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Comparison of Spatial Adjacency Matrices (Rook, Queen) of the SAR-MA Model Using MLE for Diabetes

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Abstract

The purpose of this study is to assess the impact of various adjacency matrices (Rook and Queen) on the accuracy of the spatial autoregressive-moving averages model (SAR-MA) and to examine the effects of spatial dependency on the estimates of the model using the maximum likelihood approach (MLE). The study's foundation was actual diabetes data. Concerning Iraqi children in 2024, when data was gathered from different governorates, including variables like age, gender, cumulative blood sugar level, and other factors that impact the disease's spread, the presence of spatial dependence was tested using Moran's Z test. The maximum likelihood method (MLE) was then used to estimate the model parameters. To guarantee precise estimates and expand the range of potential future uses of spatial models in urban planning and economics, the study recommended utilising the SAR-MA model in conjunction with the Rook adjacency matrix in spatial analysis. Additionally, some variables (S4, S5, S8) showed a clear geographical dependence in the results, whereas others did not.

1. Introduction

One of the most well-known contemporary techniques in scientific research is using spatial analysers to examine variables and their interactions in various situations. Spatial models, such as autoregressive models (SAR) and spatial error models (SEM), are used to more precisely evaluate these relationships to enhance statistical estimates and make better decisions .3 Models that successfully integrate geographical effects must be created, as spatial dependency is a significant data hurdle. For instance, geographical overlaps between adjacent regions may cause spatial differences in the population density or unemployment rate[10], Accordingly, one of the most popular models in the field of spatial analysis is the Spatially Autoregressive-Moving Media (SAR-MA) model, which integrates the effects of spatial lag and spatial errors to examine phenomena in greater depth [2], The use of the potential technique is essential to this investigation. Using spatial adjacency matrices like Rook and Queen, which have been successful in studying spatial relationships, maximum Likelihood (MLE) is used to estimate the parameters of this model. This analysis is a crucial step in enhancing the accuracy of spatial modelling and offering more profound insights to aid in the development of social and economic policies.

2. Research Aims

Evaluating the maximum likelihood method's (MLE) effectiveness in estimating spatial model parameters, assessing the impact of using various adjacency matrices, such as Rook and Queen, on how accurate projections are, and evaluating and assessing the efficacy While analysing spatial differences between variables using the spatially autoregressive-moving averages (SAR-MA) model and Analyzing data on childhood diabetes and its prevalence in particular governorates is the Aim of the research. Based on the values of the dependent variable V and the explanatory variables S_i.

3. The theoretical aspect

3.1 Spatial dependence

The following formula can be used to illustrate how watching at position (i) depends on seeing at location (j) when there is spatial dependence between a collection of sample data.: [8,12]

$$V_i = f(V_j)\ ,\quad i = 1,2,\ldots\ldots.,n \qquad i \neq j \tag{1}$$

The calculation above indicates that reliability can exist across many observations, since location (i) might take any value from the values of (n). The first argument that causes us to think that the sample data recorded in a particular place depends on values observed in Other websites Data collection for observations is based on geographical units like cities, provinces, and postal codes, This may be due to measurement mistakes in adjacent geographical units, or if the administrative boundaries of the information gathered do not precisely represent the nature of the underlying process that provides data for the sample, as an example, unemployment rates and labor measures may be calculated using spatially dependent data, because workers and labor mostly travel between governorate and regional borders in search of job opportunities in nearby areas. As a result, the unemployment rate and labour force calculated based on people's residence areas will exhibit spatial dependency [11].

The second reason for our expectation of dependability in the data is the spatial dimension of socio-demographic activity, or regional or economic activity, which may be the most essential aspect of the modelling task [13].

