A Comparison Analyzed to Implementation Spatial Interpolation Methods for Distribution the Patterns the Relative Humidity for West Deseret in Egypt: Influence of Network Density

Prepared by

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المستخلص:

تتزايد تطبيقات طرق الاستيفاء المكاني، في اشتقاق البيانات المتصلة خاصة بشكل اساسي في علم المناخ، حيث يوجد الكثير من البيانات المفقودة، وكما هو الحال مع أي تقنيات إحصائية أخرى، فإنها تنتج أيضًا درجة من الأخطاء المرتبطة بالتقديرات، لذلك هناك أيضًا اهتمام كبير بدقتها. تمت مقارنة العديد من SIMs في بيئة نظام المعلومات الجغرافية لتقييم أدائها ومقارنة فعالية التحليل لتقييم التوزيع المكاني لبيانات الرطوبة النسبية (2010–2022م) في الصحراء الغربية في مصر. تم استخدام ثلاث SIMs لاشتقاق التوزيع المكاني للرطوبة النسبية وهي: ترجيح المسافة العكسية، وSpline المنتظم تمامًا، وKriging العادي. تم استخدام التحقق المتبادل لتقييم دقة SIM من خلال مقارنة قيم متوسط الخطأ، ومتوسط الخطأ المعياري، والجذر التربيعي لمتوسط الخطأ. وبناءً على النتائج، تتجه التغييرات من الشمال إلى الجنوب في منطقة الدراسة كما تتأثر بمسطحات المياه الأقرب. هناك فرق كبير في تنفيذ ثلاث طرق SIM، ولكن إذا نظرنا إلى قيم خطأ التنبؤ، فيمكن القول أن OK أفضل من IDW و CR_Splineخاصة في البيانات ذات الكثافة المنخفضة. ولكن عند استخدام كثافة بيانات عالية فإن CR_Spline هو أفضل أداء مع ME 0.03 وMES 1.9. من خلال هذا البحث، نأمل أن يؤخذ في الاعتبار أهمية تأثير كثافة شبكة البيانات للمتغيرات المناخية خاصة أنه أتضح تأثيرها الهام والفعال على أداء تقنيات الاستيفاء المكاني ودقتها.

الكلمات المفتاحية: IDW، CR_ Spline، طرق الاستيفاء المكاني، الرطوبة النسبية

Abstract:

Increasing applications of spatial interpolation methods SIM specialty particularity to generating surface continuous data in climatology science so much missing data, and as with any other statistical techniques, it also produces a degree of errors associated with the estimation, so there is also a big interest in their accuracy. Various SIMs were compared in the geographical information system environment to assess it is performance and compare the effectiveness of analysis for assessing the spatial distribution of the Relative Humidity dataset (2010-2022) in the Western Desert of Egypt. Three SIMs were used to generate the spatial distribution of the studied indicator: inverse distance weighting, Completely Regularized Spline and Ordinary Kriging. Cross-validation was used to evaluate the SIM's accuracy by comparing the values of mean error, mean Standardized error and root mean square error. Based on the results there tend to be more changes from the north to the south of the Study area. It is affected by closer water areas. There is a significant difference in the implementation of three SIMs, but if we look at the prediction error Values, it can be said that the OK is better than the IDW and CR_Spline SIM special in low-density data RMSE:0.8, MSE:4.1, ME:0.1. But in the used high data density the CR_Spline is the best performance with interpolated the RH in with ME 0.03 and MES 1.9 With this research, it is hoped that it can become a consideration of the effect of the Network Density on the performance of the spatial interpolation techniques.

Keywords: IDW, Completely Regularized Spline, Invers Distance weight and Ordinary Kriging, Spatial Interpolation Methods, Relative Humidity Mapping

1. Introduction

The main key to understanding climate change is changes in the atmosphere's humidity [4]. So Accurate gridded climate datasets are vital for understanding climate change and its impact on natural disasters in mountainous regions with complex terrain and sparse ground observations [33].

Meteorological data are used in many studies, one of the main issues in meteorological analysis is the interpolation of spatial data [20]. Spatially continuous data are very important for particularly climatology [1]. Relative Humidity is Important in agricultural operations, as the precipitation process depends on the amount of moisture in the air, in addition to the role it plays in adjusting temperatures [2]. Where the mean annual relative humidity in Egypt is 35.16%, and the lowest is 25% in May and the highest is 46% in Dec [12].

This research aimed to analyze the distribution of relative humidity and predict it that is not sampled, and to provide an overview of the pattern of humidity in the period 2010-2022. And to evaluate the Influence of the Network Density Factor on the Interpolation Performance of Relative Humidity.

Using interpolation methods, and statistical tests to determine the best spatial distribution patterns between locations. Based on the result of the research, the CR_Spline method presents accurate spatial interpolation data. Meanwhile, OK has provided accurate results in spatial distribution patterns in low data density.

In this paper, Inverse Distance Weighted (IDW), CR_Spline, and Ordinary Kriging methods to be used to analyze changes in Relative humidity in the Western Desert of Egypt.

