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United Arabic Emirates Weather Stations: A Spatial Analysis with myGeoffice©

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Abstract

This paper presents a spatial analysis of weather data from ten stations in the United Arab Emirates (UAE) using myGeoffice©, a web-based Geographical Information System (GIS) tool. This study investigates patterns in rainfall, station connectivity, and the impact of various factors on rainfall prediction. Cluster analysis was applied to classify regions based on rainfall patterns, and algorithms such as Dijkstra's shortest path and Kruskal's minimum spanning tree were used to evaluate connectivity among stations. Geographically Weighted Regression (GWR) was employed to model the effects of temperature, humidity, and wind on rainfall. The results indicate that temperature is the dominant factor negatively affecting rainfall, with variations observed across different locations. The study also uses probabilistic models, such as Binomial and Poisson distributions, to predict the likelihood of rainfall and flood occurrences. Overall, the analysis demonstrates the utility of GIS statistical methods in uncovering spatial weather patterns to support more informed decision-making in weather-related studies for the UAE.

Keywords

United Arabic Emirates, Weather Stations, Spatial Analysis, myGeoffice©

1. Introduction

The United Arab Emirates (UAE) is a country with diverse climatic conditions and weather patterns, primarily driven by its geographic location between desert and coastal environments. Understanding the spatial distribution of weather phenomena such as rainfall, humidity, and wind is crucial for managing resources and infrastructure. This study leverages myGeoffice©, a web-based GIS platform, to perform a spatial deterministic and stochastic analysis of weather data collected from ten stations across the UAE.

The key objectives of this research are to explore regional rainfall patterns, investigate station connectivity using shortest path algorithms, and predict future weather events through regression modeling. By employing statistical and geospatial techniques, this study aims to provide valuable insights into the UAE's weather dynamics, which can be beneficial for policymakers, environmental scientists, and urban planners.

Besides the present preamble, section two reviews some pre-studies concerning UAE weather settings, section three briefly presents myGeoffice© platform while section four dissects a wide diverse of spatial and non-spatial techniques to answer common questions raised by UAE citizens. As expected, general conclusion is presented in the last section.

2. Literature Review on Weather in the United Arab Emirates

The UAE, situated in the arid Arabian Peninsula (**Figure 1**), experiences a unique and challenging climate characterized by extreme temperatures, low rainfall, and frequent dust storms. For instance, and according to Al-Mansoori et al. (2019), wind patterns in the UAE are influenced by the prevailing northwesterly winds during winter and the southeasterly during summer. Shahid et al. (2021) found of declining diurnal temperature ranges, indicative of increased nocturnal warming.

Figure 1. The Gulf Cooperation Council (GCC) countries.

Historical climate records, albeit limited, indicate that the UAE has experienced significant climatic variations over centuries. Studies by Al-Mansoori et al. (2016) and Al-Shamsi et al. (2017) have utilized paleoclimate proxies, such as sediment cores and tree-ring analysis, to reconstruct past climatic conditions. They suggest that the region has undergone periods of increased aridity and humidity, influenced by global climate patterns like the Indian Ocean Dipole and the El Niño-Southern Oscillation (ENSO). As well, local factors, such as urbanization and industrialization help on this pattern. Fortunately, the UAE is investing in renewable energy sources, such as solar and wind power, to reduce its carbon footprint. The UAE's National Climate Change Plan emphasizes transitioning to cleaner energy sources and enhancing climate resilience through integrated planning frameworks.

Precipitation is highly variable and often occurs in short, intense events. Al-Mansoori et al. (2017) stressed that the decline in rainfall is linked to the weakening of the Indian summer monsoon, which is the primary source of moisture for the region. In a complementary perspective, Al-Yahyai et al. (2010) utilized satellite data and ground-based observations to investigate precipitation trends, reporting sporadic increases in rainfall in specific regions, often linked to atmospheric disturbances like tropical cyclones or El Niño events.

Tropical cyclones, though rare, can cause severe flooding and wind damage along coastal areas such as the cyclones Gonu and Shaheen. Research by Thoppil et al. (2015) utilized high-resolution ocean-atmosphere models to investigate the impact of such cyclones, emphasizing the need for enhanced forecasting capabilities. Under this line of thought, the UAE became quite prone to extreme weather events, including heatwaves, dust storms, and occasional heavy storms. Mansoor et al. (2022) confirm this view is confirmed by documenting the frequency and intensity of these events and weight their potential impacts on human health and infrastructures (**Figure 2**).

Figure 2. On April 16, 2024, the estimates for insured losses in Dubai for the 24 hours thunderstorm ranged from $850 million to $3 billion, including business interruption, property, and motor vehicle damage.

Al-Abri et al. (2016) have assessed the projected changes in temperature and precipitation under various greenhouse gas emission scenarios, suggesting that this region may face more frequent and intense heatwaves, reduced water availability, and increased risk of extreme weather events. As well, Al-Abri et al. (2020) assessed the potential impacts of climate change on the UAE's water resources, agriculture, and coastal zones. They emphasized the need for adaptation strategies to mitigate the negative consequences of climate change such as implementing green roofs and increasing vegetation cover to alleviate UHI effects.

