

Research Article:

Spatio-temporal Patterns of Precipitation in Iraq: A Quantitative Assessment Using Station Datasets

Dilshad Altalabani^{1*}

¹Directorate of Information Technology and Statistics, Sulaimani Polytechnic University, Sulaymaniyah, Iraq.
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*Corresponding author info: Dilshad
Omar Altalabani
(dilshad.o.muhammad@spu.edu.iq)

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Abstract:

Background: Iraq's water security faces a critical, pressing issue due to the accelerated impact of climate change.

Aims: The study aims to conduct quantitative, long-term analyses of climate change impacts using a detailed dataset. The specific aim of this study is to investigate the impact of static geographic factors and temporal trends on climate change.

Methodology: The study used a comprehensive statistical approach to the dataset collected from four different locations: Sulaymaniyah, Baghdad, Basrah, and Al-Rutba. The methodology used for this study is spatial analysis, which uses Multivariate Analysis of Variance (MANOVA) and Multiple Linear Regression (MLR) to investigate the impact of geographic factors, and temporal analysis, which uses trend assessment and the Standardized Precipitation Index (SPI).

Results: The spatial analysis confirmed the findings of other studies that geographic location is the primary factor in the climate change baseline, with the MLR model explaining 90% of the variance in annual precipitation. This analysis revealed a significant orographic effect, whereby for every 100 meters of height, there is a corresponding 40.6 mm of precipitation. The spatial analysis also revealed a significant trend at all four locations, which corresponds with the results of the temporal analysis. Most importantly, this analysis revealed a critical drought trend as measured by the SPI.

Conclusion: The results indicate that geography provides the essential setting for the findings, and quantification confirms this. The research established a strong, statistically significant warming trend across all examined areas. The results indicate a significant negative trend in each of the cities examined. Consequently, the region is heading towards drier conditions, with a dynamic shift towards aridification and desertification potential within its stable climatic and topographic framework. This necessitates the development of region-specific water management strategies and the establishment of a national drought early warning system.

Keywords: *Applied Statistics; Multiple Linear Regression; Standardized Precipitation Index; Climate Change Impact; Drought Analysis; Spatial-Temporal Analysis; Iraq.*

1. Introduction

The hydrological cycle, as the primary driver of precipitation, plays a vital role in sustaining water security, agricultural production, and ecological systems. In arid and semi-arid regions, where freshwater availability is naturally limited, even minor changes in precipitation patterns can result in significant socioeconomic and environmental consequences [1]. This phenomenon is particularly concerning in Middle Eastern and North African countries, which are

already in a critical state, as water scarcity is exacerbated by population growth, resource mismanagement [2], and the intensified effects of climate change [3, 4].

Iraq is considered a country located in the highly sensitive region of the Tigris and Euphrates rivers. Water resources in Iraq are geopolitically critical and highly susceptible to climate variability in the river catchments [5]. In Iraq, significant climate change trends are being recorded, which, according to certain reports, may be two to seven times faster than the average global rate [6]. In addition to

temperature and precipitation, the consequences of climate change influence different aspects of thermal bioclimatic zones in different climatic regions of Iraq [7]. Although it is well known that Iraq encompasses heterogeneous climatic zones, the quantitative influence of geographic factors on precipitation trends over long periods remains poorly understood. In previous studies, researchers have investigated short-term precipitation trends using modeling techniques [8] and long-term trends without isolating geographic factors [9]. Although [10] recorded temperature trends, no study to date has investigated multi-decadal trends in drought severity across Iraq's different climatic zones.

To address these essential knowledge gaps, this study provides a comprehensive quantitative assessment of climate variability and climate change in Iraq. The first challenge is to quantify drought variability using reliable indices. Although the Palmer Drought Severity Index (PDSI) provides a comprehensive evaluation of drought severity in relation to soil moisture conditions, and the Standardized Precipitation Evapotranspiration Index (SPEI) includes temperature effects, the SPI is found to be the most appropriate method for this research [11]. As emphasized by [12], the major advantage of using SPI is its simplicity and its ability to perform multi-scalar comparisons. This focus on precipitation is consistent with recent comprehensive assessments of climate variability within the Tigris-Euphrates Basin, which also used SPI [13]. To effectively quantify these variables, the choice of statistical techniques is critical. To deal with non-normal long-term time series of climate variables, non-parametric techniques are essential.

The Mann-Kendall (MK) test is recognized for its reliability in identifying trends using nonparametric techniques and is well established in the region [14, 15].

Other advanced techniques using wavelet transformations were also used to quantify drought variability [16]. In the spatial dimension, MLR is recognized for providing a robust framework for quantifying the impact of discrete geographic factors. With this solid methodological foundation and using a 66-year high-resolution dataset from four distinct stations, this study quantifies geographic impact, analyzes long-term trends, and evaluates drought patterns to separate geography's stable fingerprint from climate change's dynamic signal.

2. Data and Methods

2.1. Study Area and Data Source

The study primarily relied on TerraClimate data, a high-resolution global dataset that provides monthly climate data and the climatic water balance [17]. The data used in the study were at an approximately 4 km spatial resolution, or 1/24 degrees. The original data are provided in a gridded Network Common Data Form (NetCDF) format. For this research, gridded data were extracted for the four selected urban centers Figure 1 using their geographic coordinates for the full 66-year period (1958-2024). This extraction process converted grid-based data into continuous time series for each location for key climatic variables, including maximum temperature (tmax), minimum temperature (tmin), precipitation (ppt), grass reference evapotranspiration (pet), wind speed (ws), downward radiation (srad), and runoff (q). The entire data processing workflow, from the initial gridded format to the final time series, is systematically detailed in the flowchart shown in Figure 2.

