Artificial Intelligence Use for Forecasting Precipitation and Assessing Groundwater Depletion: A Study Case in Chihuahua City, Mexico

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Abstract: *This study presents an integrated methodology for assessing water resource vulnerability in Chihuahua City, Mexico, by combining satellite-based hydrological data and advanced time-series modeling. Using Long Short-Term Memory (LSTM) neural networks, the research forecasts monthly precipitation trends and identifies critical drought periods, notably between 2029 and 2032. Concurrently, GRACE satellite data reveal persistent groundwater depletion in the El Sauz–Encinillas aquifer, corroborated by historical piezometric measurements. The Río Conchos 3 basin exhibits surface water deficits, with future availability projections varying significantly across hydrological models. The approach enables early detection of water stress, supports operational optimization, and informs adaptive governance strategies. These findings underscore the importance of integrating predictive analytics with physical observations to enhance resilience in semi-arid urban regions.*

Keywords: *Artificial Intelligence, Groundwater Depletion, Precipitation Forecasting, LSTM, GRACE, Chihuahua, Water Governance, Hydrological Modeling*

1. Introduction

Water scarcity is a growing concern in semi-arid regions around the world, where factors such as climate variability, population growth, and agricultural demands place increasing pressure on limited water resources. In northern Mexico, the state of Chihuahua faces significant challenges, including declining precipitation, aquifer overexploitation, and infrastructure that could be strengthened for greater resilience. The aquifers overexploitation is a well-documented issue in many parts of Mexico, leading to a long-term decline in groundwater levels [1].
Recent advances in artificial intelligence (Ai) and remote sensing offer innovative tools for addressing these challenges. Machine learning models—particularly those designed for sequential data, such as Long Short-Term Memory (LSTM) neural networks—enable more accurate forecasting of climatic variables, including precipitation. Research by Hamed and, Rao, 1998, Ni et al., 2020 [2,3] have demonstrated the effectiveness of LSTM models for hydrological forecasting. Simultaneously, satellite missions like NASA's Gravity Recovery and Climate Experiment (GRACE) provide valuable insights into terrestrial water storage dynamics, revealing trends in groundwater depletion that are often not visible through surface monitoring alone [4,5].
This paper presents an integrated approach to water resource assessment in Chihuahua City, Mexico. It combines AI-based precipitation forecasting with satellite-derived groundwater anomaly detection. By applying LSTM models to historical rainfall data and correlating the results with GRACE observations and well measurements, this research seeks to improve drought prevention, quantify aquifer stress, and propose adaptive management strategies. The findings demonstrate the value of merging predictive analytics with physical hydrological data to support sustainable water governance in climate-sensitive regions.
Chihuahua City faces challenges related to water management due to limited precipitation, aquifer overexploitation, and the need for more resilient hydraulic infrastructure. These issues are further complicated by the lack of timely and integrated data systems to support proactive water

management. An effective strategy could involve segmenting hydrometric districts based on water availability versus user demand. This would allow for better control and integration of service provision, helping to ensure the quality, quantity, and pressure of water delivery. Strengthening the system's resilience, a concept explored by Lukat et al., 2022 [6], can help mitigate the impacts of stress caused by growing populations and climate variability in semi-arid regions like Chihuahua.
Chihuahua City is located within the Río Conchos 3 basin, which is composed of three sub-basins: the Sacramento, El Granero, and Chuviscar. The Río Conchos is a critical river in Chihuahua, draining almost half of the state's territory and serving as the primary Mexican tributary to the Río Bravo (Rio Grande). The strategic importance of this basin for both Mexico and the United States has been a subject of diplomatic and scientific discourse for decades, highlighting the need for careful binational water management [7].

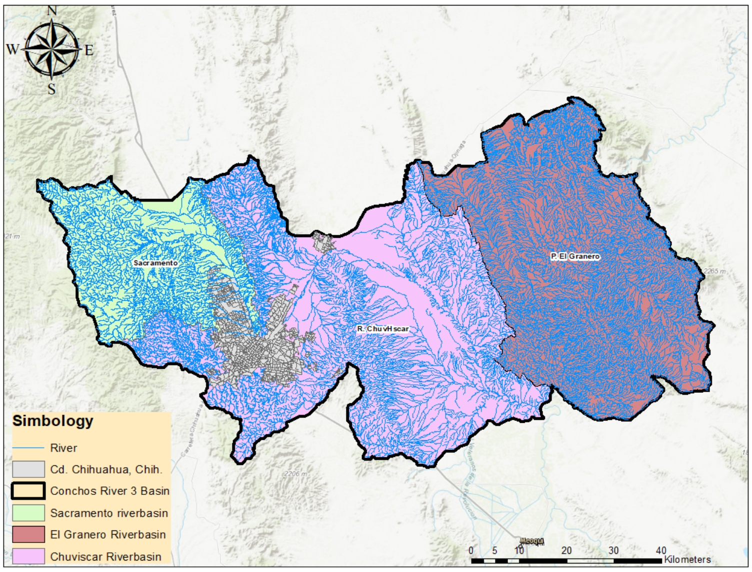

Fig. 1. Rio Conchos 3 River basin at Chihuahua City and their subbasins. Source: Own design

Although this region possesses notable surface water sources, their reliability has been significantly compromised by prolonged drought conditions. Consequently, Chihuahua city relies predominantly on local groundwater aquifers to meet its direct water supply needs (Figure 2). The primary aquifers serving the city include:

- Chihuahua-Sacramento Aquifer (CHS): This aquifer underlies most of Chihuahua City's urban area and is part of the larger Bravo-Conchos hydrological basin. It covers an area of 1,889 km².
- El Sauz–Encinillas Aquifer: Located approximately 92 km north of Chihuahua City, this aquifer is crucial for the city's water supply. It resides within a closed (endorheic) basin surrounded by mountain ranges.

