learning methods such as ANNs, SVMs, and LSTM models to improve drought modeling accuracy. Factors such as SPEI and PDSI were emphasized as crucial for incorporation into ML frameworks for improved model fidelity. However, high computational costs and the lack of interpretability of complex ML models present challenges. Together, these studies show the promise of machine learning and deep learning in environmental forecasting but also highlight challenges concerning data quality, model generalization, and computational efficiency. Moreover, this provides an avenue to assess different methodologies while also integrating advancements to improve both predictive accuracy and practical applicability, including real-time data integration, hybrid modeling techniques, and domain knowledge incorporation.

Urban groundwater vulnerability has been exacerbated by rapid urbanization and climate change, which have caused declining water levels and a deterioration of water quality. [11] emphasized that groundwater plays a critical role in India, providing 85% of the rural and 50% of the urban water demand. Their study in Karnataka used data from 272 monitoring wells and showed that decreased recharge coupled with increased pumping could lead to a 20-meter decline in groundwater levels over 20 years. They propose managed aquifer recharge projects and vertical urban design to combat groundwater depletion.

For flood mapping purposes, [12] demonstrated the effectiveness of SAR methods such as ISODATA and multi-temporal analysis in improving the accuracy of flood delineation in Chennai. Their results highlight the need for better integration of remote sensing technologies and urban planning with a specific focus on flood risk management. Building on such work, [13] employed machine learning techniques, including Gradient Boosting and Support Vector Machines, for flood susceptibility mapping over Tamil Nadu. The performance of ML models was superior to traditional GIS-based techniques in identifying flooded areas, and integrating remote sensing data with AI-based models would be essential to enhance predictive performance.

[14] provided an overview of climate change impacts on groundwater and agriculture across Asia, estimating that South Asia alone loses 60 billion cubic meters of groundwater each year. Their research highlights the critical importance of sustainable water management practices, such as the use of groundwater recharge technologies and climate-resilient agriculture. Lastly, [15] contrasted the use of deep neural networks (DeepNNs) versus swarm-optimized random forests (SwarmRFs) for groundwater spring potential identification in Vietnam. Their study found that SwarmRF was more accurate (80.2%) than DeepNN (77.9%) and emphasized the significance of geology and remote sensing indices in modeling groundwater. Future research should focus on developing robust predictive models, improving remote sensing techniques, and integrating sustainable management practices to address urban groundwater issues more effectively.

III. Methodology

The framework progressively combines data collection, prediction modelling, and geo-spatial mapping analysis for groundwater level prediction and recharge capacity assessment. The method is composed of two basic components: Data Analysis Module and Satellite Image Processing Module. Climate, groundwater, and historical records are processed in the data analysis module to analyse trends, compare ward-wise groundwater levels, and estimate recharge potential. The Satellite Image Processing Module uses Landsat satellite imagery and spectral indices (NDVI and NDWI) to help identify possible recharge places depending on land cover and moisture content. The following are the nine sub-components that collectively form the methodology:

1) **Data Collection and Preprocessing:** This module is responsible for collecting the climate, groundwater, and satellite data, and pre-processing that data. Groundwater data shows levels from the past several years in many wards, and the climate data includes temperature and rain information. Satellite data are used to assess vegetation patterns and land use, including MODIS NDVI imaging and MODIS land use and land cover. The data processing techniques include normalizing for a standard scale, cleaning for outliers and missing values, and feature selection to present the critical impact factors.
2) **Temporal Analysis:** The mean level of the groundwater of each ward is calculated month-wise and year-wise to analyze the seasonal and annual trends. This process greatly simplifies the interpretation of long-term hydrological responses—what groundwater levels might mean concerning climatic drivers such as the El Niño.
3) **Groundwater Trends Analysis:** This module ranks wards based on annual averages of groundwater levels. Wards are classified as either variable (cyclical patterns), stable/rising (same or increasing levels), or falling (continually dropping groundwater levels). This classification enables long-term sustainability assessment of groundwater resources.
4) **Ward-wise Comparison of Groundwater Levels:** Minimum, Maximum, and Average groundwater levels are calculated for each ward. To identify critical regions that are either improving or undergoing depletion, we also analyze the change in the groundwater level from 2021 to 2024.
5) **Finding Wards with Notable Post-Monsoon Rises:** This module measures post-monsoon recharge by calculating the difference between October and June groundwater levels. Wards are identified as having considerable recharge potential if they exhibit a post-monsoon spike beyond the annual norm. The average post-monsoon rise over several years is used to calculate a recharge potential score.
6) **Ward Ranking by Recharge Potential:** Within each area, wards are rated according to their potential for recharging. The places for water conservation initiatives are chosen with the aid of this prioritization. For focused efforts, the top five wards in each area with the greatest potential for recharging are highlighted.