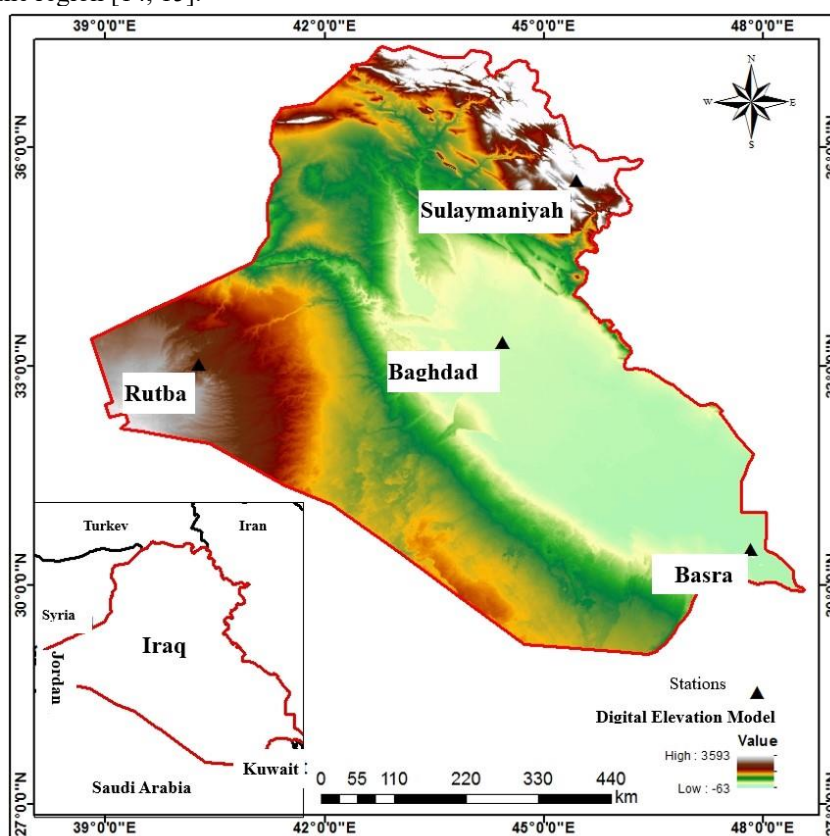


Figure 1: Republic of Iraq showing the geographical locations of the climatic stations that are the subject of the study

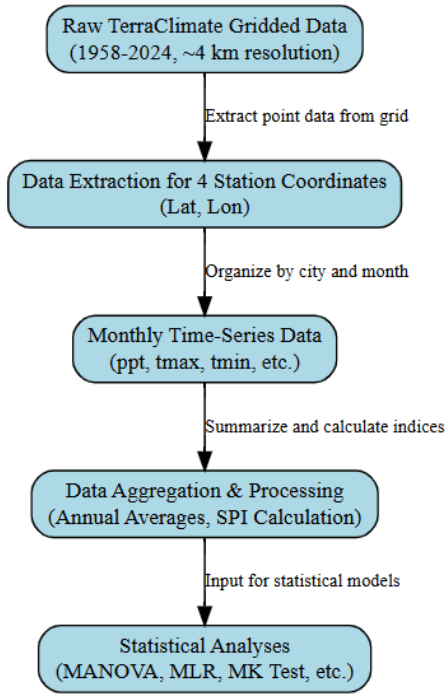


Figure 2: Flowchart illustrating the data processing and analysis workflow

2.2. Variables and Data Processing

The climatic variables used from the dataset include tmax, tmin, ppt, pet, ws, srad, and q. To do the trend analysis, these variables will be aggregated from monthly values to an annual level. The independent variables used will be the city's geographical coordinates, including elevation (in meters above mean sea level) and latitude and longitude.

2.3. Analytical Methods

2.3.1. Multivariate Comparison of Climatic Profiles

In order to find out whether statistically significant differences exist among the four locations under investigation in terms of their climatic profiles, a MANOVA analysis was carried out, where city was used as the independent variable, and the climatic characteristics, i.e., annual precipitation, tmax, and tmin, were used as the dependent variables. If the initial MANOVA analysis produced statistically significant results, then a series of univariate ANOVA analyses would subsequently be carried out to find out which of the climatic characteristics varied across the different cities under investigation. The underlying statistical model is as follows in Equation (1):

$$Y_{ij} = \mu_i + \omega_i + \varepsilon_{ij} \quad (1)$$

Where:

- Y_{ij} is the vector of dependent climatic variables for observation in the city.
- μ_i is the overall vector of population means.
- ω_i is the vector of the effect of the city.
- ε_{ij} is the vector of random error terms, assumed to be multivariate normally distributed.

2.3.2. Spatial Analysis

An MLR model was designed to quantitatively examine the impact of geography. An MLR model yields coefficients for each predictor variable, enabling the analyst to quantify each predictor's impact [18]. The model was formally specified as in Equation (2):

$$(Annual\_Precipitation)_i = \beta_0 + \beta_1 Elevation_i + \beta_2 Latitude_i + \beta_3 Longitude_i + \varepsilon_i \quad (2)$$

Where:

- $(Annual\_Precipitation)_i$: is the dependent variable for location i .
- β_0 : is the model intercept.
- $\beta_1, \beta_2, \beta_3$ are the regression coefficients that quantify the change in annual precipitation for a one-unit increase in the respective predictor, holding all other variables constant.
- $Elevation_i, Latitude_i, Longitude_i$: are the independent predictor variables for location i .
- ε_i : is the random error term for observation i .