1.1.Proposed Model: as can show in this fig1

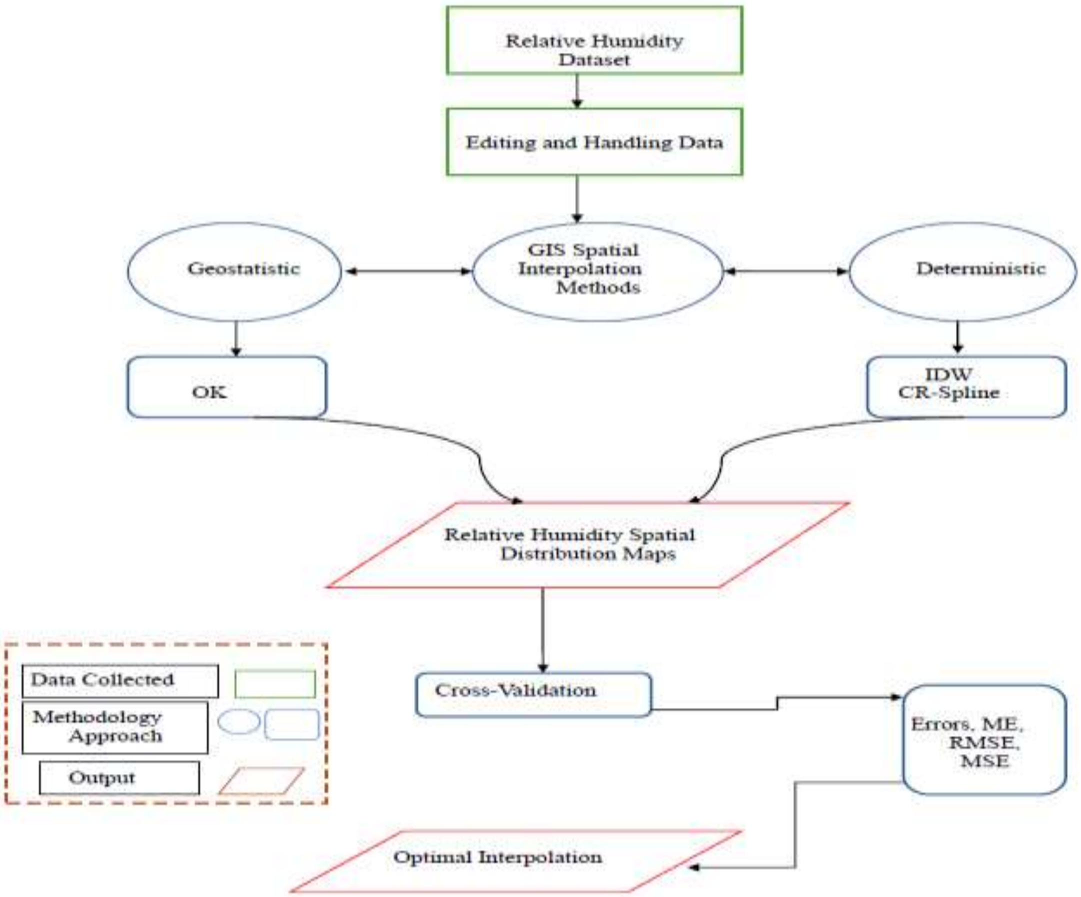

Fig 1: Flow chart methodology applied in the present study

The figure1 shows the steps of the research, where relative humidity dataset were collected from ground meteorological stations, thin the data was entered and modified within the GIS software, spatial interpolation analysis was used to produce spatial distribution maps to relative humidity, and the models produced by the different methods were evaluated with Cross-validation (ME, RMSE), and the best interpolation method was determined.

2. Literature Review

A study [9] aimed to evaluate actual spatial interpolation of air temperature and relative humidity and determine the best model among 5 interpolation algorithms: OK, MLR, IDW, NN, and KED, the results showed that the KED-Elevation method achieved the best results. The study [11] confirmed that the small distance between data samples makes spatial autocorrelation simple, and thus samples with higher density lead to higher accuracy in the estimation of the interpolation. The results of the study clarified the importance of the sample density especially in mountainous and desert locations, or environments that suffer from scarcity of climate data.

[28] Determining the errors of interpolation methods OK, CKO, IDW, and TPS Spline statistically and the impact of both the nature of the sample distribution and the addition of auxiliary variables on determining the percentage of prediction error, The results of this study confirmed that the use of temporal information and spatial variation generally improves the accuracy of spatial interpolation effectively, especially under the conditions of widely distributed stations and complex geomorphology.

[22] This study was executed to evaluate the temperature difference, used statistical analysis, and relied on spatial interpolation using the IDW; the results showed the suitability of the IDW and the disappearance of differences between the measured data and the method estimates, thus confirming the use of spatial interpolation of data values of unknown points as an effective tool for creating continuous temperature maps. The study relied on the IDW method because it is the most widely used and repeated and to achieve the required accuracy, as the study indicated the limited accuracy with the use of the Kriging interpolation method with the small amount of measured data; however, the IDW method achieved the highest degree of accuracy, especially in small areas and the absence of significant differences and severe spatial variation.table1 show the literature review .

N	Methods	Area-period	Application	Co- Variables	**Results**	Reference
1.	IDW, Spline, Kriging	Iraq 2010	Air Temperature	-----------------	**Kriging**	[23]
2.	IDW	Iraq (1992-2020)	RH	Elevation	**IDW**	[4]
3.	IDW, Kriging, CO-Kriging	Canada(2005-2010)	RH	Elevation	**IDW**	[30]
4.	Spline, IDW, Kriging	Iraq(2005-2014)	Temperature	------------------	**Kriging**	[17]
5.	TPS: Spline, SK	Germin(2000-2021)	RH	Elevation	**Spline**	[24]
6.	Kriging	Iraq(1981-2017)	RH	---------------	**kriging**	[27]

N	Methods	Area-period	Application	Co- Variables	**Results**	Reference
7.	IDW	Central Europe	RH Temperature	Elevation	**IDW**	[8]
8.	IDW, Kriging	Bangka(2019-2021)	RH Temperature	------------------	**Kriging**	[25]
9.	OK	Turkey(1975-2010)	Temperature precipitation	------------------	**OK**	[20]
10.	ANN, IDW	Tunisia(2008-2021)	Global Solar Radiation	---------------	**IDW**	[16]
11.	IDW, TPS, SK, CK, MLR	Turkey(1975-2004)	Temperature	Elevation Distance from the sea, Slope	**MLR TPS**	[19]
12.	IDW, NN, Spline, OK,UK	Iran(1970-2014)	Temperature precipitation	-------------	**OK, UK NN**	[3]
13.	IDW, OK, Spline	Sumatra (2017-2021)	precipitation	------------------	**IDW, OK**	[34]
14.	IDW, CO-Kriging, TPSS(Spline)	Hengduan Mountain China 1961-2018	Precipitation Temperature	Elevation	**Spline IDW**	[32]
15.	IDW	Sri Lanka(1981-2019	Temperature	Relative Humidity	**IDW**	[31]

Table1IDW: Invers Distance Waight, NN: Nature Neighborhood, TPS Thin-Plate Spline, ANN: Artificial Neural Networks, M-IDW: Modify Invers Distance Waight, MLR: Multiple Linear Regression, OK: ordinary Kriging, UK: universal Kriging

3. Concepts overview:

3.1. Spatial Interpolation Methods:

As geographic information systems (GIS) and modelling techniques are becoming powerful tools in natural resource management and biological conservation, spatial continuous data of environmental variables are increasingly required. Numerous methods have been developed for spatial interpolation in various disciplines. Estimations of nearly all spatial interpolation methods can be represented as weighted averages of sampled data. They all share the same general estimation formula, as follows:[15]

$$\hat{z}(x_0) = \sum_{i=1}^{n} w_j z\,(x_i)$$

where $z\hat{}$ is the estimated value of an attribute at the point of interest x_0, z is the observed value at the sampled point x_i, w_i is the weight assigned to the sampled point, and n represents the number of sampled points used for the estimation.

