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Spatial Interpolation of Monthly and Annual Climate Variables in Jordan, (Wadi Al-Wala) Case Study

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Abstract:- The goal of this research was to assess and compare the differences in climate variables, specifically precipitation (rainfall) and temperature maps, which are crucial for many hydrological models. We utilized ordinary kriging and multivariate interpolation techniques to create maps of monthly and annual rainfall in the Wadi Al-wala region of Jordan. This involved collecting climate data from four rainfall stations (Al-Muwaqqar, Jiza, Dhaba' Nursery, Muleih) and the Er-Rabba metrological temperature station between 1980 and 2012. The patterns of spatial variation in the collected climate data were analyzed using geostatistical methods to identify spatial variances and predict the potential impacts of climate change on the Wadi Al-Wala region. An experimental variogram of the data was created and compared against three common geostatistical models. Then spatial maps of the climate variables were prepared through the kriging technique by using the best-fit geostatistical model, which help choose appropriate values of model parameters. Nugget-to-sill ratio (<0.25) revealed that the surface water levels have strong spatial dependence in the area. The statistical indicators (RSS and r^2) suggested that any of the three geostatistical models, i.e., spherical, linear, and exponential, can be selected as the best-fit model for reliable and accurate spatial interpolation. However, exponential and spherical models were used as the best-fit models for the Al-Muwaqqar rainfall station with the lower residual sum of squares (RSS= 1.038) and high value of regression coefficient (r^2= 0.192), and average mean temperature from Er-Rabba station with higher r^2= 0.703 and RSS= 0.116 respectively, in the present study.

Keywords:- *Climate Variables, Wadi Al-Wala, Geostatics, Kriging Interpolation, Semivariance Analysis.*

I. INTRODUCTION

Rainfall is a phenomenon that occurs intermittently over time and space, with large variations in its distribution. Rain gauge networks only provide estimates at specific points, making it difficult to accurately characterize rainfall's spatial variability. However, water resources planners, regulators, and decision-makers are interested in understanding this variability (Ali, Abtew, Van Horn, & Khanal, 2000). To do so, it's necessary to estimate rainfall at unrecorded locations from nearby sites (Goovaerts, 2000). Climate change, caused by an increase in greenhouse gas concentrations due to human activities, has altered rainfall distribution patterns globally (Gergis & Henley, 2017; R. Singh & Biswal, 2019). Identifying the presence and magnitude of climate change is a challenging task, as any changes in rainfall behavior occur unevenly across regions and have unique local components (Bisht, Chatterjee, Raghuwanshi, & Sridhar, 2018).

Researchers from different parts of the world have studied climate change and its impact on rainfall at the regional and local levels. They have also analyzed climate indices to understand their trajectory (Singh, 2018; Tito, Vasconcelos, & Feeley, 2020). Studying long-term meteorological data is important in understanding the impact of climate change. Historical records from meteorological stations have revealed that rainfall and temperature indices have been the most affected. As a result of rising global temperatures over the past century, droughts and decreasing rainfall are likely to continue (Carrão, Naumann, & Barbosa, 2018; Gergis & Henley, 2017; Gizaw & Gan, 2017). Extreme weather events such as heat and cold waves, flooding, and droughts have serious implications for human and animal health, the environment, and the economy (Handmer et al., 2012).

The analysis of the interpolation problem has been extensively researched and geostatistical analyses have been found to be useful in mapping rainfall in different areas (Abtew, Obeysekera, & Shih, 1993; Militino & Ugarte, 2001). However, the complexity of the technique does not guarantee better performance in a specific region (Gómez-Hernández, Cassiraga, Guardiola-Albert, & Rodríguez, 2001). It is also unclear whether using rainfall data from nearby locations can improve estimations. This study focuses on analyzing trends in temperature and precipitation in Wadi Al-wala (Jordan) to predict the impact of climate change. Historical rainfall and streamflow data are used to study trends and predict climate change impacts on Wadi Al-wala. The variability and trends in rainfall and streamflow can be useful for hydrological decision-making and further modeling of hydrological and climatic processes.