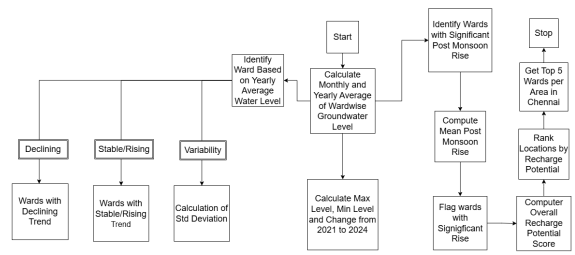

Fig. 1. Data Analysis Module (Sub-components 1 to 6)

7) **RGB Channel Extraction:** Red, green, and blue (RGB) channels are extracted from satellite images by processing. This stage makes it easier to identify possible recharging spots and visualize surface features. For moisture analysis, other spectral bands including the near-infrared (NIR) and shortwave infrared (SWIR) are taken into consideration.
8) **Calculating NDWI and NDMI:** To differentiate water bodies from vegetation and land, the Normalized Difference Water Index (NDWI) is computed; higher NDWI values denote water bodies. When choosing recharge locations, the Normalized Difference Moisture Index (NDMI) is essential for determining the moisture content of the soil and plants. Areas with higher NDMI values are more suited for groundwater recharge because they retain more moisture.

$$NDWI = \frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}} \quad (1)$$

$$NDMI = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}} \tag{2}$$

9) **Morphological Operations:** Using image processing techniques, this module improves the identification of possible recharge regions. Unwanted locations like beaches (high NDWI) and cities (low NDMI) are eliminated, and green patches are identified using a threshold (*green_band* ¿ 0.3). To ensure that only vast green regions remain, small, isolated patches are removed using a morphological opening procedure with a 10×10 kernel. Lastly, for visualization purposes, the designated recharging zones are superimposed on the original image.

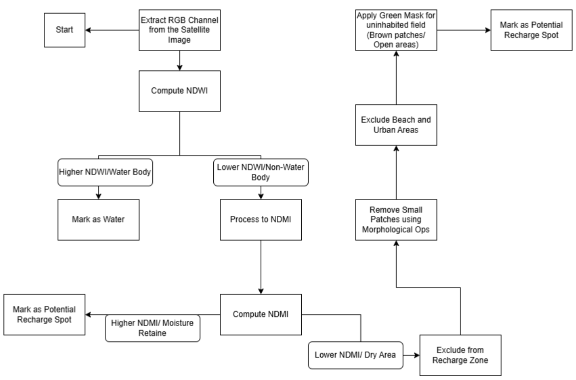

Fig. 2. Satellite Image Processing Module (Sub-components 7 to 9)

These modules allow the system to combine spatial analysis and data-driven insights to anticipate groundwater levels accurately and pinpoint the best sites for artificial recharge interventions. The findings aid in making informed decisions on water resource management, especially in mitigating the effects of El Niño on groundwater supply.

IV. Results and Discussion

The integrated approach has provided a detailed perspective on Chennai's groundwater scenario in this study. Localized issues and opportunities become clear with spatial variability in groundwater levels, while temporal dynamics highlight critical seasonal recharge periods and long-term trends. Categorizing trends into declining, stable, or highly variable wards identifies priority areas for intervention. After monsoon rise and recharge potential data analysis provides actionable information for artificial recharge and even restoration efforts. Last but not least are prioritizing wards by their recharge potential so that water management strategies are implemented effectively. Not only the challenges but also viable solutions for sustainable groundwater management in Chennai are suggested based on these findings.

