Evaluation Affected the Topography Factor for Accuracy Spatial Interpolation Methods to Producing Annual Relative Humidity Mapping for Western Desert of Egypt

Prepared by

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المستخلص:

تعتمد أفضل نتائج طرق الاستيفاء المكاني على الكثافة العالية لشبكة البيانات ، كما يعتمد أداء الاستيفاء أيضًا على التباين المكاني المحدد (تضاريس السطح) لمتغيرات المناخ. ولأن بيانات المناخ يصعب الحصول عليها من محطات الأرصاد الجوية الأرضية في صحراء مصر الغربية، فإن بحثنا يعتمد على قاعدة بيانات NASSA POWERللحصول على بيانات الرطوبة النسبية للفترة 2010–2022م، حيث أكدت العديد من الدراسات وصدقت على مدى توافق بيانات NASSA POWERمع بيانات المحطات الأرضية ويمكن الاعتماد عليها للتغلب على البيانات المفقودة. ومن ثم هدفنا إلى تطبيق عملي لطرق الاستيفاء المكاني للتوزيع المكاني لبيانات الرطوبة النسبية السنوية واختيار أفضل نماذج الاستيفاء المكاني من بين ثلاث طرق استيفاء مكاني: ordinary kriging, Empirical Bias kriging Regression Prediction and Thin Plate Smooth Spline method، تُظهر نتائج المقارنة للتقييم الإحصائي و الكارتوجرافي لخرائط التوزيع المكاني للرطوبة النسيبة أن أفضل النماذج كانت مبنية على ordinary kriging مع ME: 0.002، MS: 0.006، RMS: 1.4، RMSS: 1.1، نموذج TPS_Spline حقق الأداء الأفضل مع MS: 0.001، RMS: 1.7، طريقةEBKRP كان أدائها ليس مختلفًا كثيرًا عن الطرق الأخرى حيث إن مقاييسه الإحصائية هي ME: 0.04، RMS: 1.2، RMSS: 0.8، MS: 0.007. يشير بحثنا إلى أهمية استخدام المقارنة الإحصائية والخرائطية لنماذج الاستيفاء المكاني قبل تحديد الأساليب التي يجب الاعتماد عليها. كما يجب مراعاة ارتفاع المحطات وارتفاع المنطقة لتحسين أداء طرق الاستيفاء المكاني.

الكلمات المفتاحية: أساليب الاستيفاء المكاني، TPS_Spline، OK، EBKRP، خرائط الرطوبة النسبية

Abstract

The best results for spatial interpolation methods depend on the high dataset network density, and interpolation performance also depends on station density and the specific spatial variability (surface topography) of the climate variables. And because climate data are difficult to obtain from ground-based meteorological stations in the Western Desert of Egypt, our research depends on the NASA POWER database to obtain a relative humidity dataset for the period 2010-2022, where many studies have confirmed and validated the extent to which NASA POWER data is consistent with ground station data and can depend on overcome missing data from weather station sites. And then aimed to an operational application for spatial interpolation methods of spatial distribution to Annual data relative humidity and select the best spatial interpolation models among three spatial Interpolation algorithms Geostatistic interpolation methods (Ordinary kriging, Empirical Bias kriging Regression Prediction), and deterministic spatial interpolation methods (Thin Plate Smooth Spline). The paper shows the comparison Statistic assessment and cartography visualization that the best models were based on ordinary kriging with ME: 0.002, MS: 0.006, RMS:1.4, RMSS: 1.1, thin TPS_Spline Model the better performance with MS: 0.001, RMS: 1.7, EBKRP Performance is not big different about other methods so its Statistic measures are ME:0.04, RMS:1.2, RMSS: 0.8, MS:0.007. Our research indicates the importance of using statistical and cartographic comparison of spatial interpolation models before determining which methods to depend on. The height of stations and the area's elevation must be considered to improve the performance of spatial interpolation methods.

Keywords: Spatial Interpolation Methods, ordinary kriging, Empirical Bias kriging Regression Prediction and Thin Plate Smooth Spline method, Relative Humidity NASSA POWER dataset.

1. Introduction

Spatial interpolation needs to produce accurate weather data to correctly model climate mapping [5]. so sufficient climate datasets are essential for understanding climate change and its impact on ecosystem services, hydrological processes, and natural disasters, especially in mountainous areas with complex terrain and sparse ground observations.

Temperature and precipitation are critical climate factors [22] . Egypt has a hot-arid desert climate, and the Western Desert is one of the driest parts of the Sahara Desert, with an average annual precipitation close to zero [19] .

Here we present a study on the spatial distribution of relative humidity in the Western Desert of Egypt (WDE). The paper relied on predicting the study variable data through different climate interpolation methods, namely the ordinary kriging OK, the empirical kriging bias regression prediction EBKRP, and the thin-plate smoothed TPSS. Hence, we evaluate the performance of these methods for the distribution of relative humidity in WDE with moderate to easy terrain and aim to assess the effect of terrain surface on the accuracy of interpolation and where the performance of methods is affected by elevation. Most studies on spatial interpolation of weather data focus on accuracy. Other common limitations are reliability, the ability to perform and precision the predictive accuracy based on the differences between predicted values and observed values for new samples**.**

2. Literature Review

A study of [10] It was confirmed that the complex topography and land surface phenomena have an important impact on the spatial prediction of climate variables, where additional data such as elevation and coordinate location data relative to longitudes and latitudes were relied upon. Both IDW, OK, and KED were used, the results indicate that using the KED method with additional variables led to its superior performance over both IDW and OK.