II. MATERIALS AND METHODS

➢ *Study Area and Data Sets*

The country of Jordan is located in the eastern region of the Mediterranean, with geographic coordinates ranging from 29°11_ to 23°22_ north and 34°19_ to 39°18_ east. Even though it is a small country, occupying an area of approximately 90,000 km², it experiences a typical Mediterranean climate characterized by short, rainy winters and long, dry summers within the semiarid climatic zone. The study area, located in the central region of Jordan, covers around 2,100 km² and is situated at an altitude of 428 m above sea level, with coordinates ranging from 35˚65'E to 36˚30'E longitudes and 31˚55'N to 31˚90'N latitudes. The catchment area is bordered by the Dead Sea catchment to the west, the Zarqa basin to the north, the Azraq basin to the east, and the Hasa and Jafr basins to the south. The wadis in the lower reaches have cut down to the saturated sections of water-bearing formations, maintaining perennial base flow through spring discharges. The catchment area has a triangular shape with a longer axis oriented in an east-west direction.

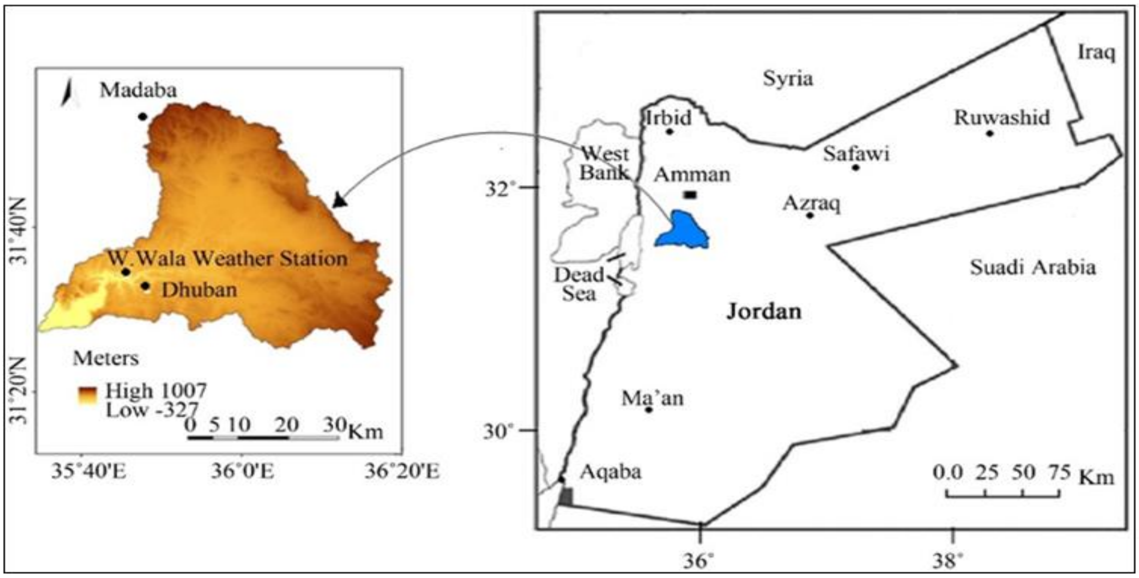

Fig 1 Location Map of Wadi al Wala Catchment Area
Source: (Farhan, 2017)

Wadi Al-Wala catchment is considered a sub-catchment area of Mujib Basin, in addition to the Wadi Mujib catchment. The rainy season in this area generally begins in October and lasts until May. The rest of the year is essentially dry with an almost continuous clear sky. Wadi Al-Wala is semi-arid to arid, with low rainfall in most parts of the basin in winter and high temperatures in summer. Precipitation in the basin results primarily from frontal depressions entering from the Mediterranean region to the west. During the rainy season, three to four frontal depression systems per month may cross the basin Because of the highly variable topography and sporadic nature of thunderstorms, rainfall varies widely, both spatially and temporally. Average annual rainfall decreases from over 300 mm near the western edge of the basin to less than 50 mm at the eastern edge (EXACT Project, 2006; JICA, 1987). Rainfall is insufficient and almost entirely occurs in the winter, occasionally as snow. There is a significant diurnal temperature difference, and it is suggested that winter temperatures will be fairly low and summer temperatures would be considerably high. The relative humidity is typically low, evaporation is strong, and the wind often blows dust, especially in the winter. The strength and duration of the thunderstorm rainfalls, which make up a significant portion of the basin's overall rainstorms, are erratic. The northern region of the basin experiences predominantly orographic rainfall.