Chihuahua City is located at a semi-arid region where groundwater is the primary permanent water source. However, the available data from Conagua indicates significant challenges:
Overexploitation: Many aquifers in Chihuahua, including El Sauz-Encinillas, are overexploited, meaning water extraction significantly exceeds natural recharge rates. Out of 61 aquifers supplying drinking water in the state, 42 are overexploited, and 9 have no reported availability.
Declining Water Levels: This overexploitation leads to a consistent drop in water table levels, a trend observed through satellite data (GRACE) and validated by historical well measurements.
Increasing Demand: Despite the deficit, water demand from Chihuahua City's growing population and the agricultural sector continues to rise, exacerbating the water scarcity issues.
Slow Recharge: Deep aquifers, which often contain "fossil" water, recharge very slowly, and prolonged extraction can lead to increased salinity, making the water unsuitable for various uses.

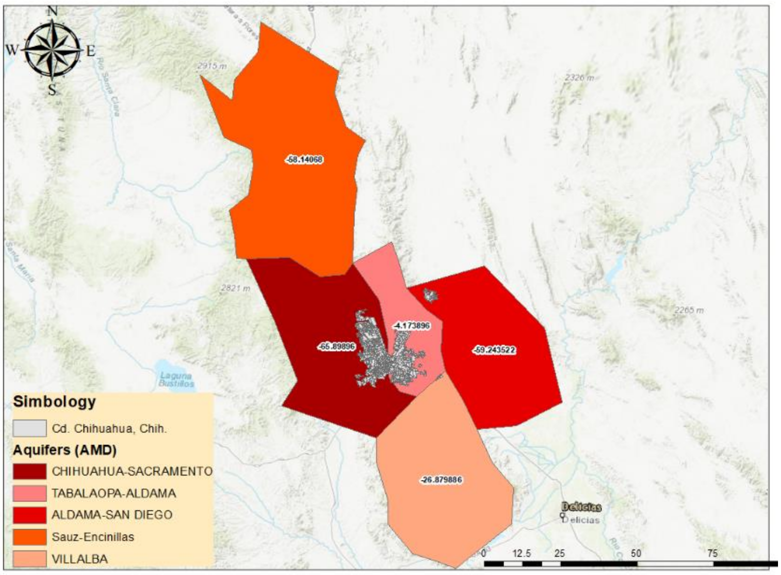

Fig. 2. Aquifers surrounding Chihuahua City and their AAD annual average availability. Source: [8]

Figure 2 shows a geospatial groundwater configuration availability in the Chihuahua region according to Conagua 2023, based on the annual average availability (AAA) as defined by the *NOM-011-CONAGUA-2015.* This standard specific the methodology for calculating groundwater availability through a balance of recharge (R), committed natural discharge (CND), and extraction volumes (EV).
In the Figure 2, at showed a groundwater availability situation according the color, for example:

- Chihuahua – Sacramento (dark red): Indicates a high deficit, a negative availability approximately –65.89 hm³/year.
- Tabalaopa – Aldama (red): Shows a negative availability around –59.24 hm³/year.
- El Sauz - Encinillas (orange): Also shows a negative availability around to -58.14068 hm³/year.
- Aldama – San Diego (light orange): Moderate deficit with availability near to –26.87 hm³/year.
- Villalba (pink): Slightly less stressed with availability near to –4.17 hm³/year.

2. Methodology

Advanced Artificial Intelligence (AI) integration models, including recurrent neural networks (RNNs) like Long Short-Term Memory (LSTM) and machine learning algorithms such as XGBoost, has significantly improved in prevention water scarcity events in Chihuahua City. These models are they proven on historical data sets taking into account temperature, precipitation, streamflow, and piezometric levels, generating projections that adapt to emerging climatic and anthropogenic patterns [9,10]. One of the key strengths of these approaches lies in their ability to identify early signals of aquifer stress and surface water deficits. By detecting subtle shifts in recharge dynamics and consumption patterns, they support the timely implementation of mitigation strategies. For instance, ensemble models combining LSTM with convolutional layers or attention mechanisms have achieved high accuracy in drought prediction, outperforming conventional models in both spatial and temporal resolution [11,12].
Beyond forecasting, these tools contribute to operational optimization. Algorithms can define efficient water redistribution routes, adjust pressure zones, and prioritize service areas based on consumption history and infrastructure vulnerability. Pilot implementations have reported reductions in water losses ranging from 14% to 22%, particularly in urban districts with aging networks.
Moreover, decision support systems enhanced by machine learning are increasingly used to visualize hydrological scenarios in real time. These platforms integrate geospatial data, alerts, and

predictive simulations, facilitating coordinated responses among agencies. Studies have shown that such systems improve institutional readiness and foster collaborative governance, especially when combined with explainable AI frameworks that clarify model outputs for non-technical stakeholders [13,14].
In the context of climate change, models are being calibrated to reflect projected increases in temperature and reductions in recharge rates. For example, simulations for semi-arid basins suggest a potential rise of +2.4 °C and a 38% decrease in aquifer replenishment, underscoring the urgency of adaptive planning. In summary, the integration of advanced machine learning techniques into hydrological modeling not only enhances predictive capacity but also strengthens institutional decision-making and public policy formulation. Future research should explore hybrid approaches that combine physical models with data-driven algorithms, ensuring both accuracy and interpretability in water resource planning.