2.3.3. Temporal Analysis

Two additional nonparametric approaches were applied to the annual time-series data to explore their temporal evolution. Since climatological data are often not normally distributed and will violate many of the assumptions underlying parametric tests, the MK test, as in Equation (3), was used to determine whether there was a trend (monotonically) in the data over time [19].

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_i - x_k) \quad (3)$$

Where:

- n is the number of observations in the time series, $n=66$.
- x_i and x_k are the data values at times i and k .
- $\text{sgn}(\theta)$ is the sign function, which is $+1$ if $\theta > 0$, 0 if $\theta = 0$, -1 if $\theta < 0$.

Following a considerable MK test, Sen's slope estimator was used to estimate the trend magnitude [20]. The magnitude of the trend (Q) as in Equation (4) is calculated by taking the median of all slopes between data points:

$$Q = \text{Median} \left(\frac{x_i - x_k}{j - k} \right) \text{ for all } k < j \quad (4)$$

- Q : Sen's slope estimator, representing the median rate of change in the variable per unit of time (e.g., °C/year or mm/year).
- $\text{Median}(\dots)$: The median value of all calculated slopes, which is used for its robustness against outliers.
- (x_j, x_k) : The change in the value of the climate variable between two points in time.
- (j, k) : The change in time between the same two points.
- $(x_j, x_k) / (j, k)$: The slope of the line connecting any two data points (k, x_k) and (j, x_j) in the time series.

To investigate intra-annual patterns, a Seasonal-Trend decomposition (STL) using Loess was applied to the monthly data [21].

2.3.4. Drought Analysis

The SPI was used to estimate the development of the hydrological balance. The SPI is a traditional method for determining drought events across different scales by standardizing precipitation deficits, thereby enabling inter-regional climatic comparisons [11, 22]. Although other, more complex indices, including the SPEI, combine temperature and precipitation as the variable of interest, the current study chose the SPI to measure precipitation, the primary variable of interest, as suggested by [12]. Consistent with this, the 12-month SPI was calculated separately for the four study sites. This was calculated by approximating the long-term annual precipitation series (1958-2024) in each city to a gamma distribution to parameterize the probability distribution of the observed precipitation amounts. The cumulative probability based on this fitted distribution was then converted into a standard normal deviate (Z-score), the value of which is the SPI. All calculations were performed with the help of the SPEI package in R (version 4.5.2), which automates the distribution fitting as well as the transformation process. This may be mathematically represented by the following in Equation (5):

$$SPI = \Phi^{-1}H(x) \quad (5)$$

Where:

- Φ^{-1} is the inverse of the standard normal Cumulative Distribution Function (CDF).

- $H(x)$ is the cumulative probability of an observed precipitation amount, typically derived from a fitted Gamma distribution.

2.3.5. Statistical Software

All statistical analyses, including MANOVA, MLR, MK trend analysis, and SPI calculation, were performed in RStudio. For the MANOVA and MLR analysis, the basic stats package in R was applied. For the MK analysis and the calculation of Sen's slope, the trend package in R was applied. In addition, the Variance Inflation Factors (VIFs) were calculated using the car package in R. For the calculation of the SPI, the SPEI package in R was applied.

3. Results and Discussion

3.1. Descriptive Statistics and Climatic Disparities

The descriptive statistics in Table 1 show that the climatic conditions in the four cities differ by geographical location. Specifically, Sulaymaniyah has the coldest and most precipitation-intensive climatic conditions of the four cities, with an average monthly precipitation of 60.9 mm, more than five times that of any of the other three cities. On the contrary, Basra has the highest mean temperature, making it the hottest city, and Rutba has the most desert-like climatic conditions of the four cities. These observations are further supported by the boxplot distributions in Figure 3, which show clear evidence of divergence in the climatic conditions in the four cities.

Table 1: Descriptive statistics of monthly climatic variables for the four Iraqi cities (1958-2024)

City	tmax_mean	tmax_sd	tmin_mean	tmin_sd	ppt_mean	ppt_sd	ws_mean	ws_sd
Baghdad	31.20	10.30	15.80	7.88	12.50	14.50	3.00	0.66
Basra	32.00	9.44	18.70	8.27	11.80	18.40	3.30	0.84
Rutba	27.40	9.20	11.80	7.34	9.08	11.70	3.30	0.80
Sulaymaniyah	25.10	10.90	12.80	8.52	60.90	66.20	2.60	0.60