➢ *Spatial Interpolation Methods*

We utilized geostatistics to assess the variation in space. This approach enables us to determine the extent of spatial dependence and the scale of spatial autocorrelation among measurement points (G.P. Robertson, 1987). We observed that the measurement points within this scale are spatially dependent. Therefore, it is only possible to efficiently detect essential spatial variation when measurements for a given factor are made at a spatial distance beyond this scale. We analyzed the patterns of spatial variation in soil respiration rate and soil water content geostatistically (Franklin & Mills, 2003; G.P. Robertson, Hutson, Evans, & Tiedje, 1988; Stenger, Priesack, & Beese, 2002). Geostatistics enabled us to calculate semivariances from field data and fit the models to semivariograms. Our goal was to gain insights into how water availability and distribution have changed over the years. By analyzing historical data, we can identify trends and quantify factors such as rainfall variability, temperature fluctuations, and changes in water storage, among others. The data used in this study can be listed into neurological and meteorological data, hydrologic data is comprised of precipitation and streamflow records. The precipitation records are analyzed out of four precipitation stations see Figure 2. The records are of daily time scale and extended during 1980 – 2012, and this study shows the average of maximum, minimum, and mean of annual rainfall in Table 1 (MWI, 2012). While the meteorological data comprised daily maximum, minimum, and mean temperature records for the same period. The data was obtained from the Ministry of Water and Irrigation (MWI, 2012). It is assumed that the data sets used in this study were collected and reported consistently and reliably. The very few missing data within the selected stations were treated with a suitable hydrological approach. Figure 2, displays the study area and the sites of the hydro-meteorological stations.

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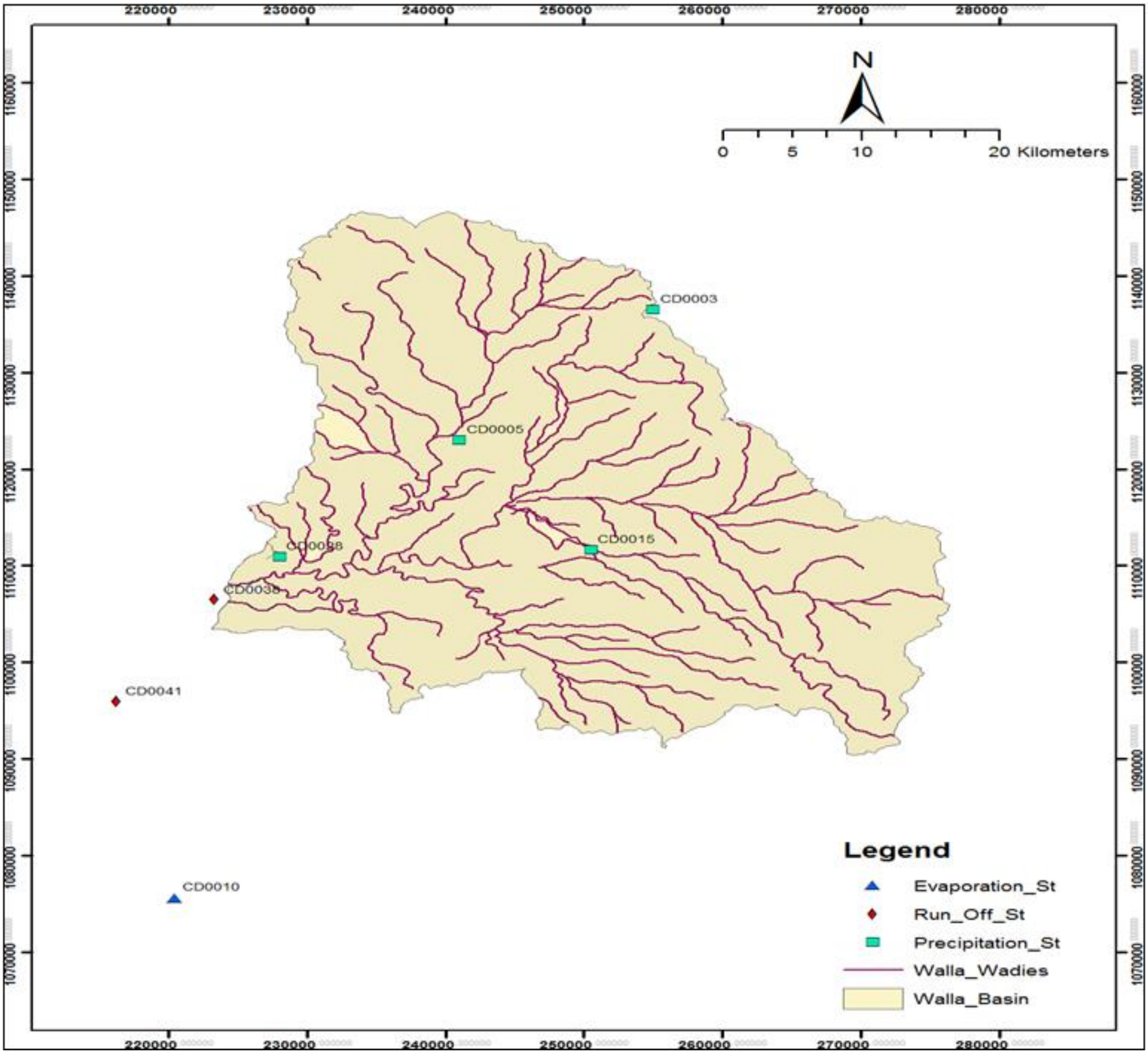