3.2 Spatial Autoregressive- Moving Average (SAR-MA)

The previously established SAR and SEM spatial models are combined to create the Spatial Autoregressive Moving Average (SAR-MA) model. There is a strong connection between spatial autoregressive models with moving averages (SAR-MA) and Autoregressive Moving Average (ARMA) in time series models. Time series processes are represented by the widely used class of (ARMA) models, which has a spatial counterpart in the form of the (SAR-MA) model. SAR-MA models link observations in the region where they occur, unlike ARMA models, which relate observations in time. The concept behind both kinds of correlation matrices is that the data is subjected to a particular structure before estimating the real parameters [9].

According to equation 2]:

$$\begin{aligned} V &= \rho W_1 V + S\beta + u \\ u &= \lambda W_2 u + \varepsilon \qquad \varepsilon \sim N(0,\ \sigma^2 I) \end{aligned} \tag{2}$$

Since V: A vector of the dependent variable's dimension (n×1). S: An explanatory variable matrix of size (n×k). W_1, W_2: spatial weight matrices are represented in dimension (n×n), where (W_1) represents the matrix of spatial adjacencies between observation and adjacent area, and (W_2) represents the adjacencies between observation and the city centre. They are usually a proximity relationship or a distance function, which are fixed and predetermined, and can be equal ($W = W_1 = W_2$). λ: Spatially correlated error parameter. ρ: Spatial dependence parameter.

If W1≠0 and W2≠0 SAR-MA (4) will be developed as a model equation (5), the following is the general equation for the SAR-MA model:

$$V = \rho W V + S\beta + (I - \lambda W)^{-1}\varepsilon \tag{3}$$

(V ،S، ε،W ،ρ, λ ، β) Indicates that a model is selected $\mathrm{SAR} - \mathrm{MA}$

$$(I - \rho W)V - S\beta = (I - \lambda W)^{-1}\ \varepsilon \tag{4}$$

3.3 Spatial Contiguity Matrix

Its dimensions are (n×n). If i and j are adjacent, then Wij=1, but if i and j are not adjacent, then Wij=0, where i and j are locations, and Wij represents an element in the matrix W.

$$W_{ij} = \begin{cases} 1 & \text{The Spatial Unit is j , and it is a neighboor of i} \\ 0 & \text{otherwies} \end{cases} \tag{5}$$

There are types of juxtapositions to build a spatial juxtaposition matrix, and the following figure explains the difference between each type of juxtaposition [5].

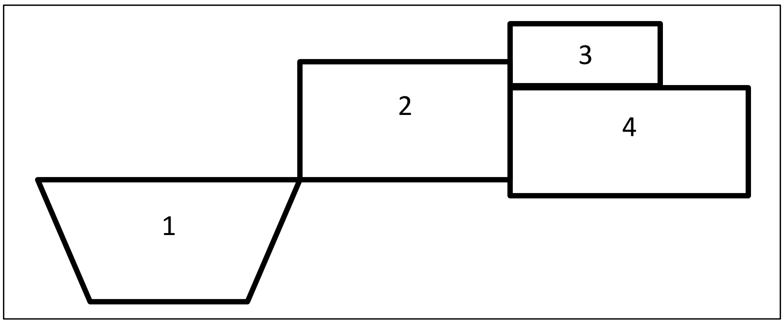

Figure 1: Adjacent areas

3.4 Rook Contiguity

The value of the elements that take the value one is that two adjacent regions share a common border on any side, while the other aspects of this matrix take the value zero 1. It is one of the most used juxtapositions.

$$W_R = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

3.5 Queen contiguity

It is a matrix whose elements are combined from the adjacency matrix Rook's components and the Bishop matrix elements [4], as shown below. The adjacency in this matrix is a common edge or a common point.

$$W_Q = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

3.6 Moran Coefficient Test

The Moran coefficient is a tool for measuring the spatial dependence in the data of the phenomenon to be studied and the extent of similarity between them. We can symbolise it with Imc, analogous to the Durbin Watson test in time series data. The value of the Moran coefficient ranges between [+1, -1]. The data's spread pattern is close if the Moran's coefficient value is near [+1]. The data spread is divergent among them if the Moran's coefficient value is near [-1]. On the other hand, we observe that the data exhibits random geographic distribution if the value of Moran's coefficient is near 0. [6]