A study of [6] This study was conducted to evaluate and compare the accuracy of the results of the EBK and EBKRP interpolation techniques to produce natural rate models for climate variables at different levels of data sample density, especially in environments with scarcity and characterized by dispersion of station locations. The study also relied on additional auxiliary data such as land cover and digital Elevation models (LULC, DEM), the results of the study generally indicated that there is a positive linear correlation between the accuracy of prediction and the density of the data sample, as the sample density affects by 85%: 87% the interpolation accuracy for both EBK and EBKRP, but EBKRP outperformed in general and at all levels of density as it is 40% more accurate than EBK in all accuracy measures (RMSE, MAE),the study also confirmed that the low density of the data sample can be overcome by coupling and adding additional auxiliary data to the interpolation methods, which helps to increase the accuracy.

[5] This study aimed to evaluate the actual spatial interpolation of air temperature and relative humidity to determine the best spatial interpolation model among 5 interpolation algorithms: OK, MLR, IDW, NN, and KED. The results showed that the

KED-Elevation method achieved the best results, especially with additional information such as elevation data obtained from GPS, where it achieved the lowest absolute error MAE. This study aimed to evaluate the effect of increasing the density of the station network on the interpolation performance by adding additional sites and several stations to improve accuracy.

The table (1) Below is the literature review that takes the of topography on interpolation performance, note KED method is similar to the EBKRP method both using auxiliary data

Methods	Area-period	Application	Covariables	**Results**	Reference
NN, IDW, OK, KED	North Germany (2009-2011)	Temperature RH	Elevation radar data	**KED**	[2]
IDW, OK, KED	Ethiopia (1983-2016)	Rainfall Temperature	Elevation Lat, long	**KED**	[10]
Kriging	Bangladesh	RH	--------	**Kriging**	[17]
NN, IDW, MLR, OKK KED	Belgium (1991-2020)	RH Temperature	Lat, Long Elevation	**KED**	[5]
TPS_Spline, SK	Germin (200-2021)	RH	Elevation	**Spline**	[21]
OK	Turkey (1975-2010)	Temperature precipitation	--------	**OK**	[14]
IDW, TPS, SK, CK, MLR	Turkey (1975-2004)	Temperature	Elevation	**MLR TPS**	[12]
IDW, NN, Spline, OK, UK	Iran (1970-2014)	Temperature precipitation	---------	**OK, UK, NN**	[1]
IDW, OK, Spline	Sumatra (2017-2021)	precipitation	--------	**IDW, OK**	[24]
IDW, CO-Kriging, TPS	Hengduan Mountain China (1961-2018)	Precipitation Temperature	Elevation	**Spline IDW**	[22]
EBK, EBKRP	Sweden (1991-2020)	Temperature	LULC, DEM	**EBKRP**	[6]

Table 1 shows the Literature review: NN: Nature Neighborhood, TPS: RBF Thin-Plate Spline, OK: Ordinary Kriging, UK: Universal Kriging, EBK: Empirical Bayesian Kriging, EBKRP: Empirical Bayesian Kriging Regression Prediction, KED: Kriging External Drift, MLR: Multiple Linear Regression.
Green is the best method

3. Concepts overview:

3.1.Spatial Interpolation methods:

Spatial interpolation refers to using known points' values to estimate the unknown points, which can be classified into deterministic and geostatistical methods. The deterministic interpolation methods estimate the values of unknown points directly based on the known surrounding points [22].

Several interpolation methods have been used in the past to generate regularly spaced grids from point measurements. Interpolated, the quality and density of observational data, the orography of the area, climate forcing factors, and the target spatial and temporal resolution [4] .

The theoretical basis of spatial interpolation methods is Tobler's First Law of Geography: "Everything is related to everything else, but near things are more related than distant things". Based on spatial autocorrelation, some climate factors' values are also controlled by other geographical factors, such as elevation, the distance to the coastline (DTC), and slope and aspect. Hence, methods taking environmental factors as auxiliary variables are developed, such as cokriging and TPSS [22] .

The correct determination of the spatial distribution of meteorological variables is as important as their measurement. Depending on the spatial attributes of the data, the accuracy of the results may vary widely among spatial interpolation methods. The choice of spatial interpolator is especially important in mountainous regions with fewer data, where the values of variables may change over short spatial scales[9]. All the interpolation methods assume that spatially distributed objects are spatially correlated; in other words, things that are close together tend to have similar characteristics [16] .

accurate climatic spatial interpolation remains an enormous challenge for regions with highly intricate terrain, diversified climate systems, and sparse ground observations [22]. Interpolation techniques can be grouped into 2 main categories: deterministic and geostatistical (fig1). Deterministic interpolation techniques create surfaces from measured points, based on either the extent of similarity (e.g. IDW) or the degree of smoothing e.g. CRS, TPS_Spline. A deterministic interpolation can either force the resulting surface to pass through the data values or not. An interpolation technique that predicts a value identical to the measured value at a sampled location is known as an exact interpolator. An inexact interpolator predicts a value that is different from the measured value and should be used to avoid sharp peaks or troughs in the output surface. TPS_Spline are exact interpolators. Geostatistical interpolation techniques (e.g. Empirical Biase Kriging Regression Prediction EBKRP, Ordinary kriging) utilize the statistical properties of the measured points. Geostatistical techniques quantify the spatial autocorrelation among measured points and account for the spatial configuration of the sample points around the prediction location for general descriptions [9] .We compared 3 spatial interpolation techniques for climate variable relative humidity, to determine the best climatic surface generation method for the Western Desert region in Egypt Fig2 The interpolation techniques were Thin Plate Smooth Spline TPSS, Ordinary kriging OK, and Empirical Bias Kriging Regression Prediction EBKPR. The chart fig1 shows the spatial interpolation methods that the research uses.