Fig 2 Distribution of the Hydro Meteorological Stations in the Study Area

Table 1 Rainfall Stations in the Catchment Area of Wadi Al-Wala Basin with Average, Maximum, Minimum, and mean of Annual Rainfall from 1980 to 2012. (Source: MWI, 2012)

Station ID	Station Name	PGN	PGE	Maximum rainfall (mm)	Minimum rainfall (mm)	Mean rainfall (mm)
CD0003	El-Muwaqqar	1136500	255000	250	46.4	141.5
CD0005	Jiza	1123000	241000	221.5	34.8	109.9
CD0015	Dhaba' Nursery	1111600	250500	252.5	11	107.2
CD0028	Muleih	1110900	228000	382.8	16	196.7

It's important to keep in mind that the rainfall gauges only provide a limited view of a storm's distribution. To conduct a thorough hydrological analysis, we need to understand the average depth of rainfall across the entire study area. Figure 3 shows the average monthly rainfall for four stations in the study area from 1980/1981 to 2012/2013.

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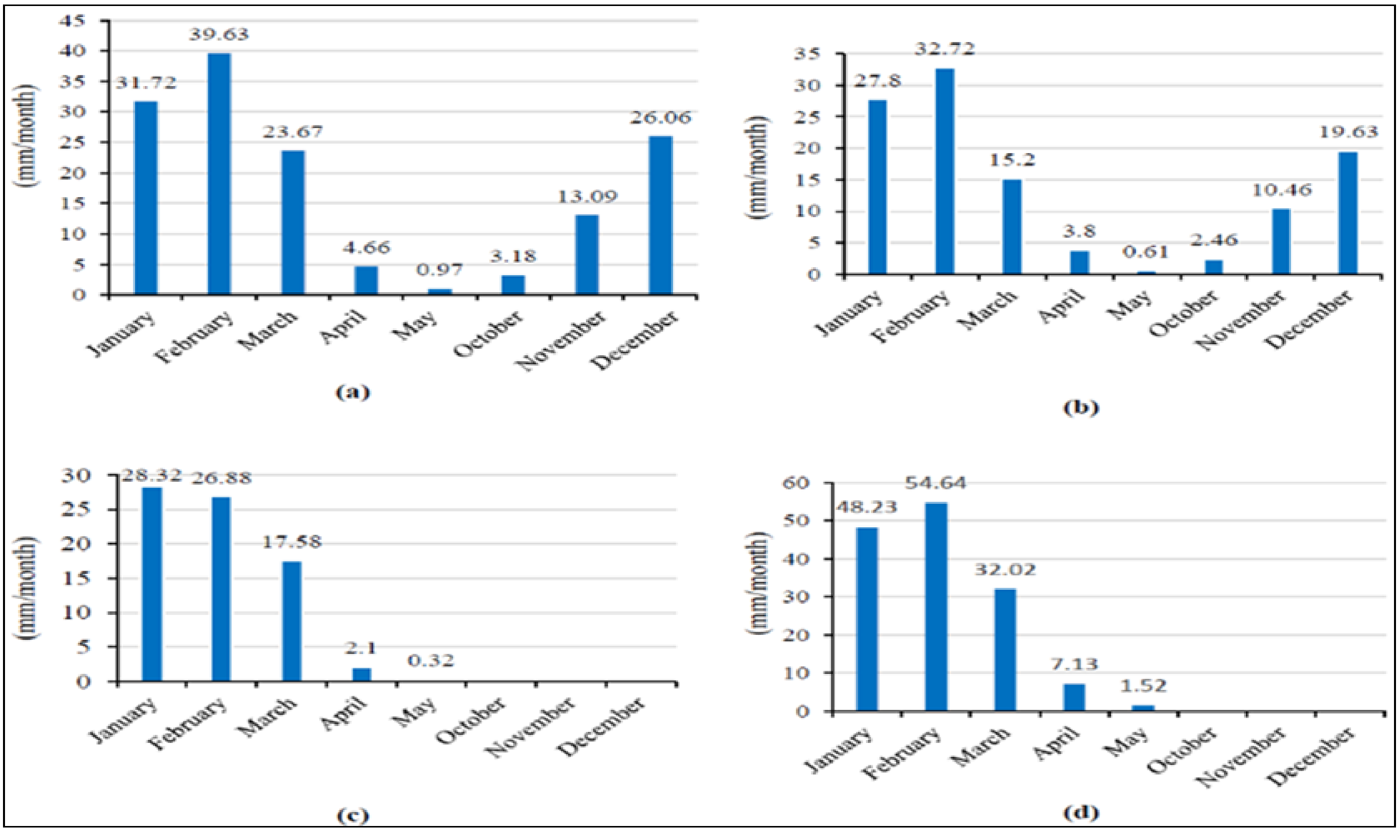