Rain enhancement represents a critical area of research and innovation in the UAE. Researchers have explored various technologies to augment precipitation in this arid region. Farooq et al. (2021) documented the UAE's extensive investments in cloud seeding operations, employing hygroscopic and silver iodide-based flares. Their study demonstrated moderate success in increasing localized rainfall, although long-term environmental impacts remain under investigation. Similarly, Mohammed et al. (2019) integrated numerical weather prediction models with observational data to enhance the accuracy of rainfall forecasts.

High humidity levels, combined with high temperatures, can lead to severe heat stress conditions. It is expected that the impact of heat stress on human health and found that extreme heat events pose significant risks to vulnerable populations, particularly the elderly and those with underlying health conditions. Dust storms, originating from arid regions, can reduce visibility, disrupt transportation, and exacerbate respiratory illnesses too. These are a common occurrence, especially during the spring and summer months, confirming the climate models predictions that the UAE will continue to experience warming and drying trends in the future.

Despite significant progress, key gaps remain in understanding the UAE's complex weather systems. Future research should focus on improving regional climate models, exploring the impacts of global teleconnections, and assessing the socio-economic implications of climate change in the UAE. Additionally, interdisciplinary approaches integrating meteorology, engineering, and policymaking are vital for addressing emerging challenges.

3. myGeoffice©

myGeoffice.org© is a Geographical Information System (GIS) for the Web (**Figure 3**). Analogous to any SaaS (Software as a Service) and as an evolution of SAKWeb©, myGeoffice© is an Internet software that provides access to a wider GIS audience by undertaking the Web solution platform which includes the Moran scatterplot, Kriging with measurement error and several nugget-effect solutions, declustering based on the nearest neighborhood analysis, geographical weighted regression (GWR), Dijkstra shortest path, raster image processing, index of Knot and Mantel, Kernel Gaussian density, sequential simulation and deterministic interpolators (Negreiros & Phillips-Lao, 2018). Still, myGeoffice© is not a comprehensive statistical package in the traditional of solving everyone's problems. Written for an Internet Information Server® (IIS) environment, it was developed with the philosophy of being a learning tool for individuals with limited geo statistical knowledge (Negreiros & Neves, 2019).

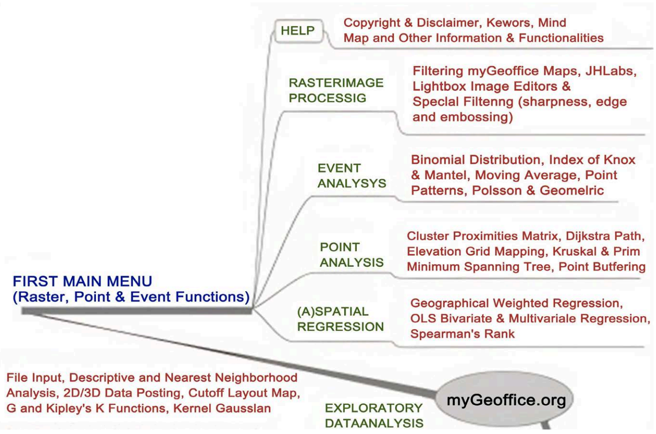


Figure 3. Partial mind map of myGeoffice©.

4. Common UAE Spatial Weather Inquiries

4.1. Rainfall in August 2024: Are There Any Region's Patterns?

Cluster analysis classifies a set of observations into two or more mutually exclusive unknown groups with the aim of data reduction. Its purpose is to organize a system of data observations into groups where members of those groups share common properties. For instance, the practitioner may be able to form clusters of customers who have similar buying habits in specific supermarkets for marketing geo segmentation goals (Silva et al., 2010). Under the GIS perspective, this methodology has proven to be quite useful in organizing cluster neighborhoods (zip codes) into different sets based on census information (such as population density, income, and age) when regarding decisions about where to locate future depots.

Cluster analysis will always produce a group (or groups) that may or may not prove useful for classifying regions (**Figure 4**). It starts with each region describing a subgroup and then combines subgroups into more inclusive subgroups until only one group remains. Again, it is up to the investigator to explain this arrangement. Logically, if those groups discriminate certain patterns, then cluster analysis can be useful. For example, if someone groups zip code areas into four categories (age, gender, education, and income) with the capability to discriminate between wine drinking behaviors, it would be a quite useful piece of information if an entrepreneur were interested in expanding a wine store into new areas.

Nonetheless, this procedure is considered aspatial since the geographical component is not used by this algorithm. Moreover, this numerical approach does not explain the reasons why a specific phenomenon behaves in a particular way. Basically, it only supplies clues or evidence for the scientist to investigate about possible explanations or causes for that group's behavior.