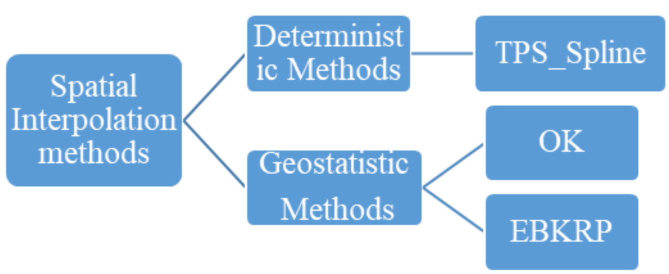


Fig1: Spatial Interpolation Method Using in Research

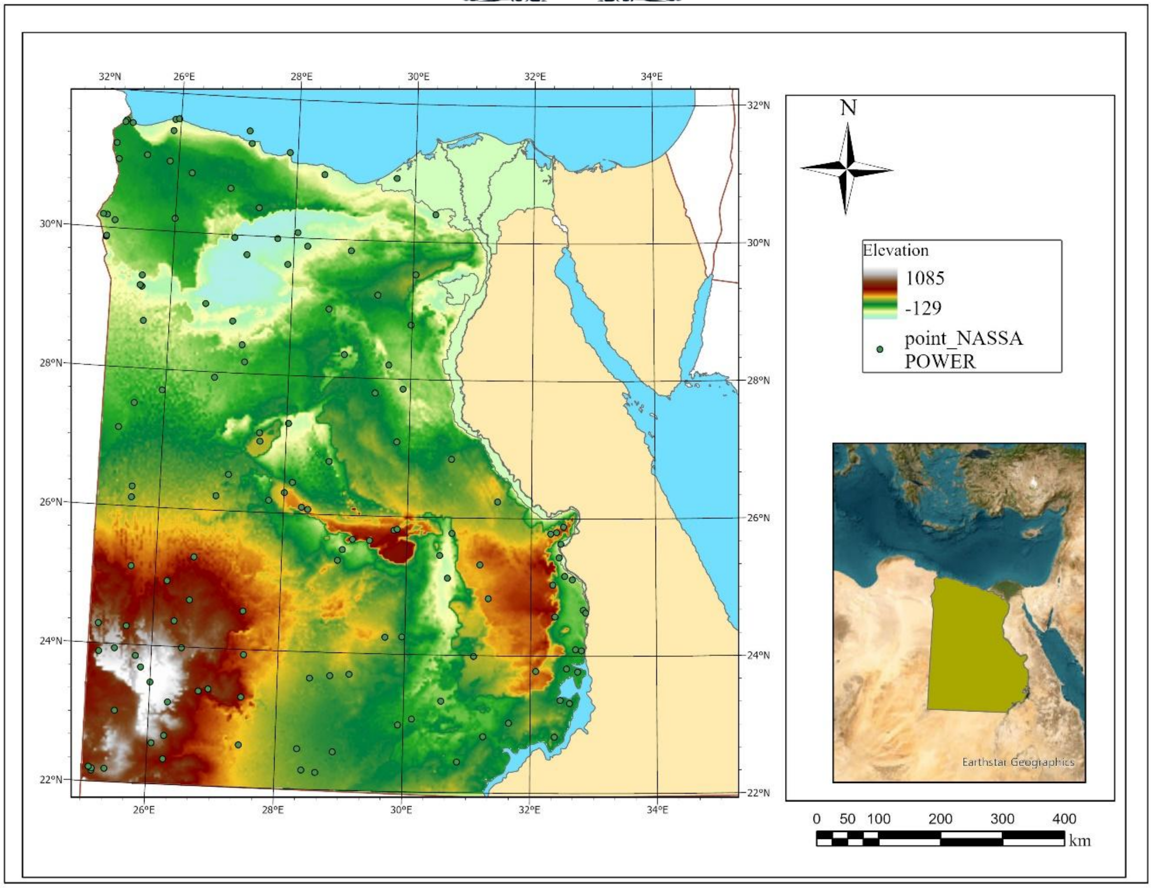


Fig2: Location of Study in the WDE region, Egypt

The following short description of deterministic and geostatistical spatial interpolation methods were used in the study:

3.1.1.TPS_Spline: As for the thin plate smooth spline (TPSS), one commonly used interpolation method adds multiple linear sub-models based on the thin plate spline function. Consequently, based on TPSS, developed the Australian National University Spline (ANUSPLIN) software package for climatic spatial interpolation. ANUSPLIN is especially suitable for spatial interpolating climate elements in a long time series because it could generate multiple surfaces of climate factors simultaneously [22] .

3.1.2.Kriging: is the name given to a class of statistical techniques for optimal spatial prediction. It was developed by Lev Gandin in 1959 for meteorological applications. It has been used in many other disciplines like environmental sciences. Kriging is a probabilistic predictor and, as such, assumes a statistical model for the data. Kriging predictors have standard errors that quantify the uncertainty associated with the predicted values. Kriging predictors are called optimal predictors because the prediction error is minimized and, on average, the predicted value and the true value coincide Kriging predictors: [7] .