3. Results and Discussion

3.1 Surface water: Río Conchos 3 Basin Analysis

The Río Conchos 3 basin, spanning an area of 6,508 km², revealed a negative surface water availability of –6.37 hm³/year in the base 2020 Study scenario, classifying it as a basin "without availability." This condition reflects a significant imbalance between the committed downstream volume (251.17 hm³) and the available runoff (244.8 hm³). This deficit is further exacerbated by registered extractions (53.6 hm³) and limited returns (57.7 hm³).

Table 1: surface Availability water at Rio Conchos 3 Basin According to DOF 2020

Parameter	Value	Unit
Area	6,508.00	km²
Available Runoff (Ab)	244.8	hm³/year
Committed Volume Downstream (Rxy)	251.17	hm³/year

Different hydrological models present varying projections for the basin's future water availability according to Bravo-Jácome et al., 2025 [15]:
TURC Model: Application of the TURC model projects a significantly improved availability of 2,007.59 hm³/year by 2034, suggesting a more favorable outlook under certain climatic conditions.
Runoff Coefficient (RC) Method: In contrast, RC method estimates a more severe decline, with an availability of –13.34 hm³/year, reinforcing the risk of water stress under conservative scenarios.

Table 2: Different hydrological models present varying projections for the basin's future water availability

Basin	Deficit (D) 2020 Study (hm³/year)	Deficit (D) 2034 TURC Model (hm³/year)	Deficit (D) 2034 Runoff Coefficient (RC) Method (hm³/year)
Río Conchos 3	-6.37	2007.59	-13.34

These discrepancies between modeling methods highlight the basin's sensitivity to climatic variations and land-use changes. They underscore the critical need for implementing adaptive management policies and continuous monitoring to ensure sustainable water resources in the face of uncertainty.

3.2 Forecasting Monthly Precipitation Using LSTM

LSTM neural networks are deep learning architectures designed to learn from sequential data. In this study, monthly precipitation records from Rio Conchos 3 Basin were preprocessed using:

- Imputation of missing values
- Rolling statistics and lag features
- Robust scaling to mitigate outlier influence

Monthly precipitation records (1982–2018) were preprocessed using imputation of missing values, rolling statistics, lag features, and robust scaling. An LSTM neural network was trained using five-fold time series cross-validation. The model achieved:

- Mean Absolute Error (MAE): 73.59 mm
- Coefficient of Determination (R^2): 0.29

Despite moderate R^2, the model effectively captured transitions from normal rainfall to prolonged dry periods. Forecasts for 2019–2033 suggest stable precipitation through 2028, followed by a severe drought from 2029 to 2032. These projections support strategic water rationing, infrastructure reinforcement, and drought contingency planning.

3.3 Time Series Decomposition

The precipitation series was decomposed into:

- Observed Component: High interannual variability with peaks (2004–2006) and dips (early 1980s, mid-1990s)
- Trend Component: Declining trend until mid-1990s, followed by gradual recovery
- Seasonal Component: Stable oscillations around zero, indicating consistent seasonal cycles

This decomposition supports the use of periodic models like RNNs and enhances interpretability for water resource planning.
The model was evaluated using five-fold time series cross-validation. Performance metrics yielded a Mean Absolute Error (MAE) of 73.59 mm and a coefficient of determination (R^2) of 0.29. Despite moderate R^2, the LSTM model successfully captured interannual variability and key shifts from normal precipitation to prolonged dry periods.
The forecast (2019–2033) indicated stable rainfall through 2028, followed by severe drought from 2029 to 2032. These predictions were translated into actionable recommendations—such as water rationing policies and infrastructure readiness—to enhance drought resilience.