The Follow flowchart Fig2 show the Spatial interpolation Method Using in this paper:

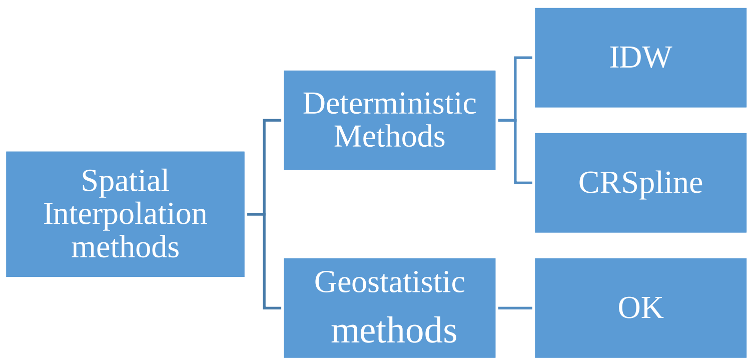

Fig2: Flow chart Spatial interpolation Methods applied in the present study

3.1.1. IDW:

The IDW technique is a traditional interpolation approach that employs distance as a weighting factor. This distance pertains to the separation between the data point (sample) and the target area for estimation. Consequently, when the sampling point and the target area for estimate are closer in distance, a higher weight is assigned, and conversely [34].

IDW is one of the most used methods among deterministic interpolation techniques. This method assumes that the measured values at a closer distance have greater weight than those further away. The influence of a known value is inversely related to the distance from the unknown data point. Consequently, this method gives greater weights to values closest to the prediction position and the weights reduce as a function of distance.

IDW determines cell values using a linearly weighted combination of a set of sample points [29]. The equation for the IDW interpolation model is presented as follows:[32]

$$z(s_0) = \sum_{i=1}^{N} w_i \cdot z(s_i)$$

Description:

$z(s_0)$ is the estimated value of interpolation points s_0,

$z(s_i)$ is the observed value of known point s_i,

N is the number of observation points,

w_i is weight of known point s_i to the interpolation point s_0,

which can be expressed as Equation:

$$w_i = \frac{\frac{1}{d(s_0, s_i)^2}}{\sum_{i=1}^{n} d \frac{1}{(S_0, S_i)^2}}$$

The power parameter p in the IDW interpolation controls the significance of the surrounding points upon the interpolated value. A higher power results in less influence from distant points [21].

3.1.2. OK:

Ordinary Kriging (OK) is the most common and most frequently applied interpolation technique in Geostatistics. It is classified as a univariate approach, i.e. it only allows for the consideration of one data source and no additional information can be considered. An important assumption is that the expected value of the underlying random function is equal within the entire domain [5]. The OK estimate is generally unbiased and calculated as follows:

$$z(s_0) = \sum_{i=1}^{n} w_i z\,(s_i)$$

where w_i is the weight of each of the n adjacent observations taken into account. The weights are obtained by solving the kriging System:

$$\sum_{j=1}^{n} w_1 \cdot \gamma(s_i - s_i) + \mu = w\gamma(s_i - s_0)$$

For

i=1..., n

$$\sum_{j=1}^{n} w_j = 1$$

Kriging aims to determine the weight value that produces a minimal variance estimator and an unbiased [25].

3.1.3. Radial basic functions (RBF) Interpolation:

The Radial Basic Functions (RBF) methods are exact interpolation techniques; the surface is forced through each measured sample value. There are five different basic functions: thin-plate spline, spline with tension, completely regularized spline, multiquadric function, and inverse multiquadric function. Each function has a different shape and results in a slightly different interpolation surface. RBF methods are a form of artificial neural network RBFs can be locally sensitive to outliers. RBFs are conceptually like fitting a rubber membrane through the measured sample values while minimizing the total curvature of the surface. The basis function you select determines how the rubber membrane will fit between the values[1]. In the present paper, using the completely regularized spline (CR_Spline).

3.2Site and Data:

In this study, Annual average Relative Humidity (2010–2022) and topographic data collected from 23 meteorological stations in Weast Desert in Egypt. Data was obtained from NASSA POWER. was conducted in Weast Desert in Egypt it was located between 22°-30° 35 North Latitude and 32°1 -30°33 East Longitude, the location map of the meteorological observation stations used in the study is shown in Fig3. The data of the stations used are presented in Table 2.

What are the characteristics of the three spatial interpolation methods being compared? Interpolated output cannot be judged only by a numeric index because many characteristics of spatial value are limited to be evaluated by quantitative assessments. Nowadays, there is no clear guideline that can explain the best estimation method that is appropriate for all situations [34].

This research aims to assess the accuracy among the Inverse Distance Weight (IDW), Ordinary Kriging (OK), and CR_Spline interpolation methods in ArcGIS pro-3.3 to understand the characteristics of the interpolation methods in Visualization The pattern of Relative of Humidity.

N	Name	Climatic Zone	WMO ID	Latitude	Longitude
1	Salloum	N-Coast	62300	31.5333	25.1833
2	Sidi Barrani	N-Coast	62301	31.6167	25.9
3	Sidi-Barrani	N-Coast	62302	31.4531	25.8814
4	Sidi-Barrani	N-Coast	62303	31.6333	25.9667
5	Mersa-Matruh	N-Coast	62304	31.5175	27.1686
6	Salloum Plat	N-Coast	62305	31.5667	25.0833
7	Mersa Matruh	N-Coast	62306	31.3333	27.2167
8	Habatah	N-Egypt	62307	31.0833	25.4667
9	Ras El Hekma	N-Coast	62308	31.2333	27.8667
10	Dabaa	N-Coast	62309	30.9333	28.4667