• Have smaller prediction uncertainty than other prediction models
• Have the ability to filleter out measurement errors
• Use information on the correlation between the variable of interest and covariates

3.1.3.Ok: Ordinary Kriging is the most general and widely used of the kriging techniques. It estimates the value of the climatic variable at a given point from the values at surrounding stations and from a variogram model for that variable [9]. OK relaxes the requirement for a known mean in SK. It assumes the meaning is constant but unknown across the area of interest. This allows for wider use of kriging. Like SK, OK relies on the spatial dependence of the data to estimate values at unsampled locations [20] . The OK estimator can be shown in Eq. (1):

$$\hat{z}(x_0) = m\left(1 - \sum_{i=1}^{k} \lambda_i\right) + \sum_{i=1}^{k} \lambda_i z(x_i) \qquad (1)$$

Which $\hat{Z}(x_0)$ is the predicted value of the function at the location x_0, m is the mean value of the function in the neighborhood, k is the number of measured values, λ_i are unknown weights for each measured value $Z(x_i)$.

3.1.4.EBKRP:EBK Regression Prediction is a geostatistical interpolation method that uses Empirical Bayesian Kriging (EBK) with explanatory variable raster that is known to affect the value of the data you are interpolating. Are more accurate than either regression or kriging can achieve on their own. and the regression kriging model is constructed by extracting the values of the explanatory variable rasters that fall under each input point. then the explanatory variables are measured at the locations where you want to interpolate [11]. Can calculate the EBK using the equation below

$$z(x) = \sum_{i=0}^{N} \lambda_{i\,i} z(x_{ij}) \qquad (2)$$

Where: Z(x) was the predicted value (ij) was the coordinate of known points, λi was the weight coefficient [20].

3.1.4.1. Semi variogram estimation:

Kriging algorithms require the use of a semi-variogram (VGM) that needs to be estimated from the data [5] . Kriging uses a semi-variogram, a function of the distance and direction separating two locations to quantify the spatial dependence in the data. A semi-variogram is constructed by calculating half the average square difference of the values of all the pairs of measurements at locations separated by a given distance h. The semi-variogram is plotted on the y-axis against the separation distance h [7] . The semi-variogram modeling involves an estimation of the spatial autocorrelation and the statistical relationship within the samples to form a weighted average of observed values within a certain distance from the predicted point. The semi-variogram is expressed in (Eq. (2))

$$\gamma(h) = \frac{1}{2N(n)} \sum_{i=1}^{N(h)} [z\chi_i + hJ \rightarrow (x_i)]^2 \qquad (3)$$

where γ(h) is the semi-variance for interval distance class h; N(h) is the total number of sample pairs for the lag interval h; and Z (x_i + h) and Z (x_i) are the values of the regionalized variable Z at the x_i + h and x_i locations, respectively [21] .as can show in the fig3 the workflow that using.

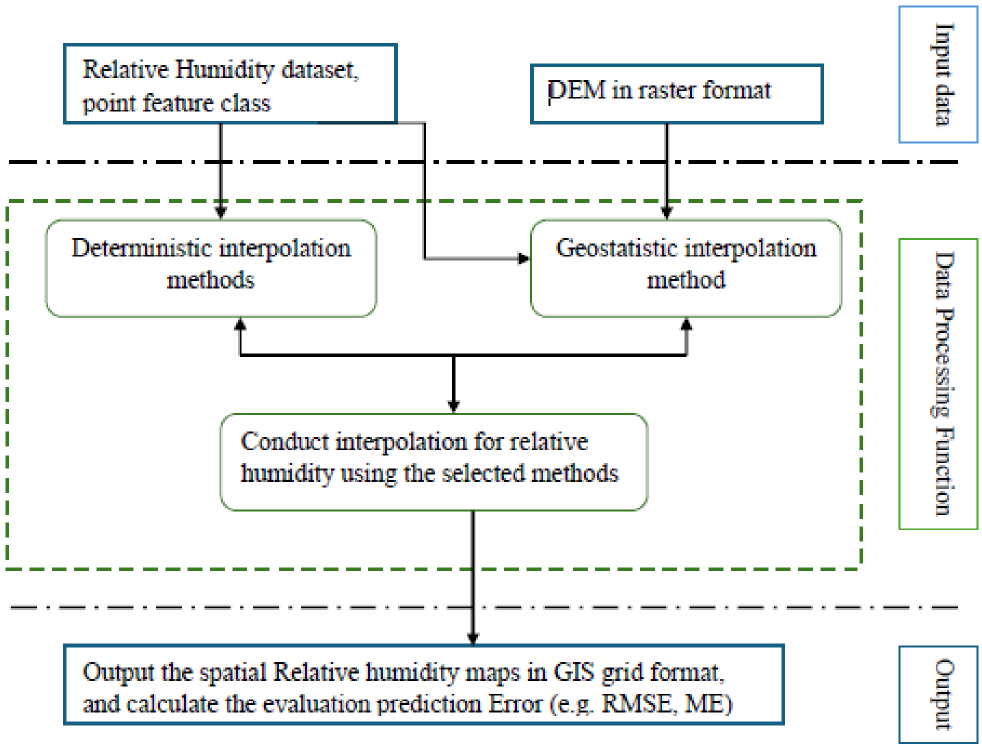


Figure3: workflow chart of GIS-based interpolation methods

4. Analysis

4.1.The Effect of Data Density and Elevation on Interpolation Methods Performance:

The best results determined that depended on the sampling density [9]. The interpolation performance depends generally on station density and the specific spatial variability of the climate information. The influences of spatial variability appear to be higher than thein fluence of station density the interpolation performance of relative humidity seems to be rather robust, due to the consideration of the DEM and the low spatial variability, Hence the best estimation accuracy is achieved for relative humidity [2]. in this research downloaded auxiliary data (SRTM 30m DEM) from OpenTopography.org

4.2.Site and Data:

4.2..1.Study area: Here we focus on the Western Desert in Egypt it was located between 22°-30° 35 North Latitude and 32°1 -30°33East Longitude, WDE located in 8 Northing latitude. The location map of the meteorological observation data used in the study is shown in Fig2.

4.2..2.Data: The low density of weather stations and high percentages of missing values of the climate data archived in most places around the world make it difficult for decision-makers to make meaningful conclusions in natural resource management [18] . The study depends on a data set from 150 points, these points are randomly distributed in the Western Desert of Egypt, where data on annual relative humidity over 13 years from 2010 to 2022 Relative humidity data can be obtained in Egypt through the Egyptian Meteorological Authority (EMA), but complete data may not be available due to temporary failures on weather stations. An alternative to obtaining meteorological data is the National Aeronautics and Space Administration Prediction of Worldwide Energy Resources (NASA POWER) satellite-based weather system.

was downloaded data from NASA POWER, from the Below website (http://power.larc.nasa.gov/cgi-bin/agro.cgi), so [13] It was mentioned that the data NASSA POWER is accurate and reliable, as its accuracy increases the higher the area is 400-7000 M.A.S.L, and its accuracy increases in dry and desert areas and in the summer. [3] It found greater correlations and better regression evaluation metrics when average daily Temperature Humidity Index values were considered, NASA POWER satellite-based weather system is a suitable tool for obtaining the average and maximum Temperature Relative Humidity Index values. And accurate [8] the results showed a high relation between the POWER reanalysis dataset and observed data for all parameters except wind speed. Additionally, POWER estimated data correlation accuracy for temperature variables increased toward higher altitudes in the study area.

Similarly, this performance was followed by relative humidity, increasing relation accuracy toward higher elevated regions. We Are using Elevation as an auxiliary factor in Spatial Interpolation methods, download the Open-source Digital Elevation model available on the NASA website. The NASA POWER dataset could predict relative humidity and give a promising result if used in research, water, and agricultural decision-making where observation data are not available [8] .the table(2) below show sample from the dataset:

Point	Latitude	Longitude	RH %2m	Point	Latitude	Longitude	RH %2m
1	30.19	25.9933	51.46	**14**	24.8299	31.3194	31
2	29.8856	28.2257	53.206	**15**	24.5583	27.4171	32.23
3	29.6109	27.9093	49.909	**16**	24.2542	29.9483	29
4	29.2128	29.421	48	**17**	22.5929	26.0636	27
5	28.6899	25.5714	42.14	**18**	22.7065	26.2569	27.026
6	27.8539	29.878	41.62	**19**	23.1921	26.2921	28.16
7	27.7917	29.421	42.88	**20**	24.2457	29.6847	28.34
8	26.2887	25.5538	35.79	**21**	22.3656	26.2569	27.026
9	26.2099	26.9073	34.97	**22**	22.1927	25.3495	26.03
10	26.131	25.5538	34.87	**23**	23.8429	25.7538	30.779
11	25.7991	29.7901	35.735	**24**	24.9474	26.1932	33.84
12	25.3393	28.8936	32.13	**25**	22.1927	25.3495	26.03
13	25.3234	31.1788	33.63	**26**	23.7785	32.0819	27.8

Table (2) Below is a sample from the dataset

4.3. Visualization Comparison of Spatial interpolation performance:

When interpreting the output surface continuously from different Spatial Interpolation Methods of Cartography Relative Humidity Spatial Distribution pattern (fig 4. 5, and 6) show that in:

4.3.1. TPS_Spline: When interpreting the cartographic map of the spatial distribution of relative humidity patterns in the WDS using the TPS_Spline method, we notice that the relative humidity decreases sharply in the south of the region, especially east of Lake Nasser and west of the Gilf Kebire Plateau.

Where the relative humidity rates decrease from the south after latitude 22 north to near latitude 28 north, we notice the effect of the Mediterranean Sea waters on the relative humidity in the north of the region from Salloum in the north to the west of the Nile Delta in the western desert of Egypt. We also note that the method does not show the interpolation of the entire southern region very close to latitude 22 north, while extrapolation data outside the region’s borders in the eastern part.