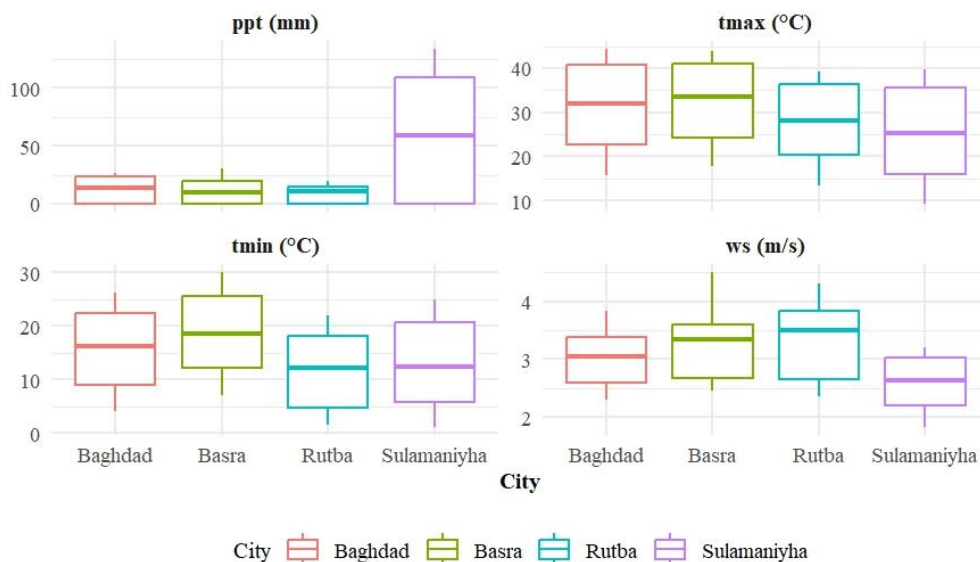


Figure 3: Boxplots showing the distribution of key monthly climatic variables across the four study cities

3.2. Multivariate Statistical Comparison

The MANOVA test has been used to assess whether there are significant differences in climate profiles across these four cities. MANOVA results clearly show a highly

significant difference between these four cities ($p < 0.001$) for all dependent variables, as shown in Table 2. This shows that there is a significant difference between these cities for each of these climatic factors. From these results, it is also clear that precipitation (ppt) has the highest F-value, making it the most significant factor in differentiating these cities.

Table 2: Results of the univariate ANOVA tests following the significant MANOVA

Response	Df	Sum Sq	Mean Sq	F value	Pr(>F)
tmax					
City	3	25429	8476.30	85.21	< 0.001
Residuals	3212	319517	99.50		
tmin					
City	3	23294	7764.70	120.84	< 0.001
Residuals	3212	206384	64.30		
ppt					
City	3	1496238	498746	393.95	< 0.001
Residuals	3212	4066478	1266		
pet					
City	3	101299	337663	44.54	< 0.001
Residuals	3212	2434894	758.10		
ws					
City	3	295.37	98.5	182.49	< 0.001
Residuals	3212	1732.92	0.50		
srad					
City	3	202816	67605	13.34	< 0.001
Residuals	3212	1627577	506.70		
q					
City	3	239391	79797	167.77	< 0.001
Residuals	3212	1527731	476		

Note: All ANOVA tests for the factor "City" were statistically significant at the $p < 0.001$ level.

3.3. Long-Term Temporal Trends

An annual-average comprehensive trend analysis over the past 66 years was carried out using the MK and Sen's slope methods, as presented in Table 3. According to the analysis, a strong, uniform temperature-increase trend has been observed over the past 66 years across all cities, with significant changes in tmax and tmin. This observation aligns with temperature trends for the Arabian Peninsula,

where [14] reported increased tmax. In the case of precipitation, the analysis shows complex trends, and for Baghdad, Basra, and Sulaymaniyah, no significant changes were observed. For Rutba, a significant decrease in precipitation was observed, with a p-value of 0.036 and a negative slope of -0.034 mm/year, which differs from the global trend reported by [23], underscoring the importance of regional studies. Figure 4 presents the analysis of the seasonal cycle, revealing differences in intra-annual variability across locations.

Table 3: Comprehensive trend analysis results (annual averages) using MK and Sen's slope

	City	Variable	Mk_p_value	Sen's slope	Is_significant
1	Baghdad	tmax	4.23e-6	2.57e-2	TRUE
2	Baghdad	tmin	7.02e-9	2.85e-2	TRUE
3	Baghdad	ppt	4.33e-1	-1.94e-2	FALSE
4	Baghdad	pet	7.76e-3	1.28e-1	TRUE
5	Baghdad	ws	1.64e-1	1.84e-3	FALSE
6	Baghdad	srad	6.11e-1	9.48e-3	FALSE
7	Baghdad	q	4.14e-1	-9.92e-4	FALSE

8	Basra	tmax	5.22e-10	3.06e-2	TRUE
9	Basra	tmin	7.51e-11	3.34e-2	TRUE
10	Basra	ppt	9.40e-1	-3.03e-3	FALSE
11	Basra	pet	1.62e-4	1.77e-1	TRUE
12	Basra	ws	4.23e-1	1.27e-3	FALSE
13	Basra	srad	2.34e-2	4.81e-2	TRUE
14	Basra	q	9.01e-1	-6.94e-18	FALSE
15	Rutba	tmax	1.66e-9	3.53e-2	TRUE
16	Rutba	tmin	2.51e-11	3.63e-2	TRUE
17	Rutba	ppt	3.58e-2	-3.41e-2	TRUE
18	Rutba	pet	9.10e-1	4.17e-3	FALSE
19	Rutba	ws	7.06e-6	-6.16e-3	TRUE
20	Rutba	srad	2.40e-1	1.67e-2	FALSE
21	Rutba	q	3.19e-2	-1.79e-3	TRUE
22	Sulaymaniyah	tmax	4.01e-6	2.84e-2	TRUE
23	Sulaymaniyah	tmin	1.25e-8	3.03e-2	TRUE
24	Sulaymaniyah	ppt	1.02e-1	-1.67e-1	FALSE
25	Sulaymaniyah	pet	8.44e-8	3.00e-1	TRUE
26	Sulaymaniyah	ws	1.91e-5	6.32e-3	TRUE
27	Sulaymaniyah	srad	9.05e-1	4.17e-3	FALSE
28	Sulaymaniyah	q	7.15e-3	-1.81e-1	TRUE