Table (2) sample of the dataset to this research of the study area

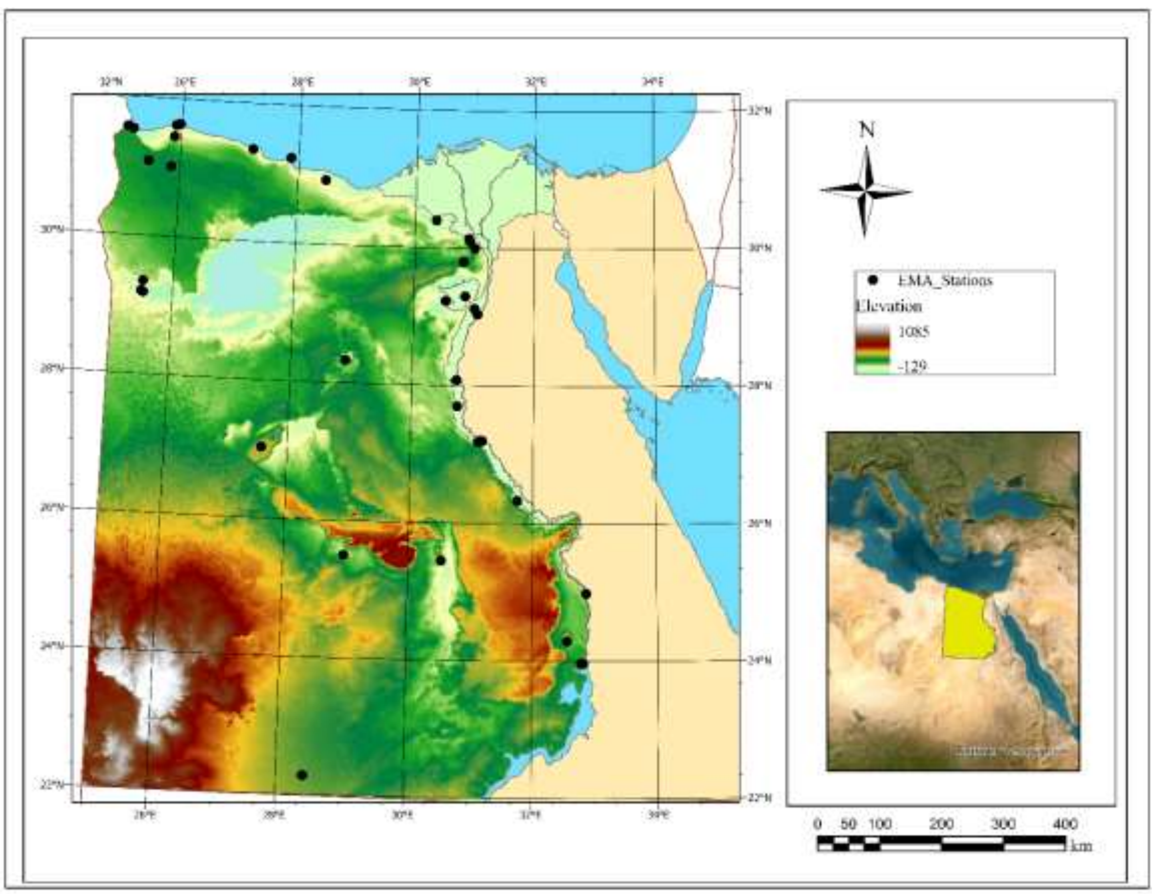

Fig3: show the station point data in study area

4. Analysis:

4.1. Visualization Comparison of prediction accuracy between IDW, CR_Spline and OK of Relative humidity in West desert:

Based on the Annual Relative Humidity data from 23 meteorological stations with a time span of 2010–2022, three spatial interpolation techniques including deterministic (IDW, CR_Spline) and geostatistical (OK) interpolation were applied to the Annual Relative Humidity, to create generate continuous Relative Humidity surfaces and represent Spatial distribution pattern to RH within GIS environment. show fig (2,3,4) are spatial variability maps to RH DATA in WDE.

4.1.1 IDW:

It is clear from the patterns of relative humidity distribution in the Western Desert using the IDW method, Fig4 that relative humidity decreases sharply in the south of the Western Desert towards the valley near Qena, and relative humidity increases in the desert the closer we get to the north near the effects of the Mediterranean Sea, where the highest humidity percentage is represented in the region from the northern coast of the Western Desert to the inside up to the South the latitude 30**.**

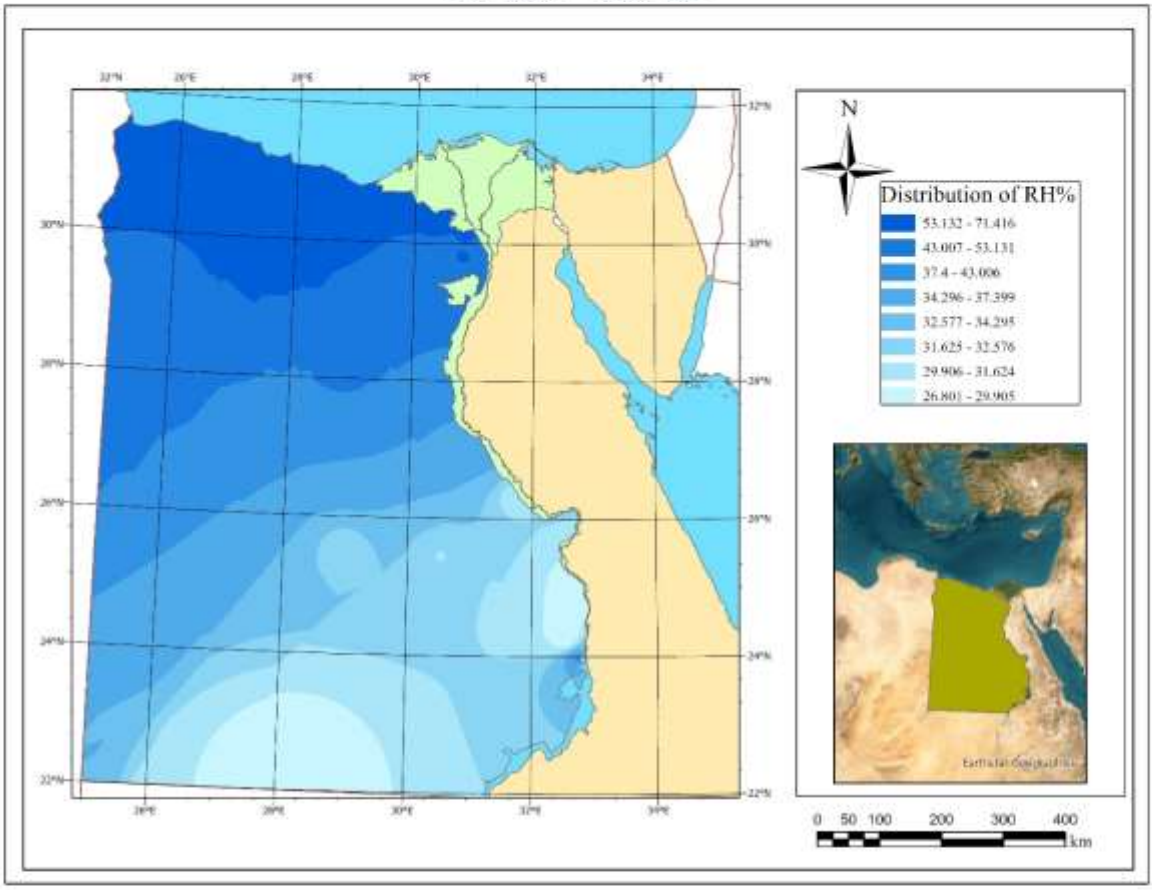

Fig 4: show the Distribution pattern of Relative Humidity data in study area using IDW

4.1.2 OK

The relative humidity distribution patterns using the method OK showed Fig5that the areas with high relative humidity appear in the north of the study area and extend to the side of the 30 degree north latitude, and the humidity percentage decreases as we move south in the study area, where the areas with the lowest humidity percentage appear in the southern area east of mountain of Al-UwayNat and west of the valley nearest from Qena and Upper Egypt, but the west of Lake Nasser is affected by factor water effects, where a high density of relative humidity appears**.**