The following is the formula for Moran's coefficient:

$$I = \frac{n(u'wu)}{S_\theta(u'u)} \quad S_\theta = \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} \tag{6}$$

The following formula can be used to execute the Moran's Z test, and the asymptotic distribution of Moran's statistic was attained because it agrees with the conventional normal distribution. (7):

$$Z = \frac{I-E(I)}{\sqrt{Var(I)}} \quad E(I) = \frac{tr(M\,W)}{n-k} \tag{7}$$

To test whether spatial dependence exists or not, we use the following hypothesis:

$H_0: \rho = 0$ There is no spatial dependence.

$H_1: \rho \neq 0$ There is spatial dependence.

Through the formula (7), if the calculated value is greater than the tabulated value at a certain level of significance, we accept the alternative hypothesis, which means that there is a spatial dependence between the items of the studied phenomenon. However, if the calculated value exceeds the null hypothesis, which states no spatial relationship between words, it is accepted based on the tabulated value and the phenomenon under study.

3.7 The maximum likelihood method for estimating SAR-MA:

Maximum likelihood estimators are stable, highly efficient, and have the property of consistency, i.e. the estimation process is done by making the maximum likelihood function estimators of the random variables as significant as possible7 .

The maximum potential function for the (SAR-MA) model is obtained as follows:

$$twone\ L(\beta,\rho,\lambda,\sigma^2 \mid V,S) = -\frac{n}{2}\ \ln 2\pi - \frac{n}{2}\ \ln\ \sigma^2 + \ln\left|\mathrm{I} - \rho w\right| + \ln\left|\mathrm{I} - \lambda w\right| - \frac{1}{2\sigma^2}\ \varepsilon'\varepsilon \tag{9}$$

$$L(\beta,\rho,\lambda,\sigma^2 \mid V,S) = -\frac{n}{2}\ \ln 2\pi - \frac{n}{2}\ln\ \sigma^2 + \ln\left|\mathrm{I} - \rho w\right| + \ln\left|\mathrm{I} - \lambda w\right| - \frac{1}{2\sigma^2} * (I-\rho w)'V'(I-\lambda w)'(I-\lambda w)(I-\rho w) - (I-\rho w)'V'(I-\lambda w)'(I-\lambda w)SB - B'S'(I-\lambda w)'(I-\lambda w)V(I-\rho w) + B'S'(I-\lambda w)'(I-\lambda w)SB \tag{10}$$

$$twotwone\ \frac{\partial(\beta,\rho,\lambda,\sigma^2/\ V,S)}{\partial\beta} = -\frac{1}{2\sigma^2} * [-\ 2S'(I-\lambda w)'(I-\lambda w)V(I-\rho w) + S'(I-\lambda w)'(I-\lambda w)\ S\hat{\beta}_{\text{mle}} \tag{11}$$

$$Numerator\ \frac{\partial(\beta,\rho,\lambda,\sigma^2/\ V,S)}{\partial\beta} = 0 \tag{12}$$

Using iterative approaches for the probability function, the correlation parameter (ρ) value is estimated as follows:

$$one\ |\mathrm{I} - \rho\,\mathrm{W}| = \prod_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{I} - \rho\, wi)\ \ln|\mathrm{I} - \rho\,\mathrm{W}| = \sum_{\mathrm{i}=1}^{\mathrm{n}} \ln(1 - \rho\, wi) \tag{13}$$

Also, to estimate the value of the parameter (λ), it is found using iterative methods, as follows:

$$|\mathrm{I} - \lambda\mathrm{W}| = \mathrm{one}\prod_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{I} - \lambda\,\mathrm{wi})\ \ln|\mathrm{I} - \lambda\,\mathrm{W}| = \sum_{\mathrm{j}=1}^{\mathrm{n}} \ln(1 - \lambda\, wi) \tag{14}$$

4. Applied Framework

The application of the maximum likelihood technique (MLE) to the estimation of spatially moving averages (SAR-MA) is covered in this section. On the experimental side, this approach will yield the best results. It will be used with actual data on childhood diabetes in every Iraqi governorate till 2024. This analysis examines how certain factors affect the disease's impact and rate of spread. Additionally, the data will be examined for the presence of spatial juxtapositions.