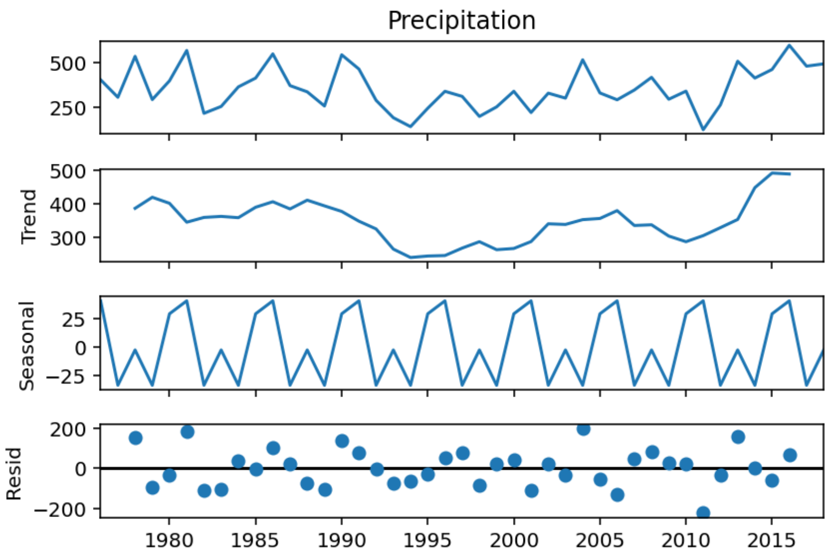

Fig. 3. Precipitation time series AI model results for Rio Conchos 3 Basin

Figure 3 breaks down the precipitation time series into three key components:
a). Observed Precipitation

- Displays the raw annual precipitation values.
- Shows high interannual variability, with peaks around 2004–2006 and dips in the early 1980s and mid-1990s.

- The fluctuations suggest alternating wet and dry years, typical of semi-arid basins influenced by regional climate patterns.

b). Trend Component
- Reveals the long-term direction of the data.
- Initially, there's a declining trend from 1980 to the mid-1990s, followed by a gradual recovery toward 2015.
- This may reflect broader climatic shifts or land-use changes affecting rainfall patterns over time.

c). Seasonal Component
- Captures recurring patterns or cycles in the data.
- The seasonal variation is relatively stable and symmetric, oscillating around zero.
- This suggests that while the magnitude of precipitation changes year to year, the seasonal rhythm remains consistent, likely tied to predictable wet and dry seasons.
- Any remaining variability not explained by the trend or seasonality.
- These are important for identifying anomalous years or extreme events that deviate from expected patterns.
- The decomposition confirms that precipitation at Río Conchos 3 Basin is highly variable, but with a recovering trend post-1995.
- The stable seasonal component supports the use of models that assume periodicity, like RNNs.
- Understanding these components helps improve forecasting accuracy and supports adaptive water management policies.

We can observe at Figure 4; precipitation series was decomposed into:
- Observed Component: High interannual variability with peaks (2004–2006) and dips (early 1980s, mid-1990s)
- Trend Component: Declining trend until mid-1990s, followed by gradual recovery
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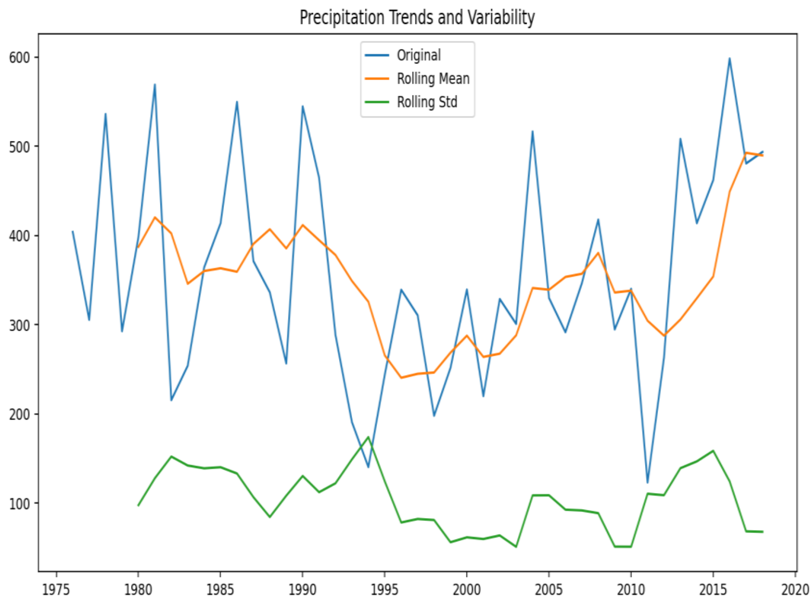

Fig. 4. Precipitation trends and variability at Rio Conchos 3 Basin

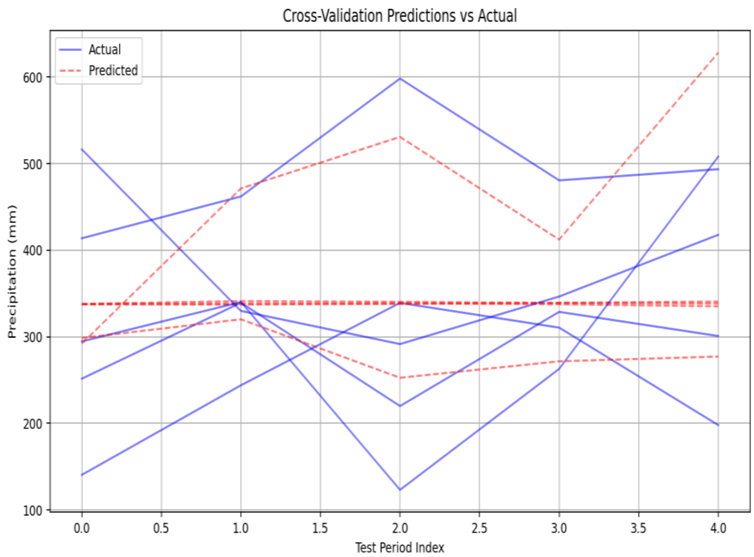

Fig. 5. Precipitation cross-validation prediction vs actual at Rio Conchos 3 Basin