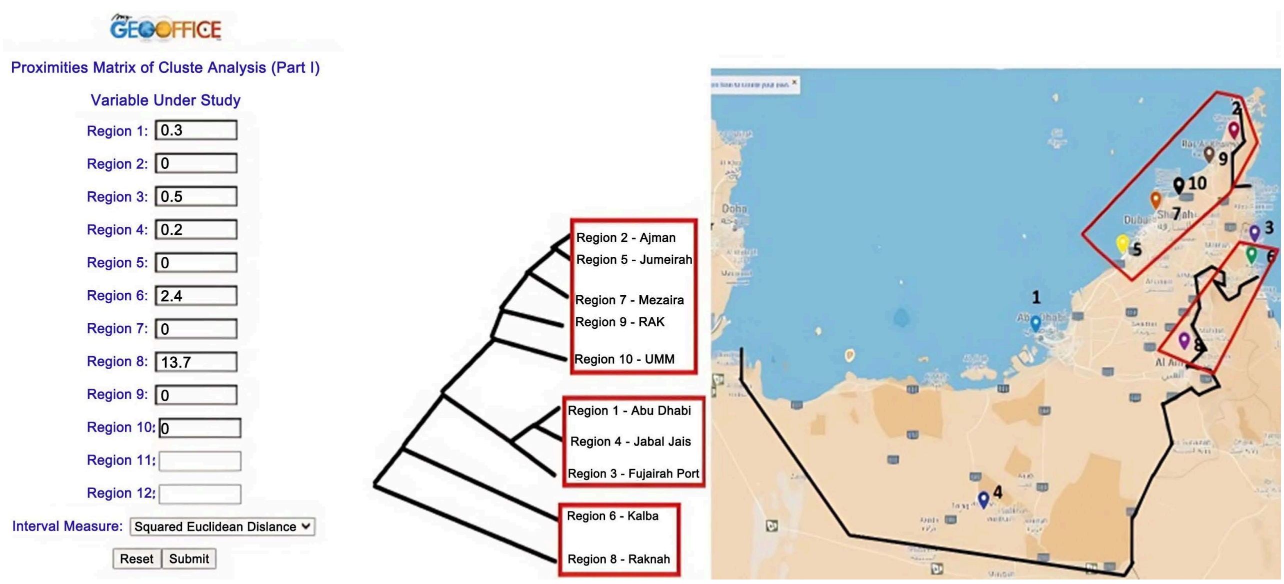
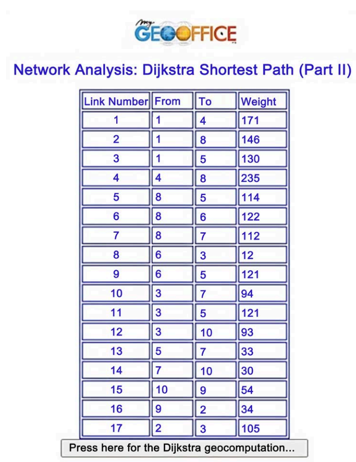


Figure 4. August 2024 rainfall (in ml) for the 10 weather stations in myGeoffice© (left). Hierarchical clustering (Dendrogram on the center and geo-mapping on the right) where three local patterns may be found for post-analysis. Probably, the proximity of the Oman mountains maybe the cause of these spatial patterns when compared with the great state of Abu Dhabi (80% of all UAE).

4.2. What Is the Shortest Distance from All UAE Stations to Its Capital?

Dijkstra algorithm was conceived by the Dutch Edger Dijkstra in 1959 and it is a graph search procedure that solves the single-source shortest path problem for a graph with non-negative path costs. For a given source vertex (node) in a graph, this procedure finds the path with lowest cost (the shortest path) between that vertex and all other vertices. As an alternative, it can be used for finding costs of the shortest connections from a single vertex to a single destination vertex by stopping the algorithm once the shortest path to the destination vertex has been determined. If the vertices of the graph represent cities and the link costs represent driving distances between pairs of cities connected by a direct road, Dijkstra's algorithm can be used to find the shortest route between one city and the remaining ones. As a result, the shortest path first is widely used in network routing protocols, most notably IS-IS (Intermediate System to Intermediate System) and OSPF (Open Shortest Path First).

In network analysis, the number of distinct links (path or connections) and vertices (nodes, edges, or endpoints) of a planar graph (drawn on the plane in such a way that its connections intersect only at their endpoints) and non-planar (where links crossing is a reality) topology may be used to derive its connectivity level or Gamma index (**Figure 5**). This index defines the ratio of the number of connections to the maximum possible number of links. If V denotes the number of vertices (5, for instance) and L denotes the existent distinct number of links between vertices (8, for instance), the minimum number of links (minimal connected network) that is required to connect all these vertices becomes (V − 1), that is, 4 (Negreiros et al., 2010). Similarly, the maximum connected networks that do not cross or intersect with each other equals 3*(V − 2), that is, 9 in a planar network. So, Gamma equals 0.88 = 8/9. For a non-planar graph, the maximum number of paths is given by V*(V − 1)/2, that is, 5*4/2 = 10. Hence, the Gamma Index equals 0.8 = 8/10. As expected, a higher index denotes a greater connectivity of the entire network in both situations.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Network Analysis: Dijkstra Shortest Path (Part II)

Link Number	From	To	Weight
1	1	4	171
2	1	8	146
3	1	5	130
4	4	8	235
5	8	5	114
6	8	6	122
7	8	7	112
8	6	3	12
9	6	5	121
10	3	7	94
11	3	5	121
12	3	10	93
13	5	7	33
14	7	10	30
15	10	9	54
16	9	2	34
17	2	3	105

Press here for the Dijkstra geocomputation...

Figure 5. myGeoffice© input data.

Based on the present distances (weight) constraints, the shortest physical distances between Abu Dhabi and the remaining nine stations are as follows: A) Ajman—281 KM; B) Fujairah Port—280 KM; C) Jabal Jais—171 KM; D) Jumeirah—130 KM; E) Kalba—268 KM; F) Mezaira—163 KM; G) Raknah—146 KM; H) Ras Al Khaimah—247 KM; I) UMM—193 KM.