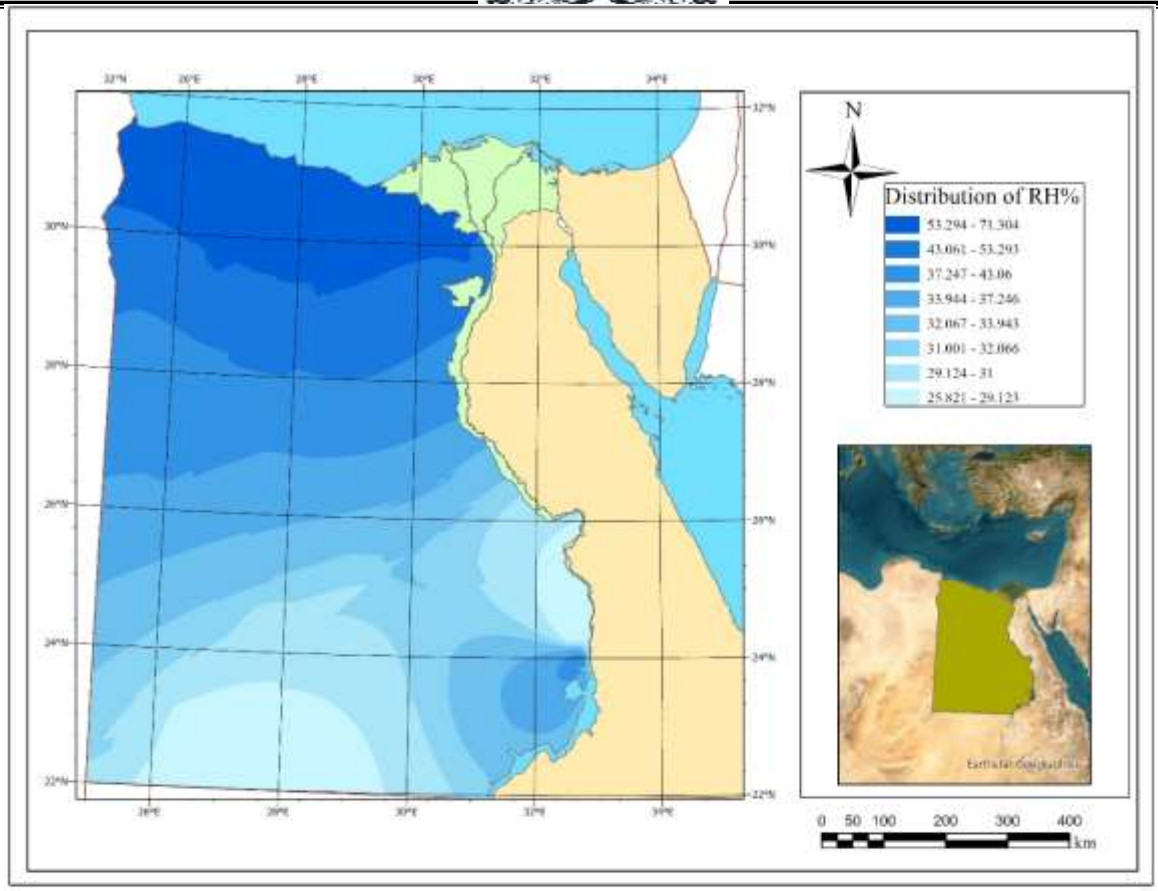

Fig 5: show the Distribution pattern of Relative Humidity data in study area using OK

4.1.3. Completely Regularized Spline:

Using The method CR_Spline of creating patterns for the spatial distribution of relative humidity data Fig6 is different from the other methods used in the study, due to its structure in simplifying the distribution of the sample data used, where it appears to us from the representation of the relative humidity data that the relative humidity percentage decreases in the south and southwest of the study area (the Gulf Kebir Plateau area), and the effect of Lake Nasser water increases to its west in the northern direction in the Western Desert to near the 24 latitude north, and we notice a sharp decrease in relative humidity west of the valley near Qena, and the spatial distribution of relative humidity varies until the north, where its percentage increases due to the influence of the Mediterranean Sea**.**

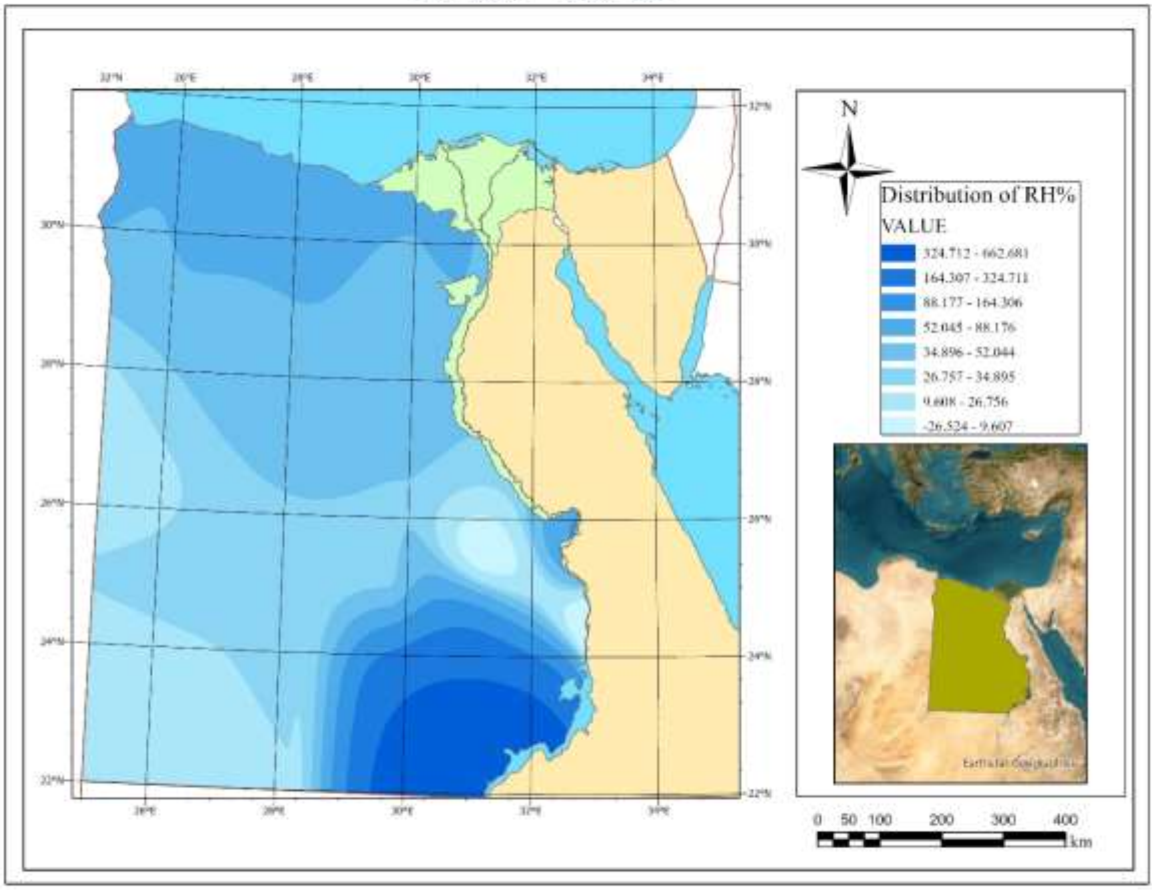

Fig 6: show the Distribution pattern of Relative Humidity data in study area using CR_Spline