1) **Data Collection and Preprocessing:** Data for this study were obtained from historical groundwater monitoring stations from across Chennai (2021–2024), supplemented with satellite data, particularly MODIS NDVI imagery, to abstract land use and vegetation dynamics. Extensive preprocessing was conducted on these raw datasets to ensure data integrity and comparability within and among sources. Key preprocessing steps included normalization, data cleaning, and feature selection. Normalization was the most important preprocessing step to apply all variables on the same scale for direct comparison. The data cleaning process involved missing value treatment via imputation with NaN fillers and outlier treatment to reduce bias. Feature selection was used to retain the most critical variables influencing groundwater dynamics, derived from monthly and NDVI values. These preprocessing steps provided strong datasets, forming a solid foundation for temporal and trend analysis.
2) **Temporal Analysis:** The temporal analysis focused on quantifying both monthly and yearly groundwater level averages for each ward. Processed datasets were saved in `./output/temporal_analysis_data.csv`, and an area-wise summary was stored in `./output/area_wise_groundwater_levels.csv`. The analysis yielded the following average yearly groundwater levels by Area Number.

TABLE I
Groundwater Levels Across Different Areas

Area Number	*Groundwater Level (m)*
I	3.47
II	3.89
III	6.76
IV	4.18
V	6.37
VI	7.75
VII	5.53
VIII	4.65
IX	6.46
X	5.30
XI	3.16
XII	4.12
XIII	2.50
XIV	3.70
XV	3.50

[a] Area VI has the highest average groundwater level.
[b] Area XIII has the lowest average groundwater level.

These variations reveal significant spatial differences in groundwater availability across Chennai.
The declining trend indicates possible over-extraction or weak recharge mechanisms.
The box plot illustrates the median, interquartile range, and outliers, highlighting post-monsoon recharge and pre-monsoon depletion.

3) **Groundwater Trends Analysis:** During this stage, a classification was performed based on average yearly variation to reflect long-term groundwater behaviour through the partition of wards. Wards were ranked based on average groundwater levels for each study year, and trends were categorized into three types: declining (consistent decrease), stable/rising (levels maintained or increased), and high variability (significant monthly fluctuations). The standard deviation was used as a measure to

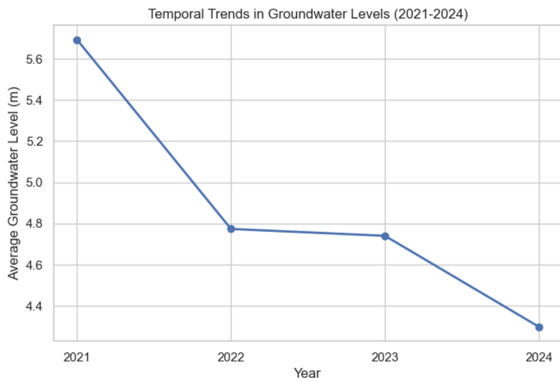

Fig. 3. Yearly average groundwater levels (2021-2024) in Chennai.

Data sourced from groundwater monitoring stations across Chennai. Missing values for 2024 (Apr-Dec) were handled using NaN imputation.

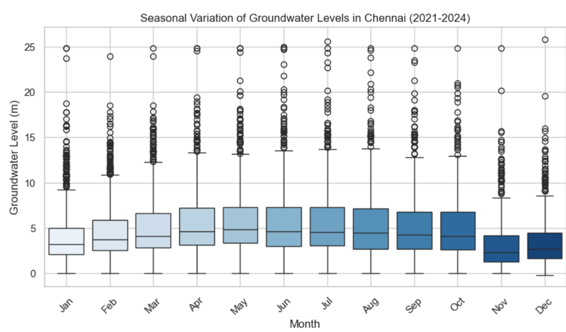

Fig. 4. Seasonal variation in groundwater levels across different months.

Data aggregated from 2021-2024. The spread of values within each month suggests significant fluctuations, influenced by rainfall patterns and water usage.

pinpoint wards with unsteady groundwater levels, stored in individual files.