4.3. What Is the Minimum Distance that Connects All UAE Weather Stations?

Kruskal is a graph algorithm that finds the minimum spanning tree for a connected weighted graph. Specifically, it finds a subset of edges (towns, for instance) within a connected tree (routes between towns, for instance) where the total connection weights (litters of gas, for example) of all edges of the present tree are minimized. If the graph is not all connected, it finds a minimum spanning forest, that is, a minimum spanning tree for each connected component (Figure 6).

This procedure works as follows: 1) Creation of a forest F (a set of trees) where each vertex of the graph is a separate tree; 2) Creation of a set S containing all the edges in the graph; 3) While S is nonempty a) Remove an edge with minimum weight from S; b) If that edge connects two different trees then add it to the forest by combining two trees into a single one; c) Otherwise, discard that edge; 4) At the termination of the algorithm, the forest has only one component and forms a minimum spanning tree of the present graph (Negreiros et al., 2012).

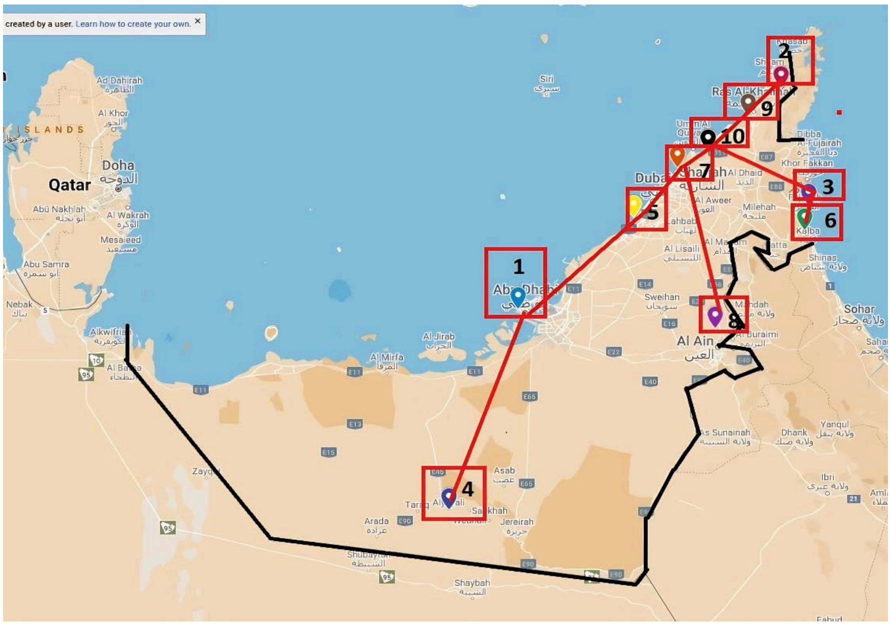
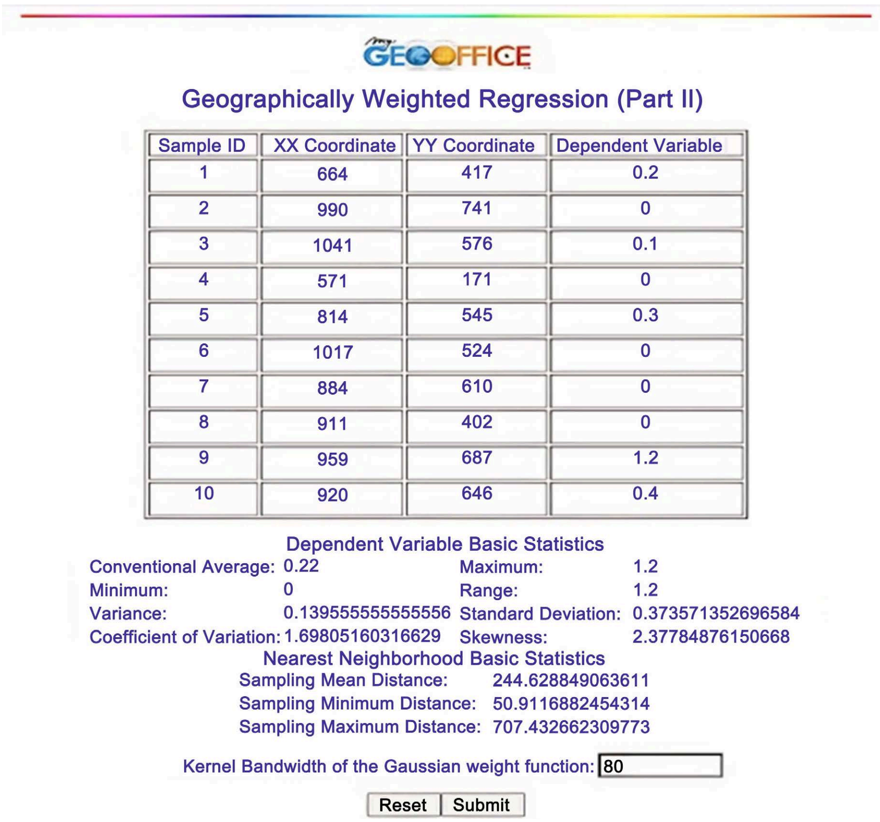


Figure 6. For the records, the minimum distance cost to connect all stations equals 669 Km.