4.2.Effects of station density on the accuracy of Relative Humidity data interpolation result:

Data density plays a significant role in the performance of the spatial interpolation methods [15]. well as the difference in the performance of IDW, CR_Spline and OK geostatistical interpolation techniques under varying sampling density set-ups. As a general trend, there was a consistent positive relationship between sampling density and interpolation accuracy for both IDW, CR_Spline and OK. So, we used extra data from NASSA POWER in same period to 51 points know value to Relative Humidity show in the fig7

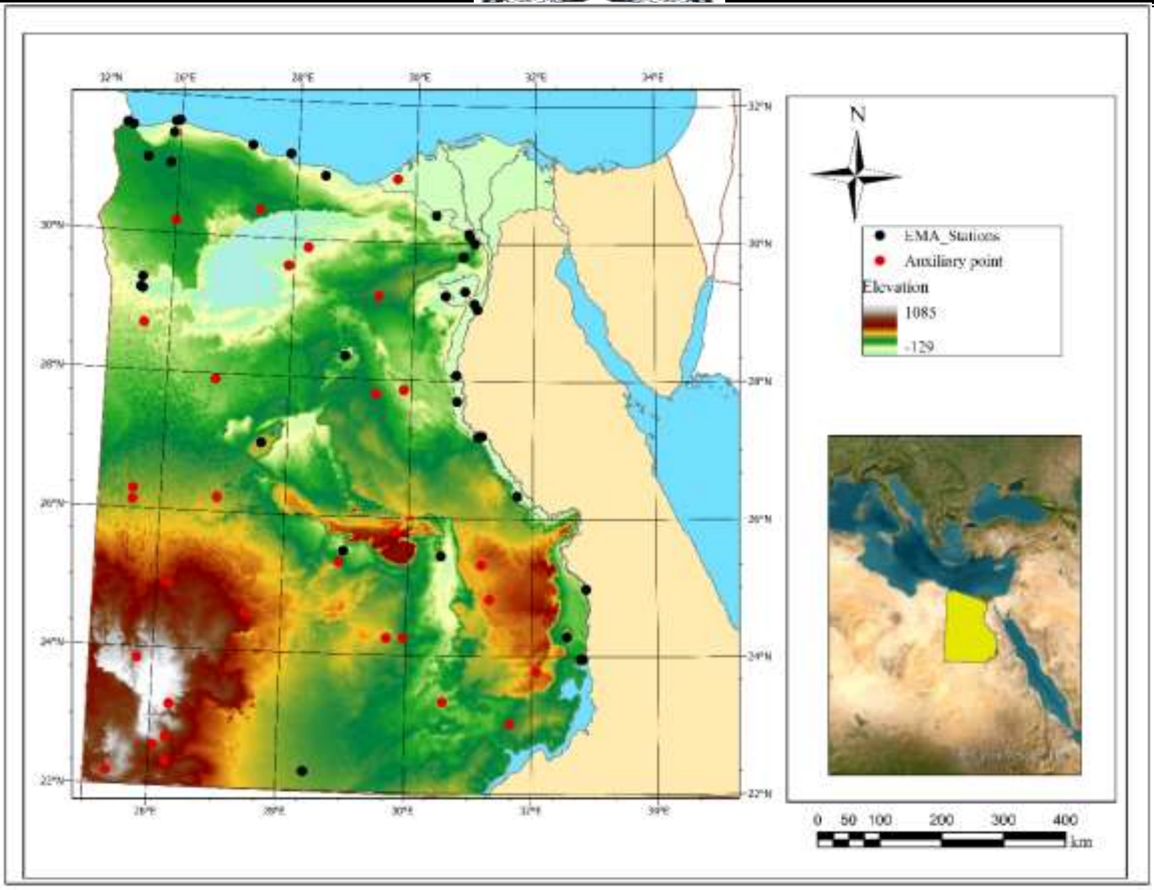

Fig 7: show the auxiliary point value to Relative Humidity, in the study area

Effects of sampling density and interpolation techniques on the spatial pattern of predicted Relative Humidity Density differentiation and detail of the Relative Humidity distribution pattern see Figs 8, 9 and 10 reflect the impact of both sampling density on the interpolation techniques.

We notice a difference in the patterns of relative humidity distribution in a WDE using the IDW method Fig 8 when increases the density of the sample data, especially in the southern regions of the study area, extending northward near the latitude 24 north