Fig 3 Average Monthly precipitation (mm) from 1980 to 2012 for four Stations El-Muwaqqar (a), Jiza (b), Dhaba' Nursery (c), Muleih (d).

According to previous figures, it appears that February and May have the highest and lowest average monthly rainfall of 54.64 and 0.32 mm for Muleih and Dhaba' Nursery rainfall stations respectively. For other climatological parameters of the study area, the meteorological data of maximum, minimum, and mean temperature are obtained from Er -Rabba evaporation station. It is located to the south of the Wadi Al-Wala catchment, and it is considered the nearest evaporation station to the basin. The meteorological data, which is obtained from the Ministry of Water and Irrigation, is a daily record for the period 1980-2012. Table 2, describes some statistical measures on the daily maximum, minimum, and mean temperature that was obtained from Er –Rabba evaporation station and used in this study.

Table 2 Some of the Descriptive Statistical Measures of the Daily Maximum, Minimum and Mean Temperature Values that are Obtained from Er-Rabba Evaporation Station

Statistical Measure	Maximum T(°C)	Minimum T(°C)	Mean Daily T(°C)
Mean	20.23	10.05	15.14
Standard Error	0.07	0.06	0.06
Median	22.00	11.00	16.00
Mode	27.00	15.00	21.00
Standard Deviation	7.80	5.91	6.68
Sample Variance	60.89	34.94	44.56
Kurtosis	-0.91	-1.06	-1.07
Skewness	-0.30	-0.14	-0.23
Range	49.00	35.00	36.00
Minimum	-2.00	-7.00	-3.00
Maximum	47.00	28.00	33.00

Source (MWI, 2012)

Table 2 shows the maximum, minimum, and mean daily temperature values were 47, -2, and 15.14°C respectively. (Byrne, 2010; Hair, 2009) argued that data is considered to be normal if skewness is between -2 to +2 and kurtosis is between -7 to +7. The skewness was -1.07, indicating that the distribution was left-skewed, negative kurtosis indicated a flat distribution compared with the normal distribution. According to Figure 4, the warmest months were June, July, August, and September, whereas the coldest months were December, January, and February in the Er-Rabba evaporation station.