Wards with high variability were documented in `ward_level_comp/high_variability_wards.csv`, while those exhibiting a declining trend were recorded in `ward_level_comp/declining_trend_wards.csv`. Similarly, stable or rising trend wards were saved in `ward_level_comp/stable_rising_wards.csv`. This classification plays a crucial role in identifying critical zones. Wards experiencing a downward trend require immediate attention, whereas those with stable or rising trends signal sustainable groundwater practices.

The analysis revealed considerable spatial variability in groundwater levels across the city. For instance, Area VI exhibited the highest average values, suggesting good recharge potential, whereas Area XIII had the lowest values, possibly indicating areas at risk of water scarcity. Wards with lower levels are more susceptible to water stress, while wards with higher levels indicate potential for better recharge.

Wards with higher variability indicate inconsistent recharge, while stable wards serve as potential bench-

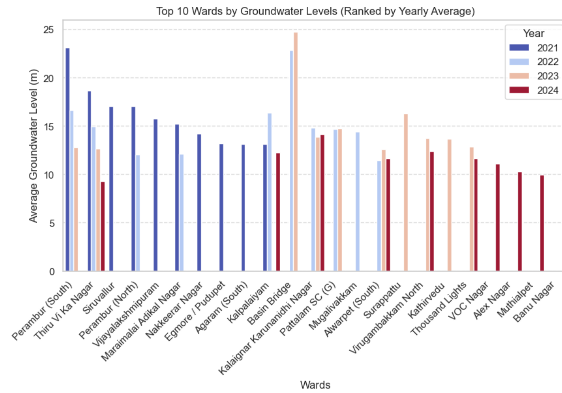

Fig. 5. Ward-wise ranking of groundwater levels from 2021-2024.

Data sourced from groundwater monitoring stations across Chennai. The bar chart provides a comparative view of ward-wise groundwater conditions over the years.

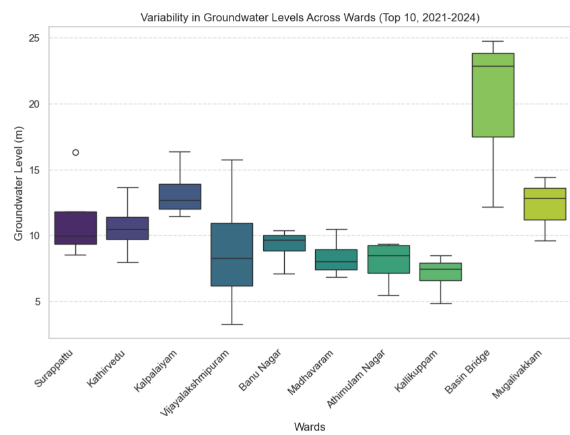

Fig. 6. Box plot displaying groundwater variability across different wards.

This visualization highlights the wards where groundwater levels fluctuate significantly, signaling inconsistent recharge and extraction patterns.

marks.

The dataset includes the following:

- Declining trend wards (425) with location, yearly average, and trend indicating continuous groundwater depletion.
- High variability wards (283) with location, yearly average, and variability indicating unstable groundwater levels.
- Stable/rising wards (375) with location, yearly average, and trend indicating rising or stable groundwater levels.

The analysis identified the steepest decline in groundwater across five key wards: Velachery (0.713mm, 0.781mm, 0.858mm), Santhome (0.950mm), and Venus Nagar (1.069mm), with continuous depletion rates. These sites require urgent action to prevent further groundwater loss.

Wards exhibiting maximum groundwater level variability included Basin Bridge (22.846mm, Variability: 7.20), Kalpalaiyam (11.451mm, Variability: 7.07), Surappattu

(16.295mm, Variability: 6.59), and Vijayalakshmipuram (15.760mm, Variability: 6.46; 9.355mm, Variability: 6.30). These locations demonstrate significant seasonal or localized fluctuations, suggesting unstable groundwater availability, which has implications for long-term water management.

Conversely, the most stable or growing groundwater levels were observed in Basin Bridge (24.741mm, 22.846mm), Kalpalaiyam (16.361mm), Thiru Vi Ka Nagar (14.966mm), and Pattalam SC (G) (14.751mm). These areas suggest sustainable water conservation strategies.