4.1 Describe And Collect Study.

An electronic questionnaire on childhood diabetes was sent to all Iraqi governorates to collect the data for the analytical component. The research aim is to analyse data on childhood diabetes and its prevalence in particular governorates. Based on the values of the dependent variable V and the explanatory variable S, a sample of 135 patients was chosen. Given that the data is usually distributed, these data sets will aid in elucidating the distinctions between the various forms of diabetes and their effects on public health, in addition to other countries where multiple forms of the disease manifest in children. The focus will be on the fundamental trends of disease spread in 2024.

4.2 Estimation of the spatially autoregressive-moving average (SAR-MA) model using the maximum likelihood method (MLE) under adjacency matrices (Rook, Queen).

The following were the outcomes of applying the MATLAB software to run Moran's (Z) test for the existence of spatial linkage using the spatial weights matrix: Two hypotheses are examined in the spatial dependency test, and the findings are shown in Table 1 using P-values:

$H_0: \rho = 0$ No spatial dependence exists.
$H_1: \rho \neq 0$ There is geographical dependence.

The variable (S5) has the lowest P-value (0.000), indicating a substantial spatial dependency. The variable (S4) has the next lowest P-value (0.0063), suggesting that the null hypothesis may be rejected. The P-values for the variables S1, S2, S3, S6, and S7 are more than 0.05, indicating the absence of geographical dependency. The P-value for the variable S8 is 0.0338, indicating the presence of spatial dependence. For the explanatory variables (S1, S2, S3, S6, and S7), the null hypothesis (H0) is accepted.

Given that these variables exhibit spatial dependency, the null hypothesis (H0) is rejected at (S4, S5, and S8). In conclusion, we discover that, in contrast to the other variables, the variables (S4, S5, and S8) exhibit robust statistical evidence of spatial dependency. Backs up this theory. The accompanying table shows that the P-value will determine whether the hypothesis is accepted or rejected.

Table (1 displays the actual data values for the P-value used to accept or reject the hypothesis.

decision	P- value	Standard value	Spatial correlation value	Variables
No spatial correlation exists.	0.2343	1.1894	0.0168	S_1
No spatial correlation exists.	0.3124	1.0102	0.0105	S_2
No spatial correlation exists.	0.6802	0.4122	-0.00010454	S_3
A spatial link exists.	0.0063	1.9802	0.0011	S_4
A spatial link exists.	0.000	11.2358	0.1964	S_5
No spatial correlation exists.	0.1221	1.5459	0.0199	S_6
No spatial correlation exists.	0.1502	1.4388	0.0179	S_7
A spatial link exists.	0.0338	1.9606	0.0306	S_8

Table (2) : It shows the estimated values of the MLE method through the Rook adjacency matrix