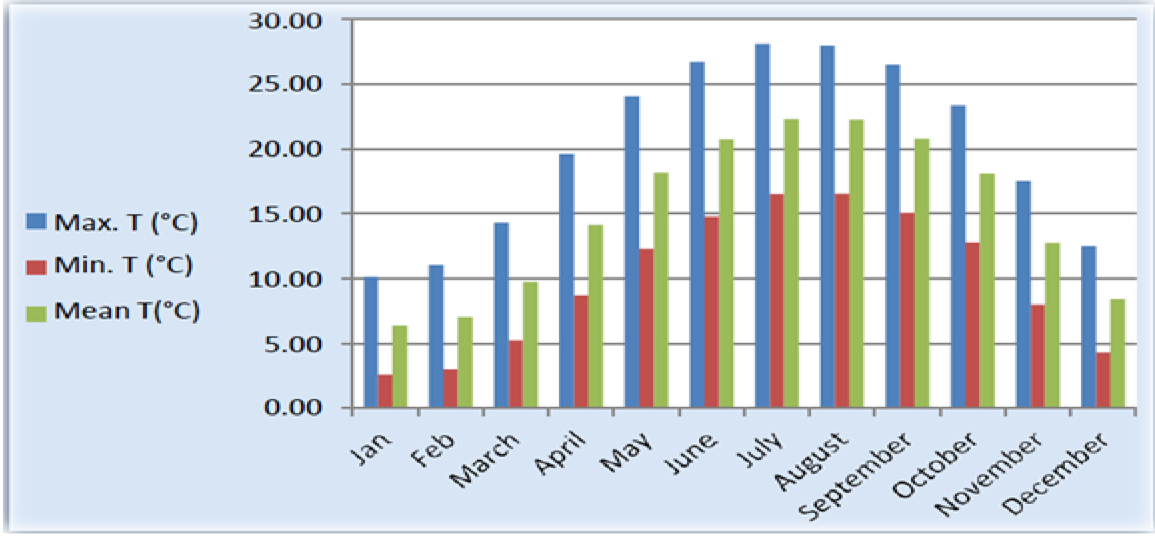

Fig 4 Long-Term Monthly Average Temperature at Er-Rabba Evaporation Station (CD 0010)
Source: (MWI, 2012)

A semivariogram is commonly used to characterize the spatial structure of a variable under study. The semivariogram quantifies the dissimilarity between sampled points as the distance between the samples increases. An experimental semivariogram is computed for two values separated by a distance h called the lag: Cross-validation results of estimating monthly and annual rainfall.

$$\lambda(h) = \frac{1}{2N(h)} \sum (z_i - z_{i+h})^2 \quad (1)$$

Where, z which represents the value of rainfall, . The measured rainfall values at two separate points, zi and $zi+h$, are denoted by zi and $zi+h$ respectively. The number of pairs separated by a distance of h is represented by N. The semivariogram is a graphical representation of (h) against h. Here, (h) indicates the degree of similarity between pairs of points that are h apart (Clark, 1979). The range of influence, or (a_o), is the distance at which (h) reaches its maximum value. According to the definition, the semivariogram [(h)]= 0 at h = 0. If the semivariogram has a positive intercept and does not pass through the origin, this intercept is called the nugget effect (Co). This effect may be caused by variations in the data at distances shorter than the sampling interval (Clark, 1979). The sill is the value at which (h) levels off and includes both (Co) and a component C that accounts for the variance due to spatial dependence. The semivariogram can be fitted to various theoretical models such as linear, spherical, or exponential.

III. RESULTS AND DISCUSSION

In this study, the first step in the statistical treatment process involved determining the semivariance models for the treated parameters. As might be noticed from Table 3, Stations CD 0005 and CD 0028 data were fit to a linear model, whereas, stations CD 0003 and CD 0015 were fit to an exponential model. Also, the CD 0010 meteorological station data of maximum and mean temperature were fit to a spherical model, while, the minimum temperature was fit to an exponential model.

Table 3 Theoretical Model Parameters Fitted Experimental Semivariograms for the Treated data Obtained from the Different Stations of the Study Area

Variable	Model	Nugget (Co)	Sill ($Co + C$)	Range (Year)
El-Muwaqqar CD 0003	Exponential	2296	4593	51
Jiza CD 0005	Linear	1736.751	1736.751	23.47
Dhaba' Nursery CD 00015	Exponential	2020	4041	51
Muleih CD 0028	Linear	5771.3308	5771.3308	23.47
Er –Rabba CD 0010 Avg. Max. Temp.	Spherical	1.07	4.78	51
CD 0010 Avg. Min. Temp.	Exponential	0.2241	4492	51
CD 0010 Avg. Mean Temp.	Spherical	0.442	1.293	51

Experimental semivariograms were used to fit theoretical models (such as linear, spherical, and exponential) with variable nugget effects depending on the month. The nugget effect (Co) is the intercept when the semivariogram does not pass through the origin. The value at which the semivariogram levels off is called the sill, consisting of Co plus a component (C) accounting for the range of variance due to spatial dependence. According to the analysis of the semivariograms and their fitted parameters, climatic element predictions for stations (CD0005 and CD0028) can only be made within about 23 years, and 51 years for other stations (as shown in Table 3 and Figure 5), according to the dependence ratio criteria outlined by Cambardella et al. (1994). The analysis was performed using GS+ version 5 (Robertson, 2000).