Here are the top 10 wards for each category:

TABLE II
TOP 10 DECLINING TREND WARDS (LOWEST YEARLY AVERAGE GROUNDWATER LEVELS)

Location	***Yearly Average (mm)***	***Trend***
Velachery	0.713	Declining
Velachery	0.781	Declining
Velachery	0.858833	Declining
Santhome	0.9505	Declining
Venus Nagar	1.069	Declining
Pannerselvam Nagar	1.109583	Declining
Sadayankuppam	1.1255	Declining
Puzhuthivakkam	1.156	Declining
Thiruvanmiyur West	1.261167	Declining
Madipakkam	1.273167	Declining

TABLE III
TOP 10 HIGH VARIABILITY WARDS (HIGHEST GROUNDWATER FLUCTUATIONS)

Location	***Yearly Average (mm)***	***Variability***
Basin Bridge	22.846	7.200725
Kalpalaiyam	11.451833	7.072919
Surappattu	16.295917	6.589309
Vijayalakshmipuram	15.760667	6.466697
Vijayalakshmipuram	9.355667	6.302345
Surappattu	10.28975	5.847530
Surappattu	8.563333	5.731948
Surappattu	9.652833	5.573618
Kallikuppam	7.7375	5.560258
Kalaignar Karunanidhi Nagar	11.827417	5.131817

Negative values indicate a decline in groundwater levels.

TABLE IV
TOP 10 STABLE/RISING WARDS (HIGHEST YEARLY AVERAGE GROUNDWATER LEVELS)

Location	***Yearly Average (mm)***	***Trend***
Basin Bridge	24.741429	Stable/Rising
Basin Bridge	22.846	Stable/Rising
Kalpalaiyam	16.361917	Stable/Rising
Thiru Vi Ka Nagar	14.966167	Stable/Rising
Pattalam SC (G)	14.751818	Stable/Rising
Pattalam SC (G)	14.6906	Stable/Rising
Mugalivakkam	14.417167	Stable/Rising
Kalaignar Karunanidhi Nagar	14.116667	Stable/Rising
Mugalivakkam	12.816833	Stable/Rising
Virugambakkam North	12.410	Stable/Rising

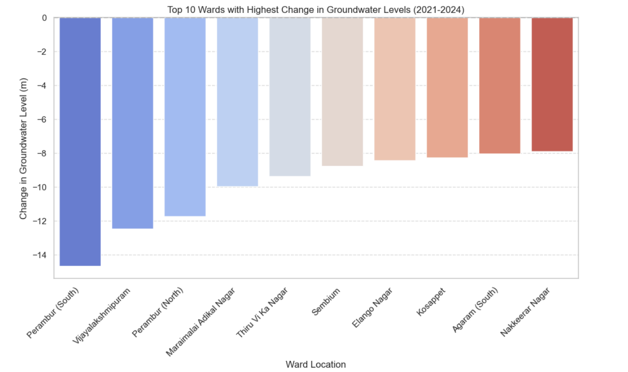

Fig. 7. Change in groundwater levels between 2021 and 2024 for the top 10 wards with the highest fluctuations.

Trends indicate potential over-extraction or recharge inefficiencies in certain wards. Wards with stable groundwater levels can be considered as benchmark locations.

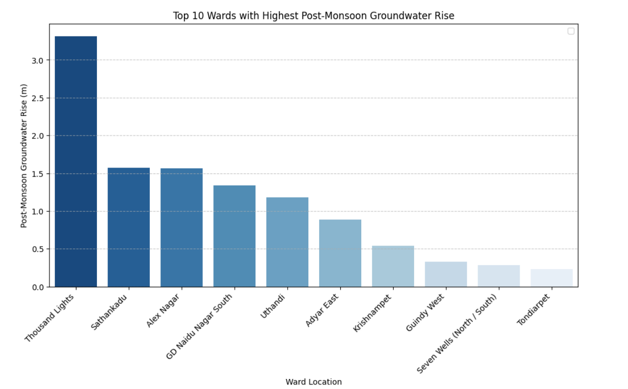

Fig. 8. The top 10 wards with the highest post-monsoon groundwater rise (October - June)

Wards with significantly high post-monsoon rises indicate natural recharge areas, whereas lower values may suggest poor recharge capacity due to urbanization or other factors.