4.4. Geographically Weighted Regression (GWR) for Rainfall Predictions in January 2024

GWR is a spatial analysis technique that takes non-stationary variables into consideration (e.g., climate; demographic factors; physical environment characteristics) and models the local relationships between these predictors and an outcome of interest. Briefly, GWR constructs a separate OLS equation for every location in the dataset, which incorporates the dependent and explanatory variables of location falling within the bandwidth of each target location. Bandwidth can be manually entered by the user (based on previous literature, for example) or it can be determined by the statistical software.

Briefly, in GWR, OLS models are run to determine the global regression coefficients (β) for the independent variables: $y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni} + \varepsilon_i$, with the estimator $\beta' = (X^T X) - 1X^T Y$. In a more detailed view, the regression models that underlie GWR equals $y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_n x_{ni} + \varepsilon_i$, with the estimator of $\beta'_{(i)} = (X^T W_{(i)} X) - 1X^T W_{(i)} Y$ ($W_{(i)}$ represents the matrix of weights specific to location i such that observations nearer to i are given greater weight than observations further away to respecter Tobler's Law).


Geographically Weighted Regression (Part II)

Sample ID	XX Coordinate	YY Coordinate	Dependent Variable
1	664	417	0.2
2	990	741	0
3	1041	576	0.1
4	571	171	0
5	814	545	0.3
6	1017	524	0
7	884	610	0
8	911	402	0
9	959	687	1.2
10	920	646	0.4

Dependent Variable Basic Statistics
Conventional Average: 0.22 Maximum: 1.2
Minimum: 0 Range: 1.2
Variance: 0.139555555555556 Standard Deviation: 0.373571352696584
Coefficient of Variation: 1.69805160316629 Skewness: 2.37784876150668
Nearest Neighborhood Basic Statistics
Sampling Mean Distance: 244.628849063611
Sampling Minimum Distance: 50.9116882454314
Sampling Maximum Distance: 707.432662309773

Kernel Bandwidth of the Gaussian weight function: 80

Reset Submit

Figure 7. Partial myGeoffice© GWR output. The decision condition for the optimal kernel bandwidth (the distance which space samples weights equal zero if their distance to the estimation point is greater than the chosen value) was based on the Akaike Information Criterion (AIC). As expected, the lower, the better since AIC estimates the relative amount of information lost by a given model. Therefore, the less information a model loses, the higher the quality of that model.

Based on the Gaussian decay function with a range of 80 KM (the distance that presents the lowest AIC), the following local OLS regressions were assessed for each UAE station as the best predictors and considering their spatial location (Figure 7):

1) Abu Dhabi Rainfall 2024 (X = 664, Y = 417) = −2.053 + 0.066MaxTemp – 0.008MaxHumid + 0.03MaxWind (GWR rainfall estimation = 0.199, Real rainfall value = 0.2); MaxTemp and MaxWind slightly increase rainfall and MaxHumid decreases rainfall minimally.

2) Ajman 2024 (X = 990, Y = 741) = 14.693 − 0.322MaxTemp − 0.029MaxHumid − 0.052MaxWind (GWR rainfall estimation = 0.244, Real rainfall value = 0); Strong negative effect from MaxTemp and MaxWind while MaxHumid has a smaller negative effect.

3) Fujairah Port Rainfall2024 (X = 1041, Y = 576) = 14.140 − 0.392MaxTemp – 0.005MaxHumid − 0.03MaxWind (GWR rainfall estimation = 0.075, Real rainfall value = 0.1); MaxTemp has the largest negative impact on rainfall among all sites. MaxHumid and MaxWind have minor effects.

4) Jabal Jais Rainfall2024 (X = 571, Y = 171) = −2.871 + 0.082MaxTemp – 0.005MaxHumid + 0.034MaxWind (GWR rainfall estimation = 0.001, Real rainfall value = 0); MaxTemp and MaxWind positively influence rainfall. On the other hand, MaxHumid has a negligible negative effect.

5) Jumeriah Rainfall2024 (X = 814, Y = 545) = 4.553 − 0.149MaxTemp + 0.006MaxHumid + 0.012MaxWind (GWR rainfall estimation = 0.315, Real rainfall value = 0.3); Mixed effects, that is, MaxTemp decreases rainfall, but MaxHumid and MaxWind increase it slightly.

6) Kalba Rainfall2024 (X = 1017, Y = 524) = 9.474 − 0.277MaxTemp – 0.001MaxHumid − 0.017MaxWind (GWR rainfall estimation = 0.035, Real rainfall value = 0); Rainfall is strongly reduced by MaxTemp and weakly by MaxWind. Negligible influence from MaxHumid.

7) Mezaira Rainfall2024 (X = 884, Y = 610) = 9.825 − 0.281MaxTemp + 0.007MaxHumid − 0.045MaxWind (GWR rainfall estimation = 0.024, Real rainfall value = 0); MaxTemp and MaxWind reduce rainfall. MaxHumid slightly increases rainfall.

8) Raknah Rainfall2024 (X = 911, Y = 402) = 1.029 − 0.057MaxTemp + 0.001MaxHumid + 0.020MaxWind (GWR rainfall estimation = 0.006, Real rainfall value = 0); Negligible effects from MaxTemp and MaxHumid though MaxWind positively influences rainfall.