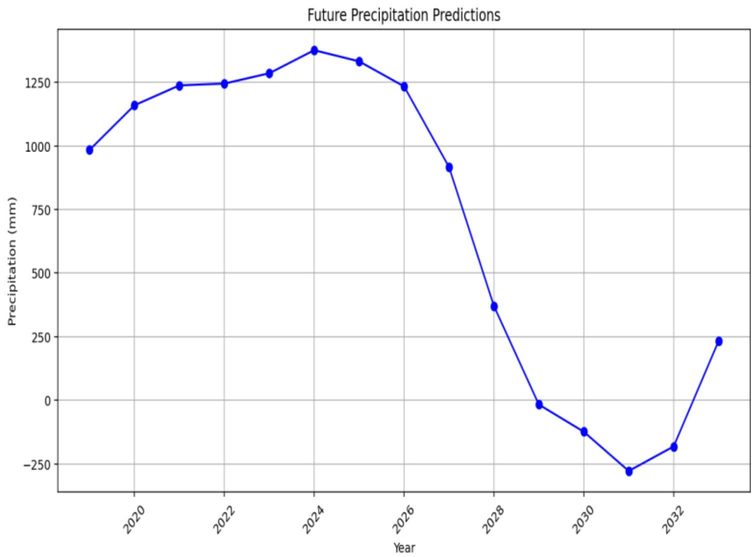

Fig. 6. Precipitation future prediction at Rio Conchos 3 Basin

- In several points, the predicted values closely follow the real ones, indicating the model captures the general trend.

At Figure 7 we can observe there are some sample indices where the prediction deviates noticeably from the actual temperature—this could be due to:

  - Sudden climate anomalies
  - Limited training data for extreme years
  - Lag effects not captured by the model

Also, it visually confirms that the model performs reasonably well but may benefit from:

  - Including additional predictors (e.g., NDVI, humidity, wind)
  - Using lagged features or temporal smoothing
  - Trying a sequential model like RNN or LSTM for better temporal learning

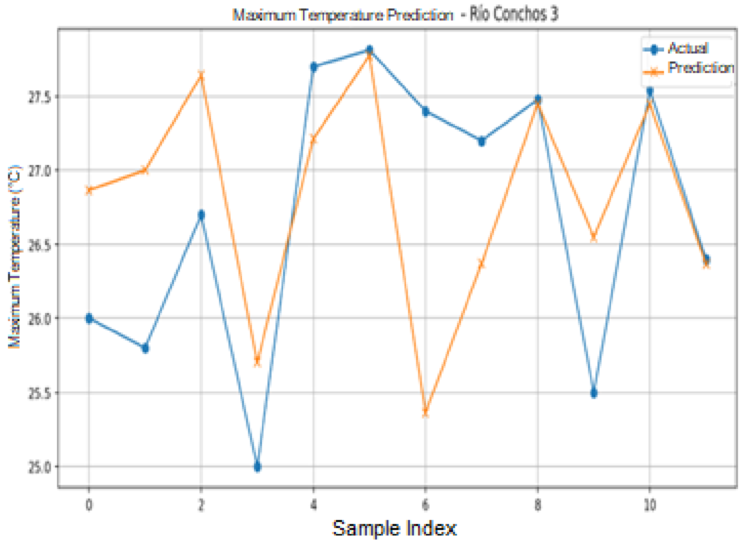

Fig. 7. Temperature Maximum prediction at Rio Conchos 3 Basin

3.4 Groundwater: El Sauz-Encinillas Aquifer

The Sauz-Encinillas aquifer (0807), is situated in the Chihuahua state central portion, in Mexico. It spans latitudes 28°53'31” N to 29°39'41” N and longitudes 106º09’35” W to 106°43´27” W, covering an area of 2,743 km². It shares its northern boundary with the Laguna de Tarabillas and Flores Magón-Villa Ahumada aquifers; its eastern boundary with Laguna de Hormigas and Laguna El Diablo; its southern boundary with Chihuahua Sacramento and Alto Río San Pedro; and its western boundary with Santa Clara and Cuauhtémoc, all within Chihuahua state. The aquifer system is characterized by heterogeneity and anisotropy. It is predominantly unconfined, though local semi-confined conditions exist due to the interdigitation of low-permeability strata. Geologically, it is situated within a tectonic graben filled with sediments of varying grain sizes. These alluvial sediments reach a maximum thickness of 800 m, thinning towards the slopes of the surrounding mountain ranges where alluvial fans are present. At greater depths, fractured volcanic rocks and limestones exhibit secondary permeability, forming an unexploited unit with evidence of its presence derived from mining operations, primarily in adjacent aquifers.

Hydraulic Parameters

As part of a 2009 study, eight pumping tests were conducted, encompassing both drawdown and recovery phases, with durations ranging from 4 to 12 hours. Interpretation of these tests, utilizing various methods, yielded transmissivity values varying from 24 to 455 m²/day (0.3 to 5.3 x 10^{-3} m²/s), with an average of 191 m²/day (2.2 x 10^{-3} m²/s). Considering an average saturated thickness of 170 m, this translates to an average hydraulic conductivity of 1.1 m/day (1.3 x 10^{-5} m/s). For the storage coefficient (S) in the central valley area, the average value was determined to be 7.1 x 10^{-4}. Specific yield (Sy) values ranged from 0.06 to 0.21 [8].