4) **Ward-wise Comparison of Groundwater Levels:** This module assessed key groundwater metrics, including the minimum, maximum, and average groundwater levels for each ward, along with the annual change from 2021–2024. These calculations help identify wards experiencing significant changes in groundwater levels, particularly those facing critically low levels or substantial increases.
5) **Finding Wards with Notable Post-Monsoon Rises:** This module tracked groundwater recharge dynamics by analyzing post-monsoon rises—defined as the difference between groundwater levels measured in October and June. The average post-monsoon rise was calculated annually to establish a baseline. Wards showing increases above the annual mean were flagged for high recharge potential, and a Recharge Potential Score was computed using multi-year averages. The database serves as an indicator of recharge potential, identifying:
   - Low recharge areas needing artificial recharge inter-

ventions.

- Stable high-recharge zones that should be preserved.
- Critical conservation zones with consistently high recharge but low annual levels.

Based on the computed post-monsoon rise, the following locations exhibit the highest recharge potential:

TABLE V
TOP 10 LOCATIONS WITH THE BEST RECHARGE POTENTIAL

Location	***Area No.***	***Post-Monsoon Rise (mm)***
Thousand Lights	IX	7.430
Alex Nagar	III	4.510
Sathankadu	I	4.028
GD Naidu Nagar South	XIII	3.534
Surappattu	III	2.990
Thiruvanmiyur	XIII	2.865
Krishnampet	IX	2.685
Uthandi	XV	2.610
Adyar East	XIII	2.599
Thousand Lights	IX	2.360

Key insights include:

- Thousand Lights (Area IX) appeared twice, suggesting a strong recharge potential.
- Surappattu (Area III) and Thousand Lights (Area IX) exhibited high post-monsoon rises and stable recharge patterns.
- Uthandi (Area XV) showed a notable recharge increase despite a lower yearly average, making it a prime candidate for artificial recharge projects.
- Thiruvanmiyur and Adyar East (both in Area XIII) demonstrated consistently high recharge, highlighting the importance of conservation efforts in these regions.

6) **Ward Ranking by Recharge Potential:** The final module of Data Analysis prioritized wards within their respective Area Nos. based on computed recharge potential. Each ward was ranked, and the top five wards with the highest recharge potential were selected. This ranking provides a valuable framework for:

- Prioritizing conservation and recharge improvement efforts.
- Identifying key locations for investments in sustainable water management infrastructure.

TABLE VI
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA I

Location	**Area No.**	**Post-Monsoon Rise (mm)**
Sathankadu	I	1.569
Chinna Mettupalaiyam	I	0.140
Thilagar Nagar	I	0.096
Kathivakkam	I	-0.066
Ernavoor	I	-0.075

TABLE VII
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA III

Location	**Area No.**	**Post-Monsoon Rise (mm)**
Alex Nagar	III	1.563
Moolakadai	III	-0.004
Kavankarai	III	-0.269
Chinna Sekadu	III	-0.430
Milk Colony	III	-0.483

TABLE VIII
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA IV

Location	**Area No.**	**Post-Monsoon Rise (mm)**
Tondiarpet	IV	0.227
Thiruvalluvar Nagar	IV	0.187
Cheriyan Nagar North / South	IV	0.180
Jeeva Nagar (North)	IV	0.053
Korukkupet	IV	0.017

TABLE IX
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA V

Location	**Area No.**	**Post-Monsoon Rise (mm)**
Seven Wells (North / South)	V	0.287
Kondithope / Peddunaickenpet	V	0.156
Sowcarpet	V	0.092
Royapuram	V	0.075
Vallal Seethakathi Nagar	V	0.046

TABLE X
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA VI

Location	**Area No.**	**Post-Monsoon Rise (mm)**
Choolai	VI	0.144
Kolathur	VI	-0.236
Venus Nagar	VI	-0.424
Siruvallur	VI	-0.510
Pulianthope	VI	-0.566