T	V	$\hat{V}$	T	V	$\hat{V}$	T	V	$\hat{V}$	T	V	$\hat{V}$
1	9.42	1.63	35	12.00	3.19	69	0.25	15.39	103	5.50	2.26
2	7.00	25.50	36	11.67	6.43	70	1.67	7.65	104	5.00	9.17
3	7.00	19.27	37	0.25	1.11	71	3.00	3.19	105	11.00	10.23
4	5.00	18.76	38	1.17	10.85	72	9.00	6.30	106	13.00	1.72
5	5.00	15.14	39	6.00	3.19	73	12.00	11.10	107	13.00	18.26
6	9.00	0.84	40	1.00	2.10	74	12.00	3.94	108	5.67	2.94
7	4.00	2.53	41	10.00	6.30	75	3.00	11.86	109	5.00	0.08
8	1.08	2.02	42	10.00	4.75	76	1.33	0.86	110	12.00	6.98
9	10.00	12.53	43	5.00	2.43	77	2.67	6.43	111	14.00	8.49
10	3.00	5.47	44	10.00	0.52	78	5.00	4.37	112	9.00	1.10
11	5.00	5.99	45	6.00	6.30	79	7.33	1.01	113	7.00	1.51
12	13.00	2.33	46	5.00	7.99	80	10.00	13.29	114	4.00	0.55
13	1.25	7.73	47	5.00	7.99	81	1.25	8.54	115	13.00	20.44
14	5.00	7.06	48	3.00	12.53	82	5.00	11.10	116	8.00	6.43
15	6.00	9.42	49	3.00	11.10	83	2.00	7.06	117	9.00	6.30
16	8.00	9.17	50	4.00	4.87	84	2.00	7.69	118	3.50	0.70
17	3.75	3.06	51	4.00	3.29	85	11.00	4.62	119	5.00	10.18
18	10.00	4.75	52	9.50	7.86	86	6.00	9.17	120	3.67	11.10
19	2.50	6.43	53	2.00	4.83	87	2.00	2.66	121	5.00	7.99
20	12.00	11.10	54	10.00	5.63	88	4.00	3.19	122	12.00	3.03
21	12.67	3.19	55	4.00	1.61	89	10.00	4.62	123	3.00	4.62
22	6.00	11.61	56	11.00	14.72	90	6.25	2.42	124	3.00	4.62
23	7.00	18.76	57	4.50	1.17	91	10.00	3.94	125	5.00	1.51
24	10.00	9.17	58	2.08	3.00	92	5.33	0.84	126	4.00	1.76
25	5.00	5.51	59	5.00	19.82	93	6.00	3.32	127	4.00	4.87
26	6.00	8.49	60	17.00	9.42	94	13.00	11.86	128	1.17	0.68

27	13.08	3.70	61	2.08	0.08	95	1.00	12.62	129	0.50	1.45
28	1.00	11.61	62	4.33	1.17	96	2.00	2.83	130	4.00	3.81
29	0.33	2.38	63	3.00	3.01	97	10.00	16.15	131	8.00	7.73
30	5.00	7.86	64	3.00	4.87	98	12.00	9.54	132	15.67	4.87
31	5.25	3.19	65	0.42	7.82	99	8.00	15.33	133	7.00	3.94
32	6.00	4.62	66	3.00	6.39	100	8.58	14.21	134	9.00	1.17
33	0.33	1.76	67	4.67	7.99	101	5.67	6.30	135	9.00	5.63
34	2.67	0.70	68	11.00	2.97	102	9.00	7.55			

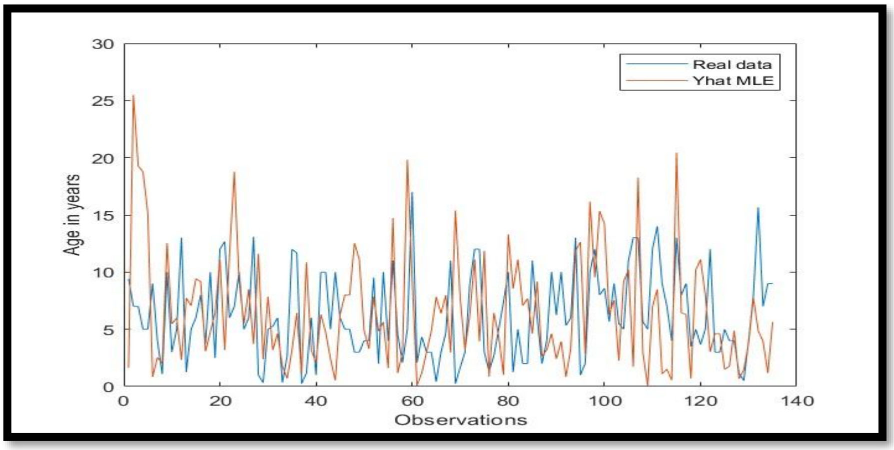

Figure (2): The plot displays the MLE method's actual and estimated values using the Rook matrix.