9) Ras Al Khaimah Rainfall2024 (X = 959, Y = 687) = 12.561 − 0.302MaxTemp – 0.013MaxHumid – 0.048MaxWind (GWR rainfall estimation = 1.074, Real rainfall value = 1.2); Significant negative impacts from MaxTemp and MaxWind whereas MaxHumid has a minor negative effect.

10) UMM Rainfall2024 (X = 920, Y = 646) = 11.341 − 0.297MaxTemp – 0.002MaxHumid − 0.046MaxWind (GWR rainfall estimation = 0.256, Real rainfall value = 0.4); Similar behavior to Ras Al Khaimah.

As expected, each parameter of GWR has a sign and a magnitude according to each location (the essence of spatial heterogeneity, that is, the structure of the model changes from place to place across the study area as the parameter estimates change towards each other inside the model). If the sign is positive, an increase of the variable value to which the parameter refers will induce an increase in the dependent variable. If the sign is negative, a decrease will be induced.

From the previous estimators, the temperature is certainly the main fact that contributes negatively for the rainfall in the UAE (except for Jabal Jais station, the only one that is far away from the mountains and the sea) while the contribution of humidity and wind is close to zero. As stated by Charlton & Fotheringham (2009), parameter estimates for a variable that are close to zero often tend to be spatially clustered indicating that in these sub-regions of the study area, changes in this variable do not influence changes to the dependent variable. This is potentially interesting and encourages further curiosity about the process, the data, the model, and the outcome (**Figures 8-10**).

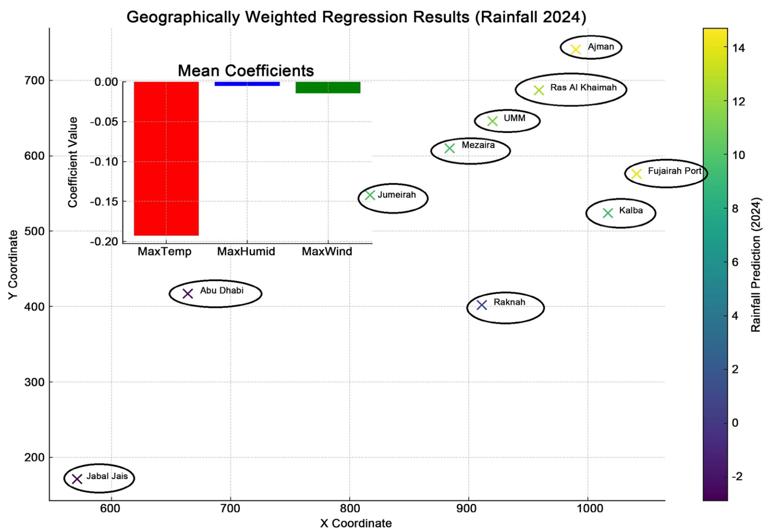


Figure 8. The upper bar chart displays the average regression coefficients for MaxTemp, MaxHumid, and MaxWind across all sites and according to the variables: red for temperature, blue for humidity, and green for wind.

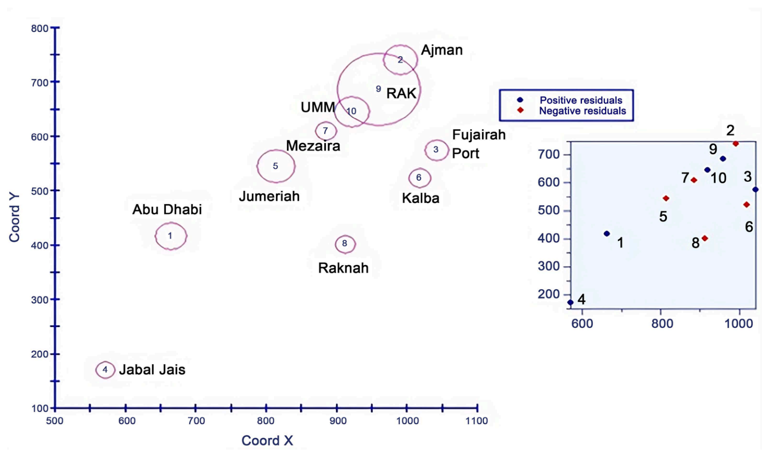


Figure 9. The left map shows the GWR estimation of the dependent variable (rainfall in January 2024) at each site while the right one stresses the random positive and negative residuals (real minus estimation) throughout the study area.