Static Water Level Elevation

In the context of Mexico’s National Water Commission (CONAGUA), piezometric levels represent measurements of groundwater pressure within an aquifer, typically obtained through monitoring wells or piezometers. These readings are essential for analyzing subsurface water dynamics and ensuring sustainable groundwater management. You can explore official data through CONAGUA’s Piezometric Measurements Portal https://sigagis.conagua.gob.mx/rp20/ [8]. Groundwater level analysis in the region is based on data collected between 2001 and 2009. In 2009, static water level depths varied significantly across the aquifer:

Range of Depths: 5 to 120 meters

Shallowest Levels: Found near Encinillas and Ejido Nuevo Delicias, located in the central and northern zones of the aquifer

Southern Sector: Depths ranged from 20 to 120 meters, with topography playing a key role in the deeper measurements

El Sauz–Chihuahua Aqueduct Zone: Near the well fields supplying this aqueduct, depths ranged from 10 to 80 meters

These variations reflect both natural geological influences and anthropogenic pressures, underscoring the importance of continuous monitoring for effective water resource planning. The static water level elevations in 2009 (Table 3) ranged from 1515 to 1570 meters above sea level (masl), showing no significant spatial or value change from previous configurations. Elevations generally increased topographically from the valley towards the mountain foothills. A more pronounced cone of depression was observed in the southern portion of the aquifer, indicative of concentrated water extraction.

Static Water Level evolution

Based on piezometric data from 2001 and 2009, the evolution of the static water level revealed average annual drawdowns varying from 0 to 3 m. As expected, the most significant drawdowns were recorded in the southernmost part of the aquifer. This area exhibits a distinct cone of depression, directly attributed to the concentration of wells extracting potable water for Chihuahua City.
Table 3 details the annual storage change calculation for the El Sauz-Encinillas aquifer from 2001 to 2009.

Table 3: Annual storage change calculation for the El Sauz-Encinillas aquifer from 2001-2009 year

Drawdown (m)	**Area (km^2)**	**Sy**	**$\Delta V(S)$ (hm^3/year)**
-24.0	28.3	0.2	-135.7
-16.0	70.0	0.2	-224.1
-8.0	33.4	0.2	-53.4
-5.6	12.9	0.2	-14.5
-4.0	90.5	0.2	-72.4
-4.0	35.1	0.2	-28.0
TOTAL	270.2	TOTAL	-528.1
Annual Average			-66.0

According to table 3 storage net change is $\Delta VS = –66.0$ hm^3/year.
Table 3 shows various segments of the aquifer experiencing different drawdown levels and their corresponding storage changes. The overall picture indicates a significant negative change in groundwater storage over this nine-year period:
The cumulative net storage change for the entire analyzed area (270.2 km^2) is -528.1 hm^3/year.
The average annual net change in storage for the aquifer is a concerning -66.0 hm^3/year. This negative value directly indicates that the aquifer is experiencing depletion, meaning more water is being extracted or lost than is being recharged annually.

3.5 Groundwater Depletion Detected by GRACE

The integrated methodology, combining Ai-based forecasting with satellite and field-based hydrological monitoring, has been specifically applied to the El Sauz-Encinillas aquifer to address its complex water management challenges. Long Short-Term Memory (LSTM) neural networks are used to predict long-term rainfall trends, offering insights into future precipitation patterns relevant to the aquifer's recharge. Simultaneously, GRACE satellite data provides crucial information on terrestrial water storage variations over the El Sauz-Encinillas aquifer, revealing a marked declining trend in water storage with persistent negative anomalies. These GRACE-derived negative trends

coincide with the predicted reduction in precipitation by the LSTM model, validating concerns over future water scarcity in the aquifer. This combined approach quantifies aquifer stress and enhances drought anticipation, thereby supporting adaptive management strategies for the sustainable water governance of El Sauz-Encinillas.
Figure 8 illustrates the terrestrial water storage anomaly in the El Sauz–Encinillas aquifer between 2003 and 2017, based on GRACE satellite data. The y-axis represents liquid water equivalent thickness anomalies in centimeters (cm), ranging from approximately –10 cm to +8 cm, while the x-axis displays the time series with monthly markers. The data line, lwe_thickness_csr, reflects fluctuations in subsurface water storage.