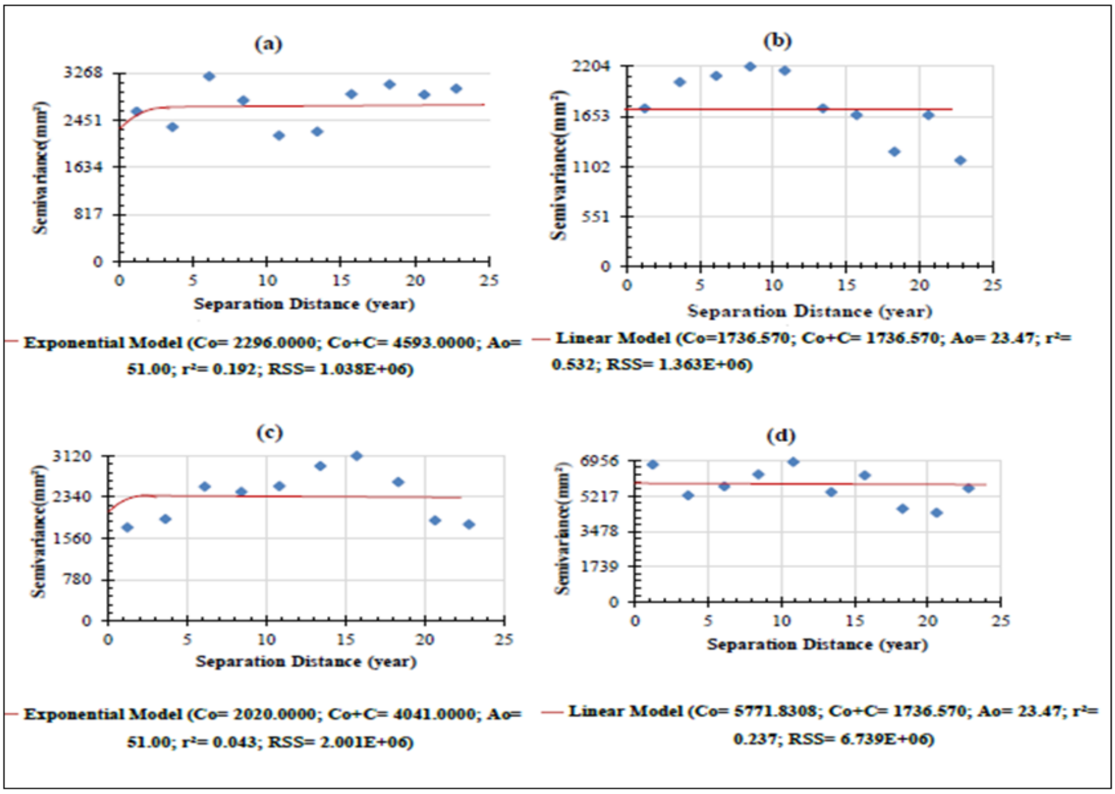

Fig 5 Isotropic Variograms for four Precipitation Stations CD 0003 (a), CD 0005 (b), CD 0015 (c), and CD 0028 (d)

An optimal theoretical model was determined by the determining coefficient (R^2) and the least residual sums of squares (RSS). We then fit the observed semivariograms to theoretical models and computing of the interpolated value using ordinary Kriging of GS^+. The output of Kriging is directly related to the semivariogram of the data. The monthly average maximum and mean temperature for Er-Rabba Evaporation Station (CD 0010) in Figure 4, exhibited a spherical experimental semivariogram, whereas the monthly average minimum temperature exhibited an exponential model see with a nugget effect for the recorded period (1980-2012) see Figure 6.