Table (3): It shows the estimated values of the MLE method through the **Queen** adjacency matrix

T	V	$\widehat{V}$	T	V	$\widehat{V}$	T	V	$\widehat{V}$	T	V	$\widehat{V}$
1	9.42	1.63	35	12.00	3.19	69	0.25	15.39	103	5.50	2.26
2	7.00	25.50	36	11.67	6.43	70	1.67	7.65	104	5.00	9.17
3	7.00	19.27	37	0.25	1.11	71	3.00	3.19	105	11.00	10.23
4	5.00	18.76	38	1.17	10.85	72	9.00	6.30	106	13.00	1.72
5	5.00	15.14	39	6.00	3.19	73	12.00	11.10	107	13.00	18.26
6	9.00	0.84	40	1.00	2.10	74	12.00	3.94	108	5.67	2.94
7	4.00	2.53	41	10.00	6.30	75	3.00	11.86	109	5.00	0.08
8	1.08	2.02	42	10.00	4.75	76	1.33	0.86	110	12.00	6.98
9	10.00	12.53	43	5.00	2.43	77	2.67	6.43	111	14.00	8.49
10	3.00	5.47	44	10.00	0.52	78	5.00	4.37	112	9.00	1.10
11	5.00	5.99	45	6.00	6.30	79	7.33	1.01	113	7.00	1.51
12	13.00	2.33	46	5.00	7.99	80	10.00	13.29	114	4.00	0.55
13	1.25	7.73	47	5.00	7.99	81	1.25	8.54	115	13.00	20.44
14	5.00	7.06	48	3.00	12.53	82	5.00	11.10	116	8.00	6.43
15	6.00	9.42	49	3.00	11.10	83	2.00	7.06	117	9.00	6.30
16	8.00	9.17	50	4.00	4.87	84	2.00	7.69	118	3.50	0.70
17	3.75	3.06	51	4.00	3.29	85	11.00	4.62	119	5.00	10.18
18	10.00	4.75	52	9.50	7.86	86	6.00	9.17	120	3.67	11.10
19	2.50	6.43	53	2.00	4.83	87	2.00	2.66	121	5.00	7.99
20	12.00	11.10	54	10.00	5.63	88	4.00	3.19	122	12.00	3.03
21	12.67	3.19	55	4.00	1.61	89	10.00	4.62	123	3.00	4.62
22	6.00	11.61	56	11.00	14.72	90	6.25	2.42	124	3.00	4.62
23	7.00	18.76	57	4.50	1.17	91	10.00	3.94	125	5.00	1.51
24	10.00	9.17	58	2.08	3.00	92	5.33	0.84	126	4.00	1.76
25	5.00	5.51	59	5.00	19.82	93	6.00	3.32	127	4.00	4.87
26	6.00	8.49	60	17.00	9.42	94	13.00	11.86	128	1.17	0.68
27	13.08	3.70	61	2.08	0.08	95	1.00	12.62	129	0.50	1.45

28	1.00	11.61	62	4.33	1.17	96	2.00	2.83	130	4.00	3.81
29	0.33	2.38	63	3.00	3.01	97	10.00	16.15	131	8.00	7.73
30	5.00	7.86	64	3.00	4.87	98	12.00	9.54	132	15.67	4.87
31	5.25	3.19	65	0.42	7.82	99	8.00	15.33	133	7.00	3.94
32	6.00	4.62	66	3.00	6.39	100	8.58	14.21	134	9.00	1.17
33	0.33	1.76	67	4.67	7.99	101	5.67	6.30	135	9.00	5.63
34	2.67	0.70	68	11.00	2.97	102	9.00	7.55			