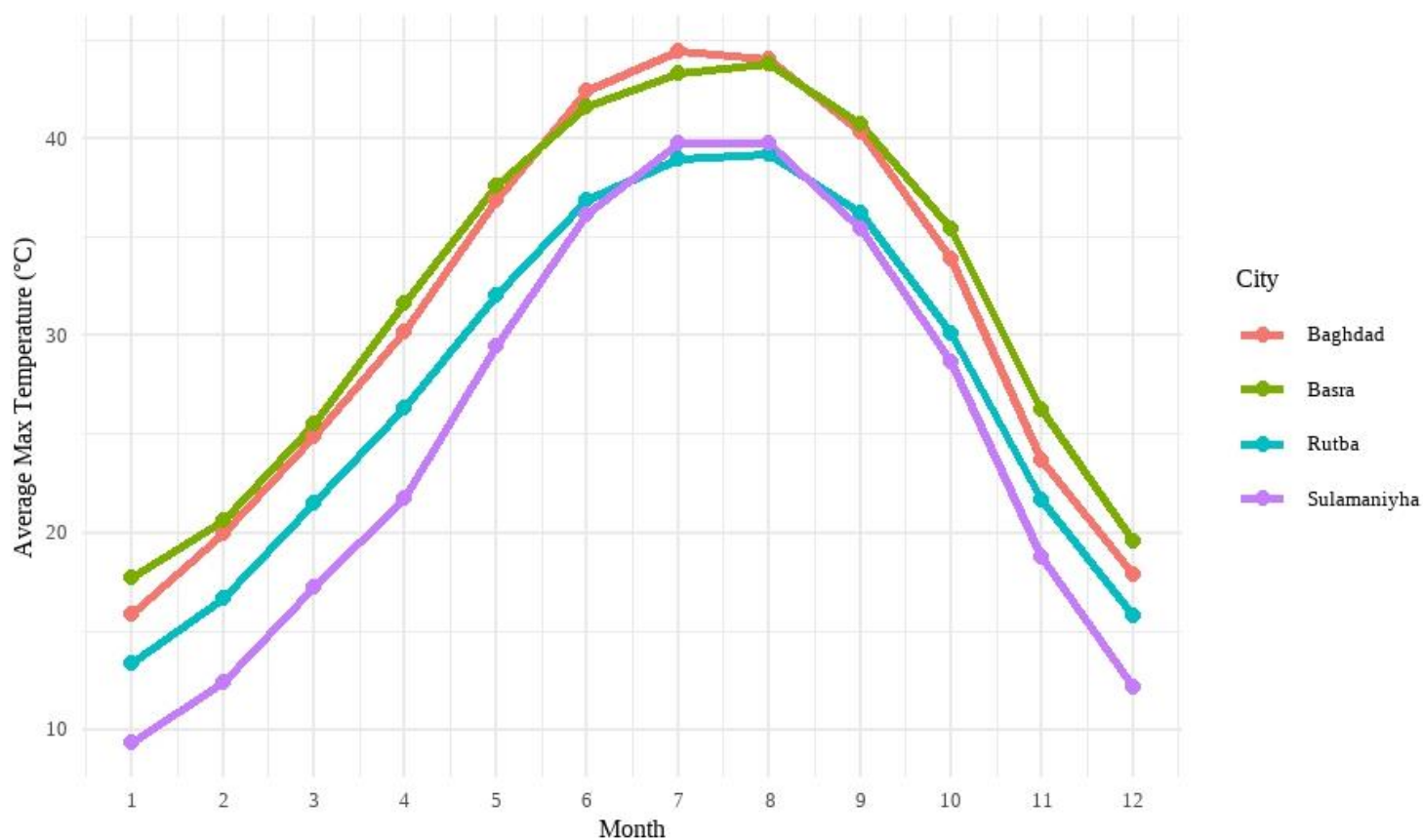


Figure 4: Seasonal cycle of average monthly tmax across four Iraqi cities (1958–2024).

3.4. Quantifying the Impact of Geography

The MLR analysis was performed to examine the relationship between annual precipitation and the geographic factors such as elevation, latitude, and longitude. As shown in Equation (6) which is the MLR equation was found to be statistically significant ($F(3, 264) = 747.4$, $p < 0.001$), and the equation was found to have substantial explanatory power, explaining 89.5% of the variance in annual precipitation (Adjusted $R^2 = 0.894$).

The MLR equation is as follows:

$$\begin{aligned} \text{Annual\_Precipitation} \\ = -5140 + 0.406(\text{Elevation\_m}) \\ + 74.8(\text{Latitude}) + 62.8(\text{Longitude}) \\ + \varepsilon \end{aligned} \quad (6)$$

Table 4: Results of the MLR model predicting annual precipitation from geographical variables

Predictor	Coefficient (β)	Standard Error	t-value	p-value
(Intercept)	-5.14e3	1.83e2	-28.09	< 0.001
Elevation_m	4.06e-1	2.46e-2	16.50	< 0.001
Latitude	7.48e1	4.94e0	15.14	< 0.001
Longitude	6.28e1	2.22e0	28.31	< 0.001

Elevation was found to be a major proxy for orographic influence among the three factors. The high positive correlation between precipitation and elevation ($\beta = 0.406$, $p < 0.001$) suggests that topography, particularly the influence of the Zagros Mountains, plays a major role in the precipitation patterns over Iraq.

3.4.1 Multicollinearity Assessment

To increase the model's robustness and address multicollinearity, Table 5 presents the correlation matrix of the predictor variables elevation, latitude, and longitude.