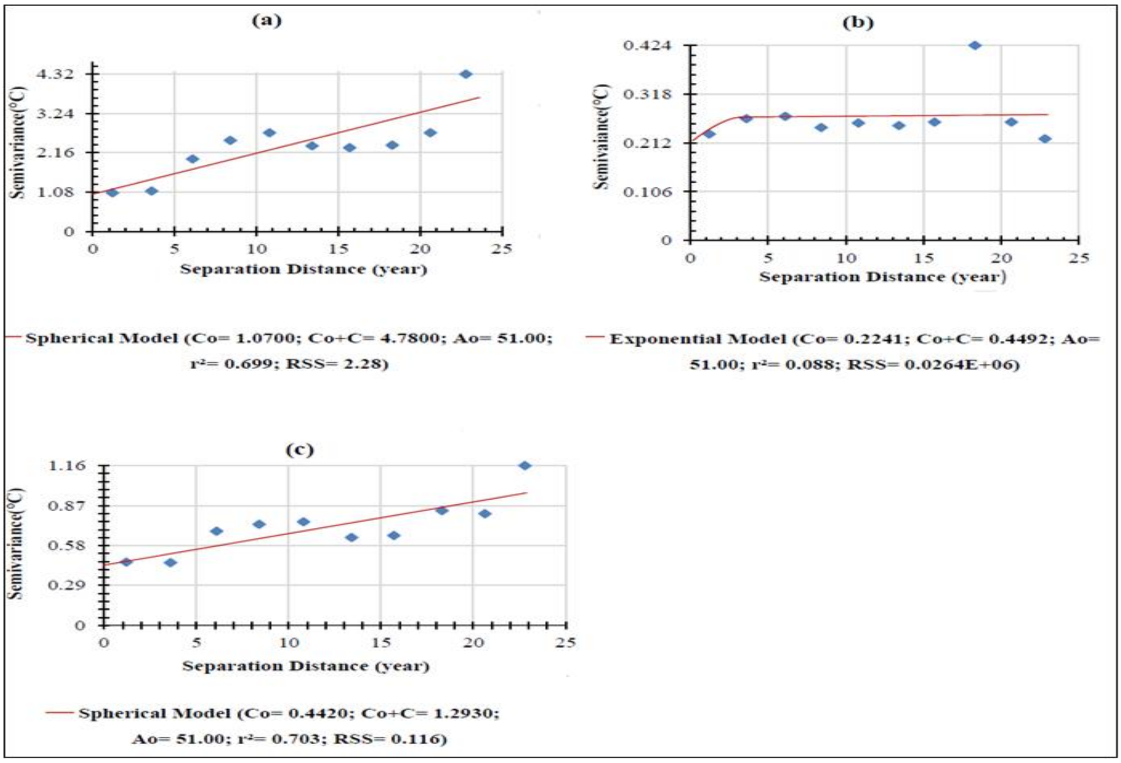

Fig 6 Isotropic Variogram for Er –Rabba Evaporation Station (CD 0010): Average Maximum Temperature (a), Average Minimum Temperature (b), Average Mean Temperature (c).

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After comparing the goodness of fit in terms of regression coefficient and residual sum of squares values, it was concluded that the best-fitted semivariogram models for reliable and accurate spatial interpolation are the spherical, exponential, and linear models. The spatial dependence of surface water levels in the study area was found to be strong. The nugget-to-sill ratio was used to classify the spatial dependence variables, and it was found to be less than 0.25, which indicates strong spatial dependence. The exponential model was selected as the best-fit model for the Al-Muaqqar rainfall station, while the spherical model showed the best correlation for the mean temperature of the Er-Rabba station in the study. The coefficient values were very high, and the residual sum of the sequence of determination was lower, which supports the selection of the linear and spherical models as the best fit.

The recorded regression coefficients (r^2) figures in Figures 5 and 6 indicate the reliability of the adopted models and the Kriging estimates. They help us understand how well the observed output is replicated based on the proportion of total variance of the simulated output data. The range of r^2 varies from 0 to 1. A positive relationship is indicated by a correlation coefficient greater than zero, while a negative relationship is indicated by a value less than zero. A value of zero means there is no relationship between the two variables. A r^2 value near 1 means the model is accurate and positive. The comparison between observed and current variables showed satisfactory results at all stations in the study area. The Er-Rabba Evaporation Station (r^2 = 0.703) had the best fitted correlation for average mean temperature, which provides the most accurate representation of the spatial correlation between temperature measurements at different locations. 70.3% of the variation in the temperature data is explained by this model. Additionally, the Al-Muwaqqar station (RSS = 1.038) showed the best fitted correlation between observed and current rainfall data. A lower RSS indicates a model with smaller residuals, which means it is closer to the actual data points and provides a more accurate representation of the variability in rainfall across space.

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