TABLE XI
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA VII

Location	**Area No.**	**Post-Monsoon Rise (mm)**
Ayyappakkam	VII	0.030
Puthagaram	VII	-0.411
Nerkundram (Part)	VII	-0.664
Anna Nagar West Extension	VII	-0.7273
Mugappair Eri Scheme	VII	-0.801

TABLE XII
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA VIII

Location	**Area No.**	**Post-Monsoon Rise (mm)**
Pannerselvam Nagar	VIII	-0.313
Chetpet / Kilpauk South	VIII	-0.448
Vasantham Colony	VIII	-0.4797
Shenoy Nagar	VIII	-0.7147
Anna Nagar (East)	VIII	-0.7463

TABLE XIII
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA IX

Location	Area No.	Post-Monsoon Rise (mm)
Thousand Lights	IX	3.3157
Krishnampet	IX	0.5417
Teynampet	IX	0.1723
Vivekanandhapuram	IX	0.0523
Chepauk	IX	-0.3333

TABLE XIV
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA X

Location	Area No.	Post-Monsoon Rise (mm)
Virugambakkam South	X	0.1517
VOC Nagar	X	0.0127
Thiyagaraya Nagar	X	-0.1043
Kumaran Nagar North / South	X	-0.2853
Kodambakkam North	X	-0.5057

TABLE XV
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA XI

Location	Area No.	Post-Monsoon Rise (mm)
Ramapuram	XI	-0.0803
Maduravoyal	XI	-0.1577
Mettukuppam	XI	-0.2347
Porur	XI	-0.305
Valasaravakkam	XI	-0.307

TABLE XVI
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA XII

Location	Area No.	Post-Monsoon Rise (mm)
Adampakkam Part	XII	-0.1667
Nanganallur	XII	-0.189
Mugalivakkam	XII	-0.365
Pazhavanthangal Part	XII	-0.3663
Balaji Nagar	XII	-0.415

TABLE XVII
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA XIII

Location	Area No.	Post-Monsoon Rise (mm)
GD Naidu Nagar South	XIII	1.3347
Adyar East	XIII	0.883
Guindy West	XIII	0.3253
GD Naidu Nagar East	XIII	0.177
Adyar West	XIII	0.05

TABLE XVIII
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA XIV

Location	Area No.	Post-Monsoon Rise (mm)
Kottivakkam	XIV	0.1947
Palavakkam	XIV	-0.202
Madipakkam	XIV	-0.715
Perungudi	XIV	-0.7778
Puzhuthivakkam	XIV	-1.0673

TABLE XIX
TOP LOCATIONS WITH THE BEST RECHARGE POTENTIAL IN AREA XV

Location	Area No.	Post-Monsoon Rise (mm)
Uthandi	XV	1.1833
Neelankarai	XV	0.1435
Okkiyam Thuraipakkam	XV	-0.2327
Injampakkam	XV	-0.296
Semmenchery	XV	-0.5083

7) **Comprehensive Findings from Satellite Image Analysis:** Based on the findings from the Data Analysis module, we selected representative examples from various wards and conducted Satellite Image Processing as outlined in the methodology (Sub-components 7 to 9). Below are the results for Thousand Lights, Alex Nagar, Sathangadu, and Guindy:

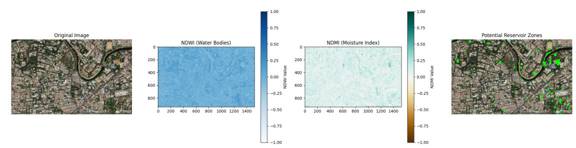

Fig. 9. Combined Output for Satellite Image Processing for Thousand Lights(module 7-9))