Table 5: Correlation matrix for geographic predictor variables

	Elevation m	Latitude Long	Longitude
Elevation m	1	0.79	-0.42
Latitude	0.79	1	-0.31
Longitude	-0.42	-0.31	1

From the correlation matrix, it is confirmed that the correlation between elevation and latitude is strong and positive, as previously mentioned ($r = 0.79$).

Despite the strong correlation between the two predictor variables, the primary concern in a regression model is the impact of their interdependence on the variance of the model's coefficient estimates. This impact is quantitatively evaluated using the VIF. Table 6 presents that the VIF of Elevation is 2.88, the VIF of Latitude is 2.62, and the VIF of Longitude is 1.21, all of which are much lower than the conservative limit of 5.

where ε is the error term.

As evident from Table 4, all three factors are statistically significant at $p < 0.001$. The coefficients of the MLR equation provide insight into the relative importance of each factor. For instance, after controlling for latitude and longitude, a unit change in elevation corresponds to a change of 0.406 mm in annual precipitation. Similarly, a 100-meter change in elevation corresponds to a change of 40.6 mm in precipitation. Also, a unit change in latitude corresponds to a change of 74.8 mm in precipitation, and a unit change in longitude corresponds to a change of 62.8 mm in precipitation.

Table 6: The VIFs for the MLR model

Variable	VIF
Elevation_m	2.88
Latitude	2.62
Longitude	1.21

Based on the VIF results, it is concluded that multicollinearity does not threaten the model's stability, as the variance of the coefficient estimates is not inflated to a level that renders the estimates unreliable. Thus, it can be concluded that the stability of the model's coefficients is guaranteed, and all three geographic variables should be statistically incorporated into the model.

3.5. Analysis of Drought Severity Trends

The SPI shows a continuous, alarming trend toward drier conditions across all study cities, as depicted in Figure 5 and Table 7. In fact, all the cities show statistically significant negative trends in SPI values ($p < 0.05$), and the Sen's slope estimates range between -0.01 and -0.05 per year. This shows a continued pattern where the hydrological balance has been moving towards an increased frequency and severity of dry spells, and this should be taken into account in future water planning. This finding is consistent with [24], which indicates that drought events are becoming more frequent and severe worldwide; therefore, it can be concluded with certainty that drought occurrences in Iraq are expected to continue to rise.

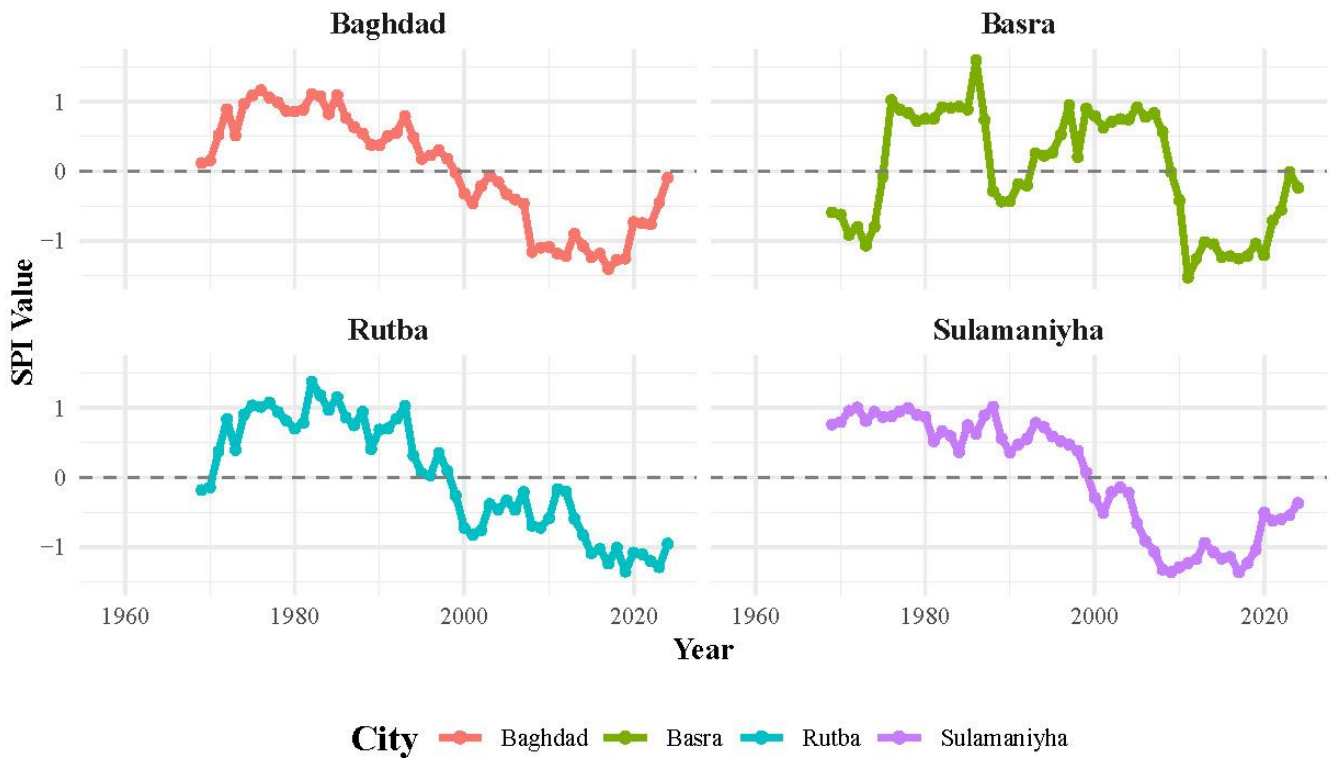


Figure 5: Time series of the 12-month SPI for the four cities, with trend lines

Table 7: Trend analysis results for the 12-month SPI

	City	mk p value	sen_slope
1	Baghdad	2.58e-13	-0.05
2	Basra	2.42e- 2	-0.01
3	Rutba	2.75e-12	-0.05
4	Sulaymaniyah	5.36e-13	-0.04