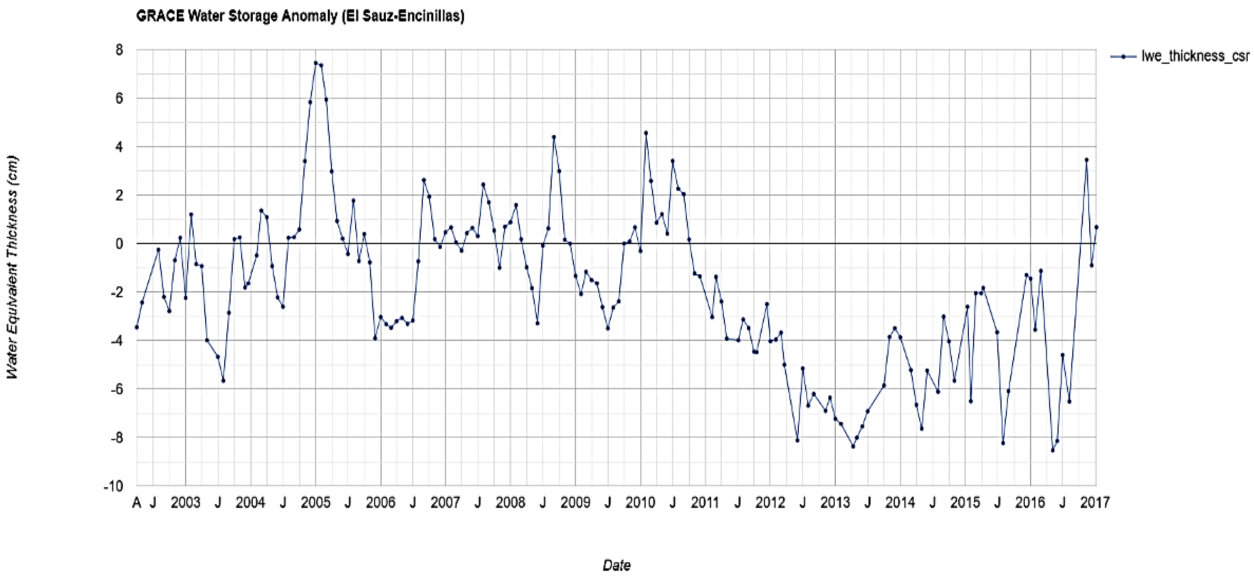

Fig. 8. GRACE satellite-derived terrestrial water storage anomaly in the El Sauz–Encinillas aquifer (2003–2017)

A pronounced downward trend is evident, particularly from 2012 onward, indicating sustained groundwater depletion. These negative anomalies are consistent with intensified extraction and reduced natural recharge, especially during dry years. Seasonal oscillations are visible, with short-term recoveries followed by deeper deficits—suggesting that wet-season recharge is insufficient to offset withdrawals and evaporation losses.
The most severe anomalies occurred between 2013 and 2015, likely linked to compounded drought conditions and increased water demand. This period underscores the aquifer's vulnerability to both climatic variability and anthropogenic pressures.
The persistent negative anomalies have significant implications for aquifer sustainability, agricultural planning, and ecological resilience. These data are critical for hydrological modeling and can be used to:

- Adjust recharge estimates
- Validate groundwater simulations
- Support early warning systems for water stress

The GRACE-derived trends align with LSTM model predictions of reduced precipitation, reinforcing concerns over future water availability in the region.
Groundwater Table Measurements from Wells Monitoring
Complementing the satellite data, historical well measurements from 1996 to 2012 across the El Sauz–Encinillas aquifer were analyzed using piezometric well records (Figure 9) obtained from CONAGUA's official repository [8]. These measurements consistently show increasing water table depths, confirming the depletion observed in GRACE data.

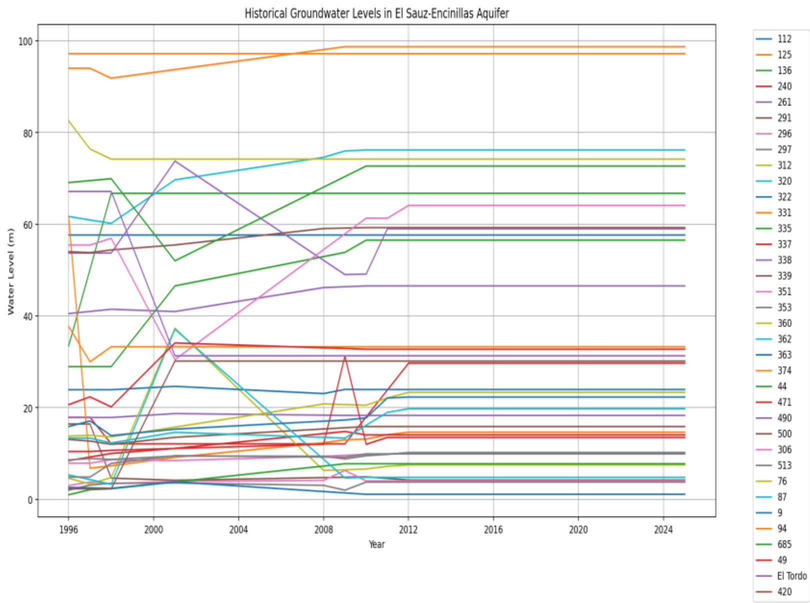

Fig. 9. Piezometric level well Behavior

Table 4 summarizes selected observations from monitoring wells, highlighting spatial variability in depletion rates due to differences in geology, recharge conditions, and extraction intensity.