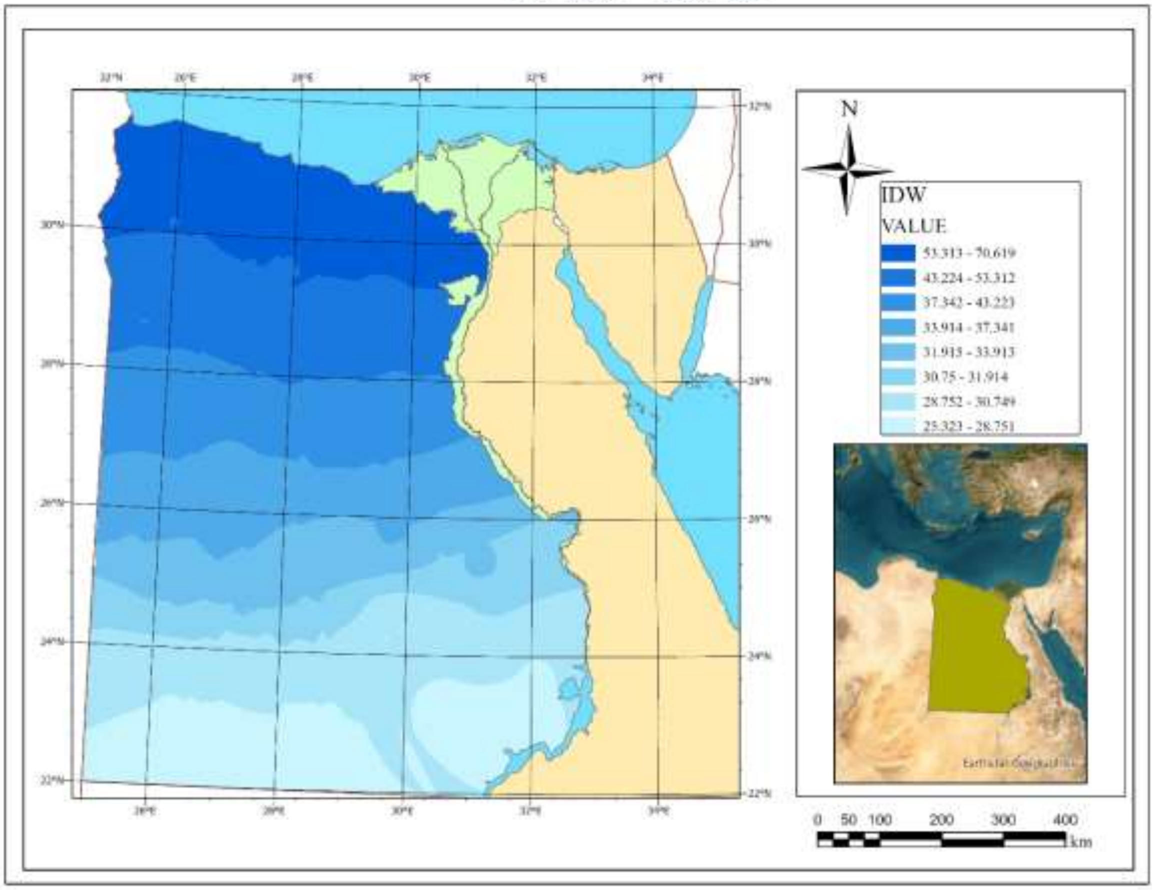

Fig 8: show the Distribution pattern of Relative Humidity using High density data in study area using IDW SIM

Fig9 show spatial distribution to Relative Humidity using OK Method After Increase Density of data so appear that south 24 latitude to 22 latitude Relative humidity increases gradually towards the north in the study area. In the south, the elevations affected the method in the south, where the Relative Humidity decreased due to the high rate of drought in the south and its distance from water bodies that help in moisturizing Atmosphere.

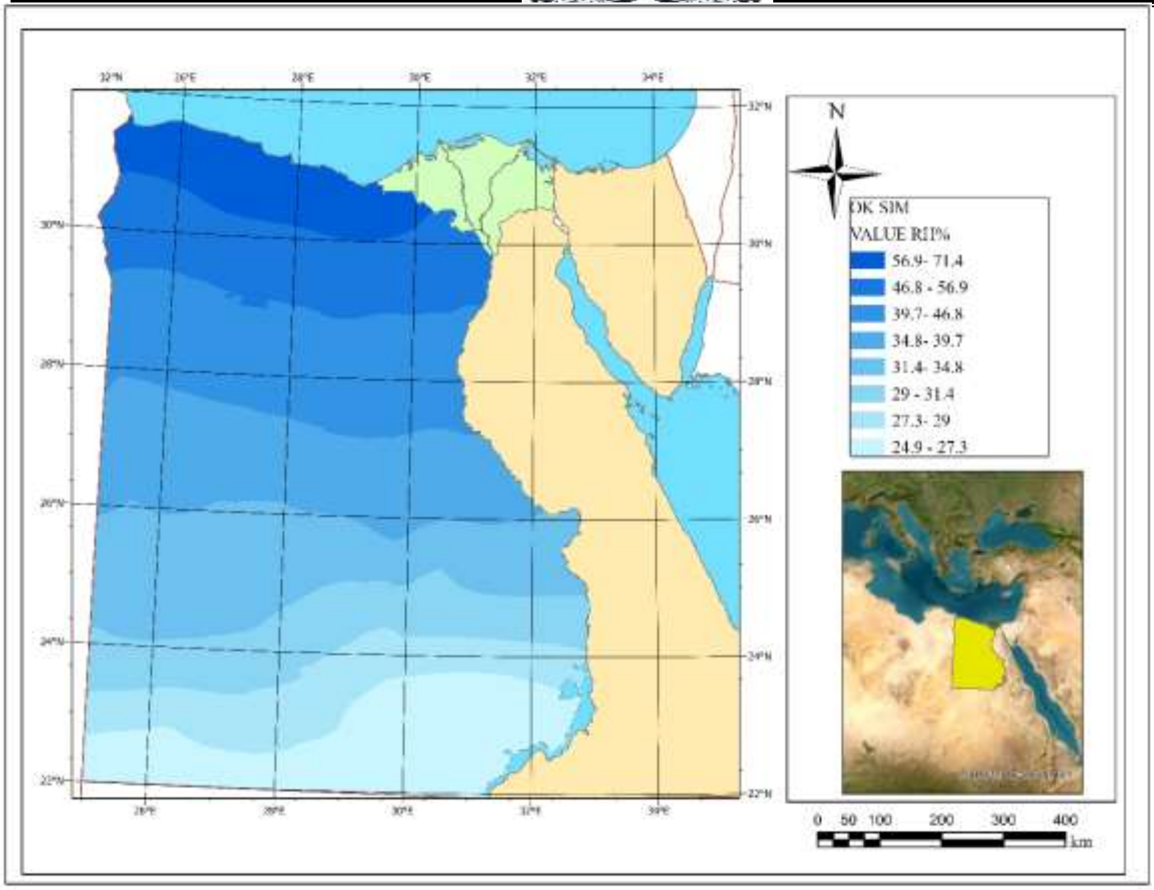

Fig 9: show the Distribution pattern of Relative Humidity using High density area using OK

When interpreting the spatial distribution map of relative humidity patterns in the Western Desert using CR_Spline method Fig10 with High dense data network and the same method, we notice from the spatial interpretation of the distribution an increase in the humidity percentage near the valley west of Qena in the same period and using the same interpolation method.

The influence of Lake Nasser water factor also disappeared, as the southern region from latitude 22 north to latitude 28 north shows the lowest humidity percentage in the region in that period 2010-2022.The influence of the Red Sea water extends inland in the Western Desert to the south of latitude 30.