3.6. Synthesis and Broader Implications

Apart from the relatively stable geographic footprint, these observations reveal a clear detrimental impact of climate change. The increasing temperature trends are statistically significant and consistent with projections from global climate models for this geographic region [25]. More worrisome, however, is the current analysis of the SPI index, which reveals an increasing trend in the severity of drought across all cities. The persistent negative trend in the SPI is consistent with previous studies showing an increasing trend in the level and incidence of drought globally [24], thereby highlighting Iraq's involvement in this worrisome global phenomenon. Should these trends persist, Iraq is set to experience an increasing incidence of drought in the coming decades, thereby worsening water scarcity in the country. The widespread phenomenon of aridification, affecting the wettest highlands and the driest deserts, is set to have an important impact on the Tigris-Euphrates river basin, given the likely worsening water scarcity in the region, which

could lead to an escalation in geopolitical tensions [26]. The trend also has significant secondary effects, such as an increasing incidence of dust storms, which is a relatively recent phenomenon in the basin [27].

The identified tendency towards aridification is not merely a hydrological issue, but also an indication of a broader environmental crisis exacerbated by the country's poor infrastructure and weak sociopolitical state [28]. These findings have important implications for water-resource management and the country's policy development. The measured influence of the mouth provides a good empirical basis for developing region-specific interventions, such as building storage facilities in high-altitude areas. Simultaneously, the strong trend towards aridification intensifies the need to implement extensive water-demand management measures, particularly in the agricultural sector, to ensure long-term water and food security. These findings also demonstrate the acute need for integrated water-management strategies, reinforced by recent literature on the aggravating water crisis in the Tigris-Euphrates Basin, driven by both climate change and man-made factors [29]. As a result, the abandonment of monolithic water-management paradigms is not only a good idea but also a precondition for the country's increased resilience in the foreseeable future.

4. Conclusion

This study presents a quantitative analysis of climate variability and trends in Iraq over the years. It confirms that geography is the main determinant of Iraq's fundamental climate. The multiple linear regression model can explain

nearly 90% of the geographic variance in precipitation patterns. The model is an effective tool for interpreting and predicting rainfall patterns in the region. Previous studies provided qualitative analyses of the effects of geography on the climate in Iraq. This study presents a new quantitative fact.

Despite its strong findings, this study has limitations. The results are limited to 4 cities and to a gridded dataset. Despite the fact that this gridded data is based on high-quality station data, it is an interpolation and is not necessarily representative of microclimatic variations. Future studies must focus on making the network of climate stations more densely distributed to improve spatial analysis, and on combining climate outcomes with hydrologic models to forecast future river flows and groundwater renewal. Moreover, clarifying the interdependence between climate forecasts and socioeconomic information will be crucial for assessing the impact of such cascades on food security and population health.

Finally, the current research has identified two-fold threats to Iraq's climate: a stagnant, geography-based climatological paradigm and an active, unstable trajectory toward aridification driven by anthropogenic climate change. The study advocates for the application of regionally based water-management policies and the design of national drought early-warning systems to mitigate the growing risks. Drought early -warning systems have become an essential part of drought management procedures in arid areas, and institutionalizing them in Iraq is now a dire need.

Contributorship Statement

As the single author of this manuscript, I take full responsibility for its content. My contribution to this manuscript includes conceptualization, data curation, formal analysis, and preparing the initial draft. I have made the necessary revisions and prepared it for submission. I am grateful for the editor's input, which I have integrated into this manuscript, particularly during the review process.