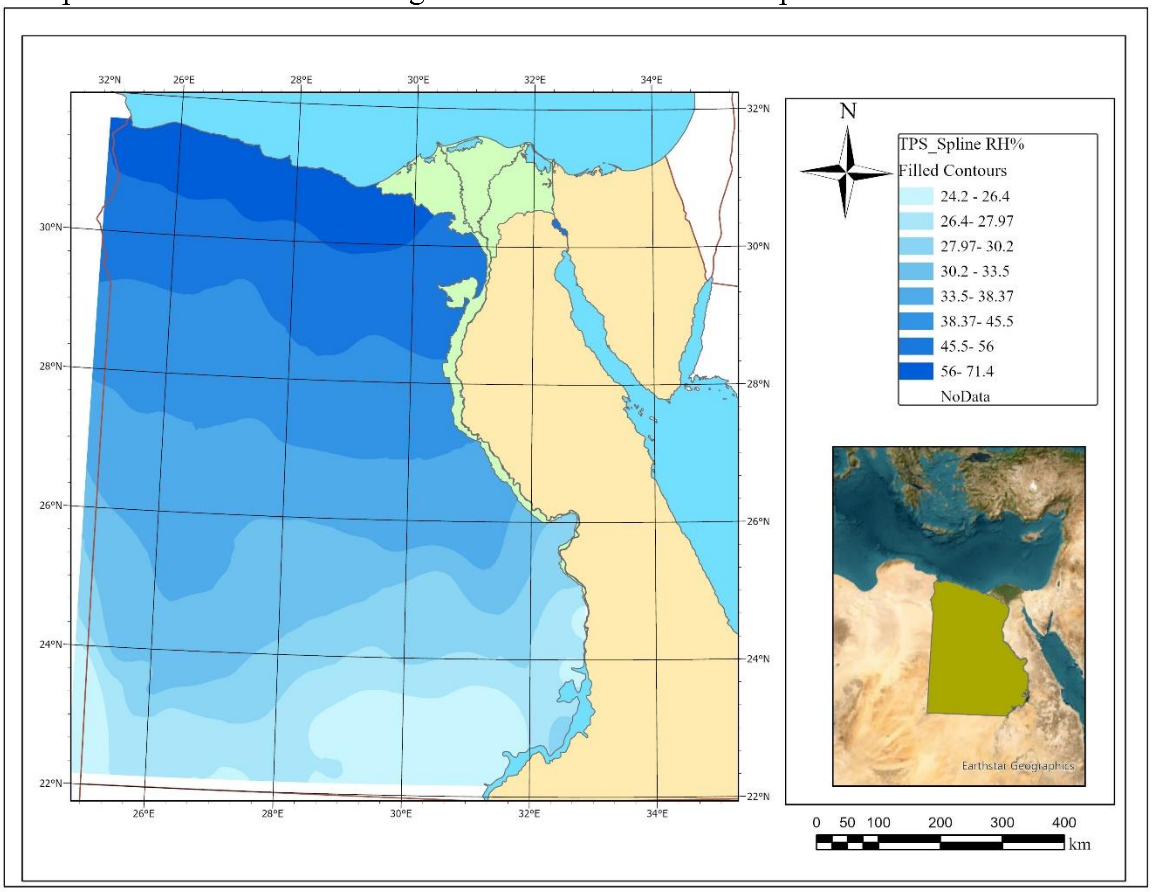


Fig4: The distribution pattern of Relative Humidity data in the study area using TPS_Spline

4.3.2. Ok: Relative humidity distribution maps using the OK method that shows the decrease in relative humidity from the south to the center of the Western Desert. This is due to the intensity of the drought in the region and its distance from any water bodies, as the effect of the Nile River or Lake Nasser on relative humidity disappears south of latitude 28 north to 22 north. The effect of the Mediterranean Sea waters extended to latitude 30 north. The model included the fall area and boundaries of the study, as shown by the contrast curve between the measured values and the predicted values in Figure 6 using the model.