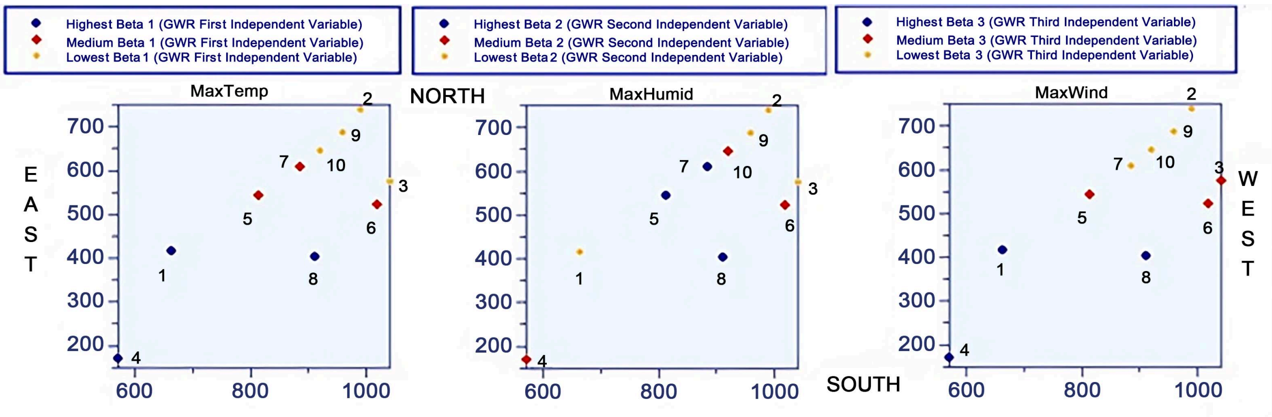


Figure 10. Since temperature (left map) is the main negative contributor of rainfall in the UAE, it is curious to check the decrease weight of this independent variable if we move North and closer to the mountains of Oman.

Table 1. A further sensitivity analysis view.

MaxTemp Coefficients	MaxHumid Coefficients	MaxWind Coefficients
Range from −0.392 (Fujairah Port) to 0.082 (Jabal Jais).	Range from −0.029 (Ajman) to 0.007 (Mezaira).	Range from −0.052 (Ajman) to 0.034 (Jabal Jais).
Most sites exhibit negative coefficients, indicating that higher maximum temperatures generally reduce rainfall.	Coefficients are small across all sites, suggesting that humidity has a minor impact on rainfall.	Positive coefficients (e.g., Jabal Jais, Raknah) suggest wind increases rainfall.
Positive coefficients (e.g., Abu Dhabi, Jabal Jais) suggest exceptions where temperature increases rainfall.	Positive and negative coefficients suggest varying effects depending on location.	Negative coefficients (e.g., Ajman, Ras Al Khaimah) suggest wind reduces rainfall.

The summary of the key findings from Table 1 are as follows: A) MaxTemp generally reduces rainfall (strongest effects in Fujairah Port and Ajman); B) MaxHumid holds a minimal impact, that is, it varies in sign but does not strongly influence rainfall; C) MaxWind has mixed effects with strong site-specific variability.

4.5. What Is the Probability of Raining between September 2024 and August 2025 in Abu Dhabi?

The Binomial distribution is used for discrete random variables and it is appropriate when an event has only two possible outcomes: success (p probability of first outcome) or failure ($q = 1 - p$, that is, probability of second outcome). Recalling that probabilities of all outcomes should sum to one, it is mandatory, thus, that $p + q = 1$ (p represents the probability of a car being robbed in a particular city, for instance, while q equals the complementary probability of not being stolen).

Other appealing features for GIS characterize this distribution: 1) All trials are independent events; 2) All trials are subject to the same probability distribution; 3) The probabilities sum of all possible combinations (n = 1, 2, 3, ⋯, N) for a given success probability of p with a size population of N equals one; 4) The N number of trials is considered fixed (**Figure 11**). As in our car example, this means that the number of sampled automobiles for that city must be known. Obviously, when the number of trials changes, the number of all possible outcomes and their distributions across the values of the random variable will change, too (if we survey six cars instead of four, we will have $64 = 2^6$ possible outcomes instead of $16 = 2^4$). Again, the considered n number of successes (stolen cars) must be a positive integer below or equal to N (Negreiros, 2011).

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Binomial Probabilities Distribution for Discrete Random Events (Part II)

P(X=0) = 2.3864206836931E-06
P(X=1) = 5.55895641613216E-05
P(X=2) = S.93500346781169E-04
P(X=3) = 3.84029636152521E-03
P(X=4) = 1.67730591084263E-02
P(X=5) = 5.20951482897005E-02
P(X=6) = 0.117980188773733
P(X=7) = 0.196303171236968
P(X=8) = 0.23816193569191
P(X=9) = 0.205473042557726
P(X=10) = 0.11965783066597
P(X=11) = 4.22321755291659E-02
P(X=12) = 6.83167545324743E-03

Figure 11. The value expression P (X = 6), for instance, represents the probability of six events (rainfall months) for the UAE within 12 months and whose individual monthly probability of having a rainfall equals 0.66 (the ratio between the number of months that rained between September 2023 and August 2024 in Abu Dhabi). As expected, if you are looking for the sum event probability of being between four and seven months, $P(4 \le x \le 7)$, the practitioner only needs to add their respective probabilities.

4.6. What Is the Likelihood of Raining in 4 Months' Time (February 2025) in Abu Dhabi Considering That We Are in October 2024?

Consider a sequence of trials, where each trial has only two possible outcomes: Rain or Not Rain. The probability of success is assumed to be the same for each trial. In such a sequence of trials, the Geometric distribution is useful to model the probability of the number of trials needed before the first success appears. Basically, the researcher is searching for the number of Bernoulli trials, each having p probability of success, required to achieve just one success (**Figure 12**).

For instance, a newly-wedding couple plans to have children and will continue until the first girl (Wikipedia, 2024). What is the probability that the first child is the first girl, the second child is the first girl, the third child is the first girl and so on? Regarding assumptions, the following three conditions must be meet: A) The phenomenon being modelled is a sequence of independent trials; B) There are only two possible outcomes for each trial, often designated success, or failure; C) The probability of success, *p*, is the same for every trial.