Conflict of interests

None

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5. References

- [1] IPCC. (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. <https://doi.org/10.1017/9781009157896>
- [2] World Bank. (2018). Beyond Scarcity: Water Security in the Middle East and North Africa. World Bank Group. <https://doi.org/10.1596/978-1-4648-1144-9>
- [3] Lelieveld, J., Proestos, Y., Hadjinicolaou, P., Tanarhte, M., Tyrlis, E., & Zittis, G. (2016). Strongly increasing heat extremes in the Middle East and North Africa (MENA). *Climatic Change*, 137(1-2), 245-260. <https://doi.org/10.1007/s10584-016-1665-6>
- [4] Asad S, Kumar Sahu R, Fridman D, Willaarts B, Kahil T. (2024). Hydro-economic assessment of the impact of climate and socio-economic changes on water resources in the MENA region. *EGUsphere*. <https://doi.org/10.5194/egusphere-egu24-17546>.
- [5] Al-Ansari N. Management of Water Resources in Iraq: Perspectives and Prognoses. *Engineering*. 2013;5(8):667-684. <https://doi.org/10.4236/eng.2013.58080>.
- [6] Muslih, K. D., & Abbas, A. M. (2024). Climate of Iraq. In *The Geography of Iraq* (pp. 125-144). Springer, Cham. https://doi.org/10.1007/978-3-031-71356-9_2
- [7] Al-Timimi, Y. K., & Al-Lami, A. M. (2024). Impacts of climate change on thermal bioclimatic indices over Iraq. *Iraqi Journal of Agricultural Sciences*, 55(2), 250-263. <https://doi.org/10.36103/j93nst49>
- [8] Sarma G, Hajani E. (2023). Artificial neural network technique for annual rainfall generation applied to three selected sites in Kurdistan Region, Iraq. *Acad J Nawroz Univ.*, 12(4). <https://doi.org/10.25007/ajnu.v12n4a1672>.
- [9] Dezfuli AK, Razavi S, Zaitchik BF. (2022). Compound effects of climate change on future transboundary water issues in the Middle East. *Earth's Future*. 10(2):e2021EF002683. <https://doi.org/10.1029/2022EF002683>,
- [10] Omer, A. M., Al-Zuhairi, M. H., & Al-Salihi, A. M. (2019). Climate change impacts on water resources in Iraq. *Journal of Environmental Hydrology*, 27(1), 1-12.
- [11] McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology* (pp. 179-184). American Meteorological Society.
- [12] Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, 23(7), 1696-1718. <https://doi.org/10.1175/2009JCLI2909.1>
- [13] Çelik, M. A., Bilik, A., & Türkeş, M. (2025). Spatio-temporal analysis of observed drought events in the Tigris–Euphrates Basin during the 1960–2023 period via SPI and SPEI drought indices. *Pure and Applied Geophysics*. <https://doi.org/10.1007/s00024-025-03863-3>
- [14] Almazroui, M., Islam, M. N., Athar, H., Jones, P., & Alkhalaf, A. (2019). Observed trends of climate extremes over the Arabian Peninsula. *Journal of Geophysical Research: Atmospheres*, 126(4), e2020JD033517. <https://doi.org/10.3390/atmos10110675>
- [15] Ngatchou-Wandji J, Ltaifa M. (2023). A Cramér–von Mises test for a class of mean time dependent CHARN models with application to change-point detection. *Stat Inference Stoch Process.*, 27(4):27. <https://doi.org/10.1007/s11203-023-09295-x>
- [16] Yaşa, İ., & Partal, T. (2024). Drought trend and variability based wavelet transform in Euphrates-Tigris Basin, Türkiye. *Atmospheric Research*, 291, 107110. <https://doi.org/10.1016/j.atmosres.2024.107291>
- [17] Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015. *Scientific Data*, 5, 170191. <https://doi.org/10.1038/sdata.2017.191>

- [18] Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics* (4th ed.). Sage Publications. <https://doi.org/10.1002/bjs.7040>
- [19] Hirsch, R. M., Slack, J. R., & Smith, R. A. (1993). Techniques of trend analysis for monthly water quality data. *Water Resources Research*, 29(12), 4033–4043. <https://doi.org/10.1029/WR018i001p00107>
- [20] Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association*, 63(324), 1379–1389. <https://doi.org/10.1080/01621459.1968.10480934>
- [21] Cleveland, R. B., Cleveland, W. S., McRae, J. E., & Terpenning, I. (1990). STL: A seasonal-trend decomposition procedure based on loess. *Journal of Official Statistics*, 6(1), 3–73.
- [22] Hayes, M., Svoboda, M., Wall, N., & Widhalm, M. (1999). The Lincoln Declaration on Drought Indices: Universal meteorological drought indices recommended. *Bulletin of the American Meteorological Society*, 80(1), 197–199. <https://doi.org/10.1175/2010BAMS3103.1>
- [23] Donat, M. G., Lowry, A. L., Alexander, L. V., O'Gorman, P. A., & Maher, N. (2016). More extreme precipitation in the world's dry and wet regions. *Nature Climate Change*, 6(5), 508–513. <https://doi.org/10.1038/nclimate2941>
- [24] Spinoni, J., Barbosa, P., De Jager, A., McCormick, N., Naumann, G., & Vogt, J. V. (2022). A global database of drought events and their socioeconomic impacts from 1950 to 2021. *Earth System Science Data*, 14(5), 2219–2236. <https://doi.org/10.1016/j.ejrh.2019.100593>
- [25] Xin X, Wu T, Zhang J, Yao J, Fang Y. (2022). Comparison of CMIP6 and CMIP5 simulations of precipitation in China and the East Asian summer monsoon. *Int J Climatol*, 40(15):6423–40. <https://doi.org/10.1002/joc.6590>
- [26] Darvishi Boloorani A, Soleimani M, Neysani Samany N, Papi R, Nasiri N. (2024). Climate change, drought, and water scarcity in the MENA region. *The handbook of environmental chemistry*. https://doi.org/10.1007/698_2024_1143
- [27] Boloorani, A. D., Soleimani, M., Papi, R., & Nasiri, N. (2024). Assessing the role of drought in dust storm formation in the Tigris and Euphrates basin. *Science of The Total Environment*, 912, 169225. <https://doi.org/10.1016/j.scitotenv.2024.171193>
- [28] Ali, S. H., Qubaa, A. R., & Al-Khayat, A. B. M. (2024). Climate change and its potential impacts on Iraqi environment: Overview. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1331, No. 1, p. 012001). IOP Publishing. <https://doi.org/10.1088/1755-1315/1300/1/012010>
- [29] Boloorani, A. D., Papi, R., Soleimani, M., Samany, N. N., & Vazifiedoust, M. (2026). Human interventions and climate change trigger water crisis in the Tigris and Euphrates Basin. *Science & Policy*, 27, 102757. <https://doi.org/10.1016/j.envsci.2025.104300>