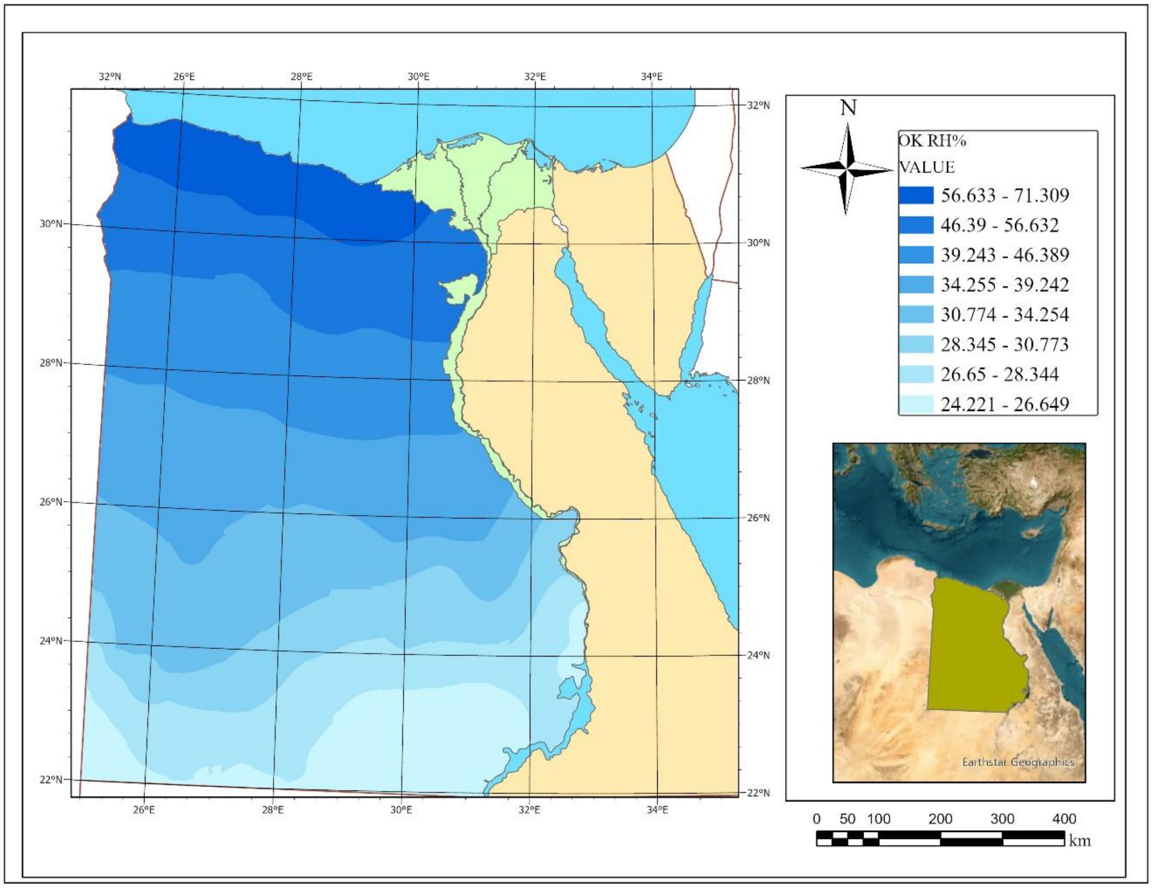


Fig5: show the Distribution pattern of Relative Humidity data in the study area using OK

4.3.3. EBKRP: It is clear from the spatial distribution of relative humidity data using a model EBKRP with the addition of the DEM as auxiliary data that improves the model's performance that it is clear from the visual distribution of relative humidity that its percentage is high in the north of the Western Desert and decreases inward towards the south of the region where it is affected by the dryness of the region near the Gilf Kebire Plateau until it reaches latitude 22 north. also, it is no Data on the Southern Border hence the method cannot mapping the Distribution of RH Data.

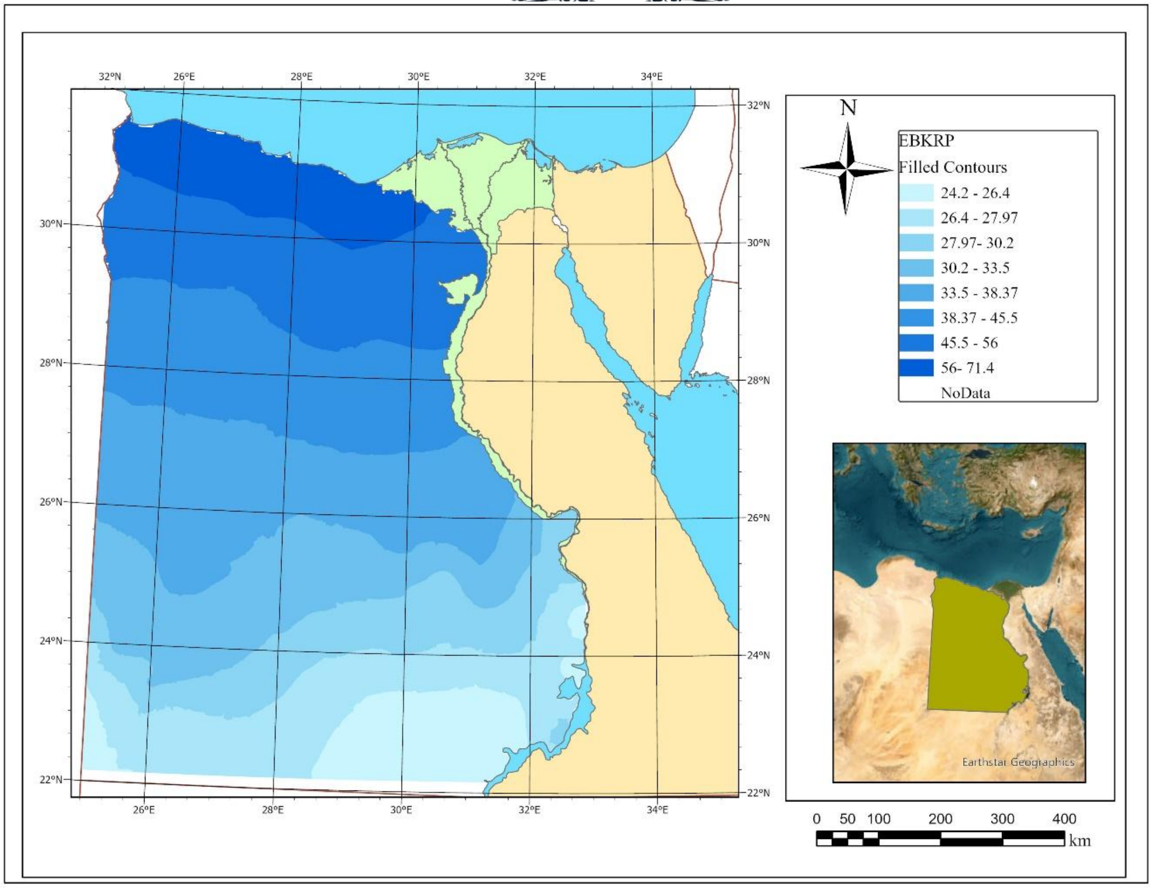
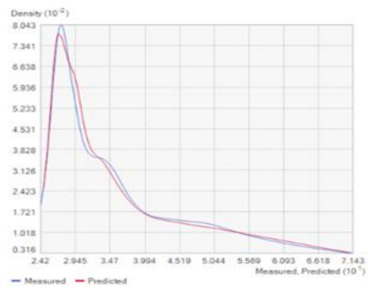
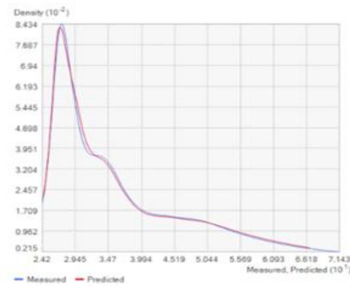