Fig. 10. Original Image - Thousand Lights

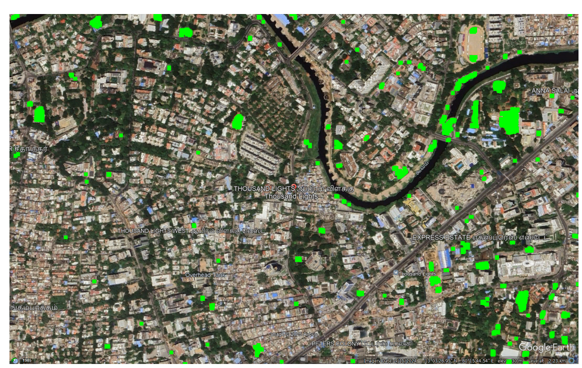

Fig. 11. Potential Recharge Spots - Thousand Lights

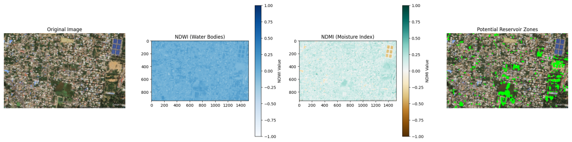

Fig. 12. Combined Output for Satellite Image Processing for Alex Nagar(module 7-9))

Fig. 13. Original Image - Alex Nagar

Fig. 14. Potential Recharge Spots - Alex Nagar

Fig. 15. Combined Output for Satellite Image Processing for Santhangadu(module 7-9))

Fig. 16. Original Image - Santhangadu

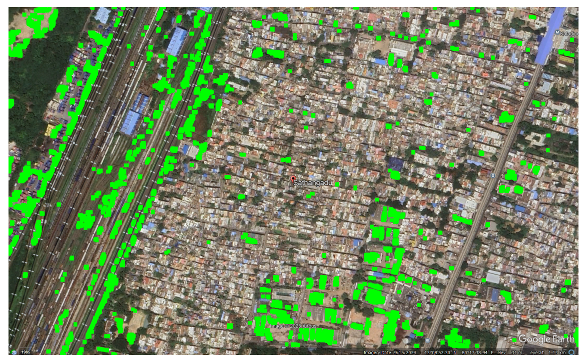

Fig. 17. Potential Recharge Spots - Santhangadu

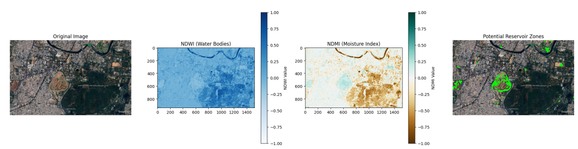

Fig. 18. Combined Output for Satellite Image Processing for Guindy(module 7-9))

Fig. 19. Original Image - Guindy

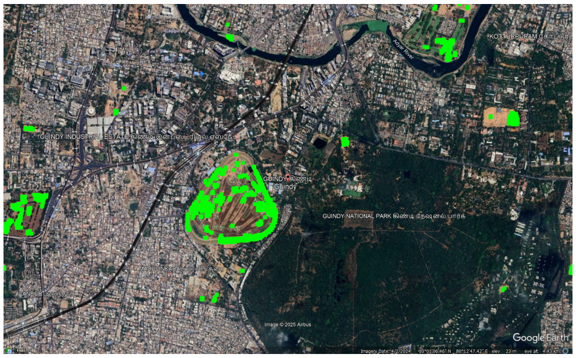

Fig. 20. Potential Recharge Spots - Guindy

V. Conclusion

This study presents a comprehensive analysis of Chennai's groundwater scenario by combining spatial and temporal assessments for identifying concerns and priority areas for intervention, based on critical trends. The mapping of wards into the declining, stable and highly variable groundwater level enables focused conservation actions while the assessment of post-monsoon rise and recharge explains from where groundwater recharge has come and where artificial recharge and restoration efforts should be focused. This enables prioritizing wards according to recharge potential and to implement the interventions that are specific to the challenges faced along with the sustainable solution to groundwater conservation in Chennai.

An interesting next step would be to define recharge areas through the application of satellite imagery and machine learning algorithms to classify land use patterns. Satellite data with a high classification level will help differentiate open fields from private property, and barren lands from urban spaces. This classification can also help policymakers and urban planners find feasible locations for groundwater recharge projects to maximize the use of available land for conservation. The accuracy can also be improved using machine learning models, which automate pattern recognition and predict optimal recharge areas based on historical patterns and environmental variables.

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