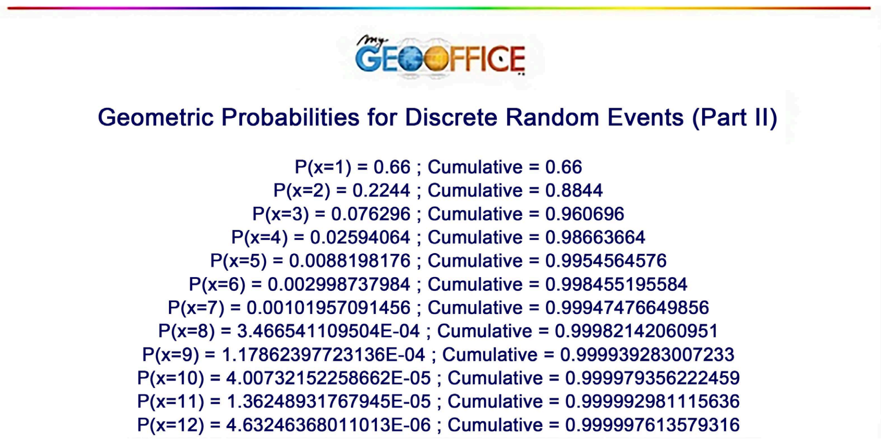

Figure 12. The expression P (X = 4) that equals a total cumulative probability of 98.66% denotes the likelihood of the first event (such as monthly raining) happening within a particular region (Abu Dhabi) in 4 months' time (considering the event raining chance of 66% per month).

4.7. What Are the Chances of 5 Floods in Dubai between September 2024 and August 2030?

The Poisson distribution is applicable for count variables. It is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time and/or space, that is, if these events occur with a known average rate and are independent of the time since the last event (**Figure 13**). It is different from the Binomial distribution since it relies on an average estimate which may be derived from the long-term average of occurrences such as the number of landslides along a mountain slope over a period of 50 years. Hence, the Poisson distribution allows us to determine the possibility of having a given number of occurrences. For instance, after studying hurricane statistics over the past 20 years, it is possible to compute an average expected number of hurricanes having landfalls across the Florida, USA coast in this coming year (Negreiros, 2017).

Based on the following notation (L is the average number of occurrences, E equals the Napierian value of 2.71828 while X denotes the random variable, representing the number of occurrences of an event over time or across some geographic extent), the probability of observing the event X times in each condition can be computed using the following Poisson function: $P(X = x) = (E^{-L} \times L^{X})/X!$

5. Conclusion

This paper tries to answer some of the frequent weather and spatial questions among UAE residents with myGeoffice©. Some of the main findings are as follows:

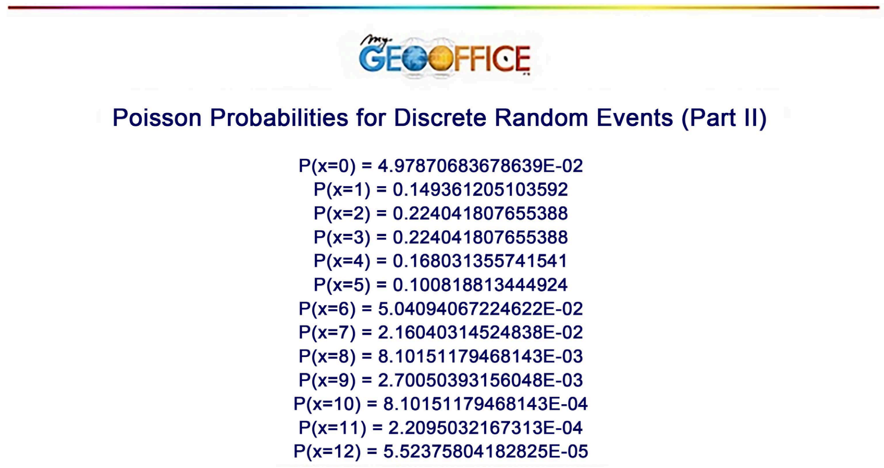

Figure 13. In Dubai and according to the present rainfall records, there were 3 major floods (≥ 100 ml) in the last six years (72 months), which means 3/(6*12) = 4.1% per month. Based on the Poisson distribution, the chances of having 5 major floods in Dubai for the next six years equals 10.08% while the likelihood of having between two and four floods is 22.4% + 22.4% + 16.8% = 61.6%.

A) The study identified regional patterns in rainfall across ten UAE weather stations. While clustering techniques helped to organize observations, these clusters did not always provide clear explanations for regional behavior. B) Dijkstra's algorithm was applied to find the shortest physical distances between Abu Dhabi and nine other UAE weather stations, revealing key distances ranging from 130KM to 281KM). C) Kruskal's algorithm was exploited to calculate the minimum distance required to connect all the stations, which totaled 669 KM. D) Geographically Weighted Regression (GWR) was employed to model rainfall predictions at each weather station. The analysis found that temperature negatively impacted rainfall, while humidity and wind contributed minimally. These patterns varied across stations, highlighting spatial heterogeneity in the UAE's climate. E) Binomial, Bernoulli and Poisson discrete distributions evaluate other inquiries raised by UAE locals.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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