Fig6: show the Distribution pattern of Relative Humidity data in the study area using EBKRP

4.4 Quantitative evaluation of interpolation accuracy:

To objectively evaluate the applicability of TPS_Spline, OK, and EBKRP for climatic spatial interpolation in WDE, we compared their performance in the spatial interpolation of annual Relative Humidity from quantitative evaluation of interpolation accuracy through five statistical measures metrics. To assess accuracy objectively compare the interpolation accuracy of the Three spatial interpolation methods. To evaluate the interpolation performance of three interpolation methods the following accuracy metrics were calculated to assess the performance of the interpolation models: ME: Mean Error, RMSS: Root Mean Square Standardized Error, RMS: Root Mean Square Error, MS: Mean Standardized, ASE: Average Standard Error shows in table3. The semi-variogram from EBKRP and OK Methods is shown in Fig 9 It shows the variation in measured data and predicted data for relative humidity values. Fig 8 also shows the correlation between the measured data and the predicted data for relative humidity values. We notice that the EBKRP method is affected by the height limits, while the TPS_Spline method has a strong correlation between the measured data and the predicted data.





OK: EBKRP:

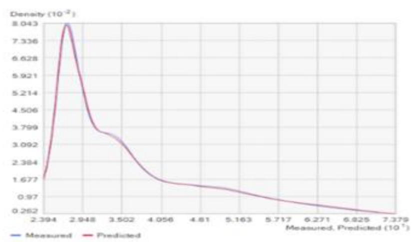
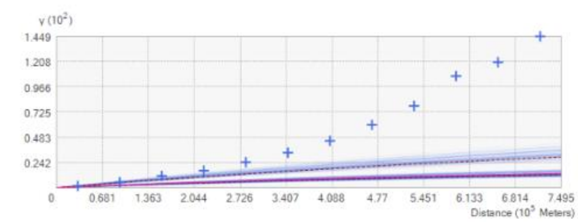


fig 8: TPS_Spline:



EBKRP Semi Variogram

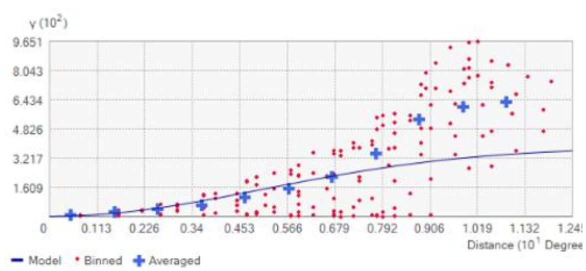


Fig9 OK semi variogram

Method	point	Neighborhood	ME	RMS	MS	RMSS	ASE

		Max	Min					
TPS_Spline	143	10	5	0.001	1.7			
OK	143	15	10	0.002	1.4	0.006	1.18	1.14
EBKRP	138	10	5	0.04	1.2	0.007	0.8	1.27

Table 3 accuracy assessment for three spatial Interpolation Methods, ME = Mean Error, RMSS = Root Mean Square Standardized Error, RMS = Root Mean Square Error, MS= Mean Standardized, ASE= Average Standard Error

5. Result:

Errors were calculated as 'actual minus predicted' and the mean of these errors was calculated in 5 ways: mean error (ME), indicating the degree of bias; root mean square error (RMSE), providing a measure that is sensitive to outliers [9]. The study's results reached the importance of statistical and cartographic comparison of spatial interpolation methods to determine the least error-estimating methods and the most accurate methods for representing relative humidity data in the Western Desert.

The study also stressed the importance of adding auxiliary data that works to increase the accuracy of prediction and spatial distribution of climate variables (Elevation). Here in our research, such as the geostatistical method (OK, EBKRP) and deterministic methods (TPS_Spline), semi-approximate results for the distribution of relative humidity patterns in the study area were obtained, as the size of the neighbors in the search circle of each method was determined with the least error in the estimates, with the number of sample data increasing to 150 points. Where an OK method came in the first level with high-performance accuracy, followed by the TPS_Spline method and then an EBKRP method for representing relative humidity data in the Western Desert in Egypt in the period 2010-2022 AD

6. Conclusions:

The study based itself on a dataset of NASSA POWER, according to previous studies that approved the extent of their credibility and effectiveness in relying on data in areas deprived of meteorological stations or due to technical failure in existing stations. Data from 150 sites were downloaded for relative humidity values in the Western Desert in Egypt, as the research aimed to study the spatial distribution of relative humidity and its consequences in environmental studies related to the relative humidity percentage, especially in agriculture.

The study also deboned the environment of geographic information systems that provide us with spatial interpolation models. It was conducted by comparing three methods, including a deterministic method (TPS_Spline) and two geostatistical methods (OK, EBKRP), to study and compare statistical measures to ensure the lowest error rate in estimates and predictions of relative humidity values. The study recommends the importance of a visual cartographic comparison of the outputs of spatial interpolation methods with a statistical comparison to estimate the lowest error rate between the outputs of these methods.

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