Table 4: Well, piezometric levels from Sauz-Encinillas aquifer (1996-2012 year)

Well	Curb Elevation	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
112	1585.65			57.73														
125	1656.73		94	91.85											98.71			
136	1593.85	33.48		66.73														
240	1549.95		17.89	12.1											12.1			29.7
261	1552.45			17.85			18.7								18.3			
291	1528.25		16.43	4.62			4.15									4.9		4.2
296	1525.20	3	3.78	3.42			3.9							4.13	6.3	4.01		
297	1530.95	2	3.12	3.5			3.56							3.05	2	3.76		
312	1544.70	4.59	3.34	4.75			37.33							6.3		6.61	7.2	7.5
320	1610.10	61.68		60.18			69.67							74.58	75.96	76.18		
322	1561.30			23.9			24.64							23.06	23.98	23.95		
331	1541.20	61.5	6.8	7.32			9.16							12.35	12.97	13.14	14.1	14.65
335	1538.05	1	2.1	2.3											7.76			
337	1545.98	8.45		10			11.11								14.8	14.06		
338	1585.40	40.5		41.45			40.95							46.18		46.54		
339	1542.30	13.06	12.7	12			13.52									15.87		
351	1529.15	7.89	7.88	8.64			8.46							9.4		9.8	9.9	10.1
353	1529.30	8.6	8.89	8.7			9.45							9.4	8.8	9.5	9.8	10.21
360	1562.20	13.8	13.95	13.63			15.75							20.8		20.52	22.1	23.34
362	1534.80	5.32		3.28			37.08								4.67	4.79		
363	1535.70	2.6		2.4			3.81									1.1		
374	1659.05			97.22														
44	1568.15			28.94			46.54								53.85	56.52		
471	1528.68		10.43	10.68			11.09							12.02	31.25	12.01	13.5	

Well	Curb Elevation	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
490	1605.40			53.7			73.77								49.02	49.11	59	59
500	1596.95	54	53.8	54.38			55.48							59.05		59.25		
306	1601.29		55.46	56.92			30.46									61.32	61.3	64.1
513	1543.36		4.85	7.84			9.51								9.18	9.91		
76	1601.30	82.53	76.4	74.2														
87	1562.98		13.35	12.29			14.62								13.35		18.96	19.75
9	1555.78	15.86	17.1	13.9			15.3								17.3	17.76	22.1	22.3
94	1577.60	37.7	30	33.28														
685	1609.80	69.08		69.92			52.01									72.68		
49	1543.30	20.65	22.35	20.16			34.1									32.74		
El Tordo	1618.02			67.13			31.3											
420	1528.05			2.3			30.15											

Together, the GRACE satellite anomalies and field-based piezometric measurements present a consistent and compelling narrative of long-term groundwater depletion in the El Sauz–Encinillas aquifer. This convergence of evidence highlights the urgent need for adaptive management strategies and continuous hydrological monitoring.

Figure 9, which displays GRACE-derived terrestrial water storage anomalies from 2003 to 2017, offers independent, satellite-based validation of the depletion trend. This figure reveals a pronounced decline in liquid water equivalent thickness, with persistent negative anomalies—particularly from 2012 onward—some exceeding –8 cm. These anomalies are indicative of intensified groundwater extraction and insufficient natural recharge. Satellite observations align closely with field data presented in Table 4, which documents negative annual storage changes between 2001 and 2009. This cross-validation between remote sensing and in-situ measurements reinforces the severity of aquifer stress and underscores the reliability of the findings across different methodologies and temporal scales.

Moreover, the GRACE anomaly trends coincide with precipitation reductions forecasted by the LSTM model, further substantiating concerns over future water scarcity. The integration of satellite data, machine learning forecasts, and field measurements provides a robust framework for understanding aquifer dynamics and guiding sustainable water resource planning in the region.

4. Conclusions

This paper demonstrates the valuable potential of integrating advanced artificial intelligence (AI) with both satellite and field-based hydrological data to enhance water resource management in semi-arid regions. The detailed analysis of the El Sauz-Encinillas aquifer and the Río Conchos 3 basin offers key insights into current and future water availability challenges.

This finding shows that Long Short-Term Memory (LSTM) models are effective in anticipating drought conditions and forecasting rainfall variability. This predictive capability is a useful tool for a more proactive approach to water management.

Data from the GRACE satellite provides strong evidence of long-term groundwater depletion. For the El Sauz-Encinillas aquifer, GRACE data from 2003–2017 revealed a clear declining trend in water storage. This aligns with and is reinforced by field data, which showed an average annual storage loss of -66.0 hm^3/year for the 2001-2009 period. The confirmation of GRACE observations with historical well measurements further validates this evidence. Within the Río Conchos 3 basin, hydrological modeling confirmed the methodologies used. The basin faces a surface water deficit, and future projections show significant variability depending on the model used. These discrepancies highlight the basin's sensitivity to climate and land-use changes. AI models proved essential for predicting periods of low water availability in advance, identifying vulnerable urban areas, and optimizing operational responses.

The synergy between predictive analytics and physical hydrological data provides a robust toolkit for building resilience to climate impacts. We recommend that future research explore integrating additional factors such as evapotranspiration, land cover, and socio-economic indicators for more holistic and effective planning.
Scaling these successful models to other cities in northern Mexico and investing in the necessary digital infrastructure and personnel training are suggested next steps. The widespread adoption of AI-powered tools holds the potential to significantly improve water security across arid and semi-arid landscapes. This integrated approach is essential for building resilient water infrastructure, guiding effective policy, and ensuring sustainable water availability in regions facing climate uncertainty.

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