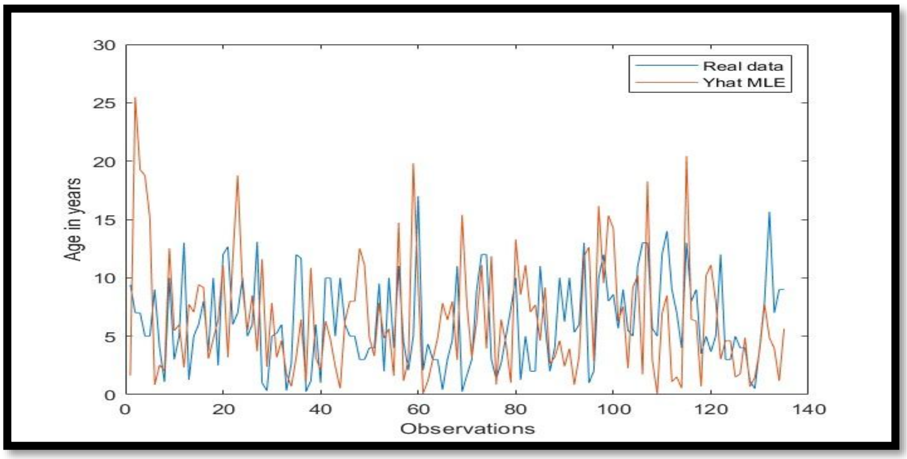

Figure (2): The graphic shows the actual and estimated values of the MLE approach using the Rook matrix

4.3 Discussion:

Tables (2) and (3) represent the actual and estimated data for the dependent variable (V). We notice that the estimated data have become better and closer, and this is represented by figures (1) and (2), where it is clear that the line for the estimated values has become closer between the values, while the line for the actual data was more disparate between them.

5. Conclusions

1- Regarding the impact of adjacency matrices on estimate accuracy, the findings demonstrated that the model's accuracy was much increased, and spatial dependency was better described by using adjacency matrices (Rook and Queen).

2- The maximum likelihood approach (MLE) and adjacency matrices offer a potent tool for evaluating geographical data and obtaining precise estimates of the spatial dependency between variables.

3- From the results obtained, it is clear that the three variables with spatial influence are of great importance in knowing the effect of the explanatory variables on the dependent variable, and that the spatial influence is of great significance in explanation.

6. Recommendations

1-When researching phenomena with a high degree of spatial dependence between variables, it is recommended to use the spatially autoregressive-moving average (SAR-MA) model. The Maximum Likelihood (MLE) method should be used to improve model estimates, as this approach has been successful in producing precise and objective estimates.

2- The Rook and Queen Matrix in particular should be carefully considered when selecting adjacency matrices, since the findings showed that these two matrices aid in reducing the relative error in model estimations and improving prediction accuracy.

3-To increase the usefulness of spatial models in analyzing complicated data, future research should broaden its focus to encompass more applications in a variety of domains, such as public health, urban planning, and regional economics.

4- More experimental research is required to identify other spatial aspects that can influence the model given. Additionally, new analytical methods must be developed to help improve the interpretation of spatial data in a variety of domains.

Developing the theoretical and practical framework for the research,

7. Supplementary material
(None).

8. Author's Contributions
Heba Aboud Ali: developing the theoretical and practical framework for the research. Wadhah S. Ibrahim: interpreting the results, designing and formatting the research

.9. Funding
(None).

10. Data availability statement
Data were obtained by sending an electronic questionnaire on diabetes in children to all Iraqi governorates.

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12. Conflict of interest
The authors declare no conflict of interest.