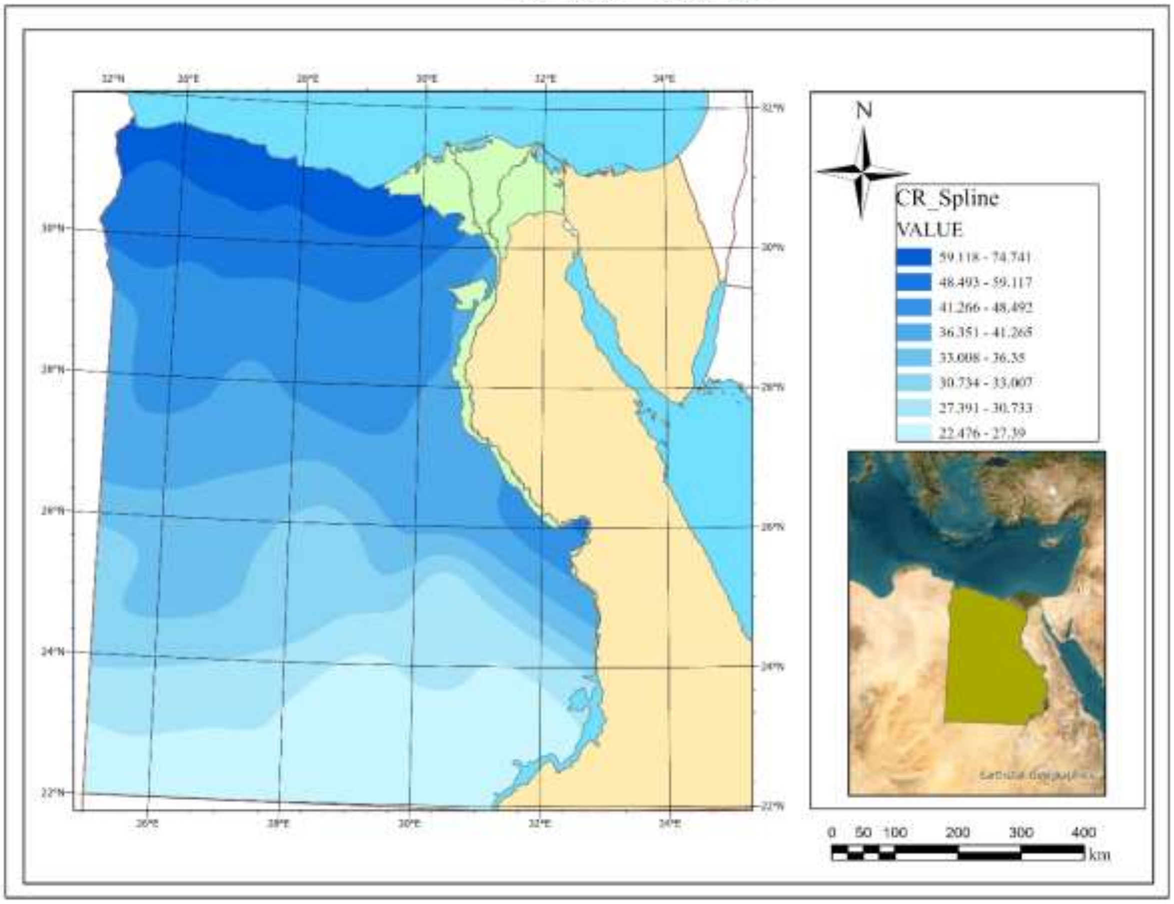

Fig 10: show the Distribution pattern of Relative Humidity using High density area using CR_Spline SIM

4.3.Accuracy assessment of IDW, CR_Spline and OK interpolation techniques at varying sampling density scenarios:

The prediction performance of IDW, CR_Spline and OK interpolation techniques was assessed in two sampling density scenarios. Validation and cross-validation operations were performed to assess the accuracy of the interpolation outcomes.

These error metrics are frequently used in comparing model performance because of their adequacy, The Mean Error (ME) represents the arithmetic average of all the estimated errors in the interpolation. It indicates the direction and the average of the estimated errors. The positive bias represents an overestimation of the variable whereas the underestimation is represented by negative bias [10].

Mean Error= $\frac{1}{N}\sum_{i=1}^{N}[p_1 - Q_1]$

Root mean square error (RMSE) is the most widely and commonly used cross-validation parameter. It has the advantage that it holds the same measuring unit as the predicted value. Lower RMSE indicates higher performance:

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}[P_1 - Q_1]^3}$$

Where: Q_i represents measured value, P_i is the predicted value, Q is the average of measured values, N is the number of samples

The Mean Standardized Error (MSE) provides the average of the standardized errors. For optimal model, the value of MSE should be close to Zero 0:

MSE values range from 0 to positive infinity, with the smaller the value, the higher the accuracy of the interpolation model [33]:

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(\hat{z}(s_i) - z(s_i)\right)^2$$

To assess accuracy objectively compare the interpolation accuracy of the Three spatial interpolation methods. And to evaluate the interpolation performance of three interpolation methods using the following accuracy metrics were calculated to assess the performance of the interpolation models: mean error (ME), mean Standardized error (MSE) root mean square error (RMSE) shows in table 3.

Method		Neighbours		ME	MSE	RMSE
		Max	Min			
IDW	High Density	5	5	**0.01**	2.73	
	Low Density			0.42	5.01	
OK	High Density	10	5	0.02	2.14	0.91
	Low Density			**0.1**	**4.1**	0.88
CR_Spline	High Density	20	15	0.03	**1.9**	
	Low Density			0.27	5.13	

Table 3 accuracy assessment for three spatial Interpolation Methods, ME = mean error, MSE: mean standardized error, RMSR = root mean square error,

5. Results:

Errors were calculated as 'actual minus predicted' and the mean of these errors was calculated in 3 ways: mean error (ME), indicating the degree of bias; providing a measure of how far the estimate can be in error relative to the measured mean; root mean square error (RMSE), providing a measure that is sensitive to outliers Conclusions [14] .

The results showed that the method CR_Spline was the best performance in high data density with ME 0.03 and RMSS 1.9 and that IDW method with the lowest error rate outperformed ME 0.01in high data density, but the OK method it best performing in low density ME 0.1, RMS 4.1, RMSS 0.88.

6. Conclusions:

The results of this study provide information that there will be changes relative humidity from. Based on the deterministic Spatial Interpolation method like (IDW, CR_Spline) and geostatistical spatial interpolation methods like ordinary kriging OK results, predict an increase in Relative Humidity in the northing area WDE area. In general, there is a significant difference in implementing these three methods, but if we look at the prediction errors, in this case, the Ordinary Kriging method is better than the IDW method. With this research, it is hoped that it can become a consideration for related parties related to climate change in the WDE.

Three spatial interpolation methods were applied to study the spatial distribution of relative humidity patterns in the Western Desert of Egypt, using two sets of data grid density, one of which is low, with 23 points distributed randomly in the area, and the other with a high-density data with 51 data points. The surface continuous created by the three interpolation methods were interpreted and a difference was found in the visualization and cartographic interpretation of the spatial distribution of relative humidity patterns in the study area. The evaluation of the accuracy of the performance of the spatial interpolation methods was applied using statistical accuracy measures to estimate the error in predicting these surfaces. It was found that the CR_Spline method is the best when using high density, while the method is the best in performance using the method.

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