References:
[1] Akkar, A. A., Anber, J. A., & Ibrahim, W. S. (2023). The Study of Spatial Effect on Some Variables of Water Pollution in Baghdad Regions. Al-Rafidain University College For Sciences, (54). https://doi.org/10.55562/jrucs.v54i1.582

[2] Akkar, A. Abdali, & Hussein, S. Mohammad. (2019), "Some estimation methods for the two models SPSEM and SPSAR for spatially dependent data", Journal of Economics and Administration Sciences Vol.25, No. (113), 499-525. https://doi.org/10.33095/jeas.v25i113.1710

[3] Anber, J. A., Majeed, G. H., Abed, M. Q., & Ibrahim, W. S. (2025). Using the Spatial Autoregressive Model to Study the Effect of Some Variables on the Mean. Iraqi Statisticians journal, 2(special issue for ICSA2025), 158-163. https://doi.org/10.62933/ns1nxx54

[4] Anselin, L. (1988). Spatial Econometrics: Methods and Models. Dordrecht: Springer. https://doi.org/10.1007/978-94-015-7799-1

[5] Anselin, L. (1992). Spatial data analysis with GIS: An introduction to application in the social sciences (92-10). https://escholarship.org/uc/item/58w157nm

[6] Anselin, L. (2010). Thirty years of spatial econometrics. Papers in regional science, 89(1), 3-26. . https://doi.org/10.1111/j.1435-5957.2010.00279.x

[7] Cliff, A. D., & Ord, K. (1970). Spatial Autocorrelation: A Review of Existing and New Measures with Applications. Economic Geography, 46(sup1), 269–292. https://doi.org/10.2307/143144.

[8] Cressie, N. A. C1993) .). Statistics for spatial data .. John Wiley & Sons

[9] Elhorst, J. P. (2014). Spatial econometrics: from cross-sectional data to spatial panels (Vol. 479, p. 480). Heidelberg: Springer. https://doi.org/10.1007/978-3-642-40340-8

[10] Ibrahim, W. S., & Mousa, N. S. (2022). Estimation of the general spatial regression model (SAC) by the maximum likelihood method. International Journal of Nonlinear Analysis and Applications, 13(1), 2947-2957. http://dx.doi.org/10.22075/ijnaa.2022.6027

[11] Ibrahim, W. S., Majeedb, G. H., & Hussain, W. J. (2021). Comparison and estimation of a Spatial Autoregressive (SAR) model for cancer in Baghdad Regions. Int. J. Agricult. Stat. Sci. Vol, 17(1), 1921-1927. https://connectjournals.com/03899.2021.17.1921

[12] LeSage, J., & Pace, R. K. (2009). Introduction to spatial econometrics. Chapman and Hall/CRC. https://doi.org/10.1201/9781420064254

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مقارنة بين مصفوفتي التجاور المكاني (Rook, Queen) لأنموذج SAR-MA باستخدام MLE لمرض السكري

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المستخلص

الهدف من هذه الدراسة هو تقييم تأثير مصفوفات التجاور المختلفة (روك وكوين) على دقة نموذج الانحدار الذاتي للاوساط المتحركة المكانية (SAR-MA) وفحص تأثير التبعية المكانية على تقديرات النموذج باستخدام داله الإمكان الاعظم (MLE.) , واعتمدت الدراسة على بيانات مرض السكري الفعلية المتعلقة بالأطفال العراقيين في عام 2024، حيث تم جمع البيانات من محافظات مختلفة، بما في ذلك المتغيرات مثل العمر والجنس ومستوى السكر التراكمي في الدم وعوامل أخرى تؤثر على انتشار المرض، تم اختبار وجود الاعتماد المكاني باستخدام اختبار موران .Z , وقد تم استخدام طريقة دالة الإمكان الاعظم (MLE) لتقدير معلمات النموذج، واقترحت الدراسة استخدام نموذج SAR-MA مع مصفوفه التجاور روك في التحليل المكاني لضمان دقة التقديرات وتوسيع نطاق التطبيقات المستقبلية للنماذج المكانية في مجالات مثل الاقتصاد والتخطيط الحضري. وعلاوة على ذلك، أظهرت النتائج اعتمادًا مكانيًا ملحوظًا في بعض المتغيرات (S_4، S_5، S_8)بينما لم يظهر في البعض الآخر.

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