

High Order Spatial Weighting Matrix Using Google Trends

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ABSTRACT

This research aimed to form a high-order spatial weighting matrix based on various simulations. The simulation was the determination of the center of the country based on the capital and google trend data. The keywords that have been used in the Google Trends data are "gold price" and "deposit". These keywords have been translated into 6 official languages of the United Nation including Arabic, Chinese, English, French, Russian, and Spanish. Each language has been represented by 1 country. The determination of the country center that has been used based on the capital as well as keywords and time influenced the form of the high-order spatial weighting matrix. In simulations 1, 2, 4, and 5 the highest spatial order formed was 6. It was different with simulations 3, 6, and 7 the highest spatial order formed was 5.

Keywords: language, simulation, gold price, deposit

INTRODUCTION

Spatial weighting matrices have been used in various statistical models including spatial autoregressive [1][2][3][4] generalized space time autoregressive [5], spatial dynamic panel data [6], spatial autoregressive binary probit [7], etc. The selection of the center of the country based on the distance in the spatial weighting matrix was usually the capital of the country. At the country level, if the example of Indonesia taken then the center point of the country was Jakarta. Meanwhile, if in a smaller regional level such as a province, if

the example of West Java has been taken, then the central point of the province that has been taken was Bandung. This research had an alternative to choosing the center of the country based on google trends data according to the research keywords. The research keywords that have been tried in this study are also not only 1 so that it shown the difference in the city that is the center for each country. Google trends data which is easily obtained for free, has been widely used for research in various countries including New Zealand [8], United States [9][10][11], South Korea [12], Turkey [13], Germany [14], Italy [15], United Kingdom [16], etc.

Generally, the spatial weighting matrix which used order 1. So that the development of theories related to higher orders was very potential to be discussed. Mubarak et al. discussed higher orders that are more than 3 which adopted the radius technique [17]. However, the object of the research limited to the island of Sumatra, Indonesia. The study also used the provincial capital (government) as the center point of distance between provinces. The advantage of this research that was not only forms a high-order spatial weighting matrix from google trends data but also changed in the center point of a country from different keywords and times. Keywords that have been translated into various major languages of each country. For example, if the UK used the "gold price" keyword, then in Indonesia it has used the "harga emas" keyword. In addition,

this study compared the central point of the country based on google trends data and the capital city of the country. Finally, from the central point that has been obtained, a high-order spatial weighting matrix has been formed.

METHODS

Google trends data that has been used in this study between October 13, 2017-October 13, 2021. This time divided into 3 parts. Part 1 was October 13, 2017-October 13, 2019, part 2 was October 13, 2019-October 13, 2021, and the last part was October 13, 2017-October 13, 2021. And there were also 6 United Nations languages that have been used for keyword searches on google trends data included Arabic, Chinese, English, French, Russian, and Spanish. Each language has been represented by 1 country. The Arabic language has been represented by Saudi Arabia. In addition, it has been represented by each country according to the language. The keywords that have been used the “gold price” and “deposit”. The keywords that have been translated into each language shown in **Table 1**. This research has been limited to web searches in the google trends data because this menu was the most widely used when compared to other menus such as image search, news search, google shopping, and YouTube search.

Table 1. Keywords for google trends data

No	Language	Country	Keyword 1 “gold price”	Keyword 2 “deposit”
1	Arabic	Saudi Arabia	سعر الذهب	الوديعة
2	Chinese	China	黄金价格	订金
3	English	United Kingdom	Gold Price	Deposit
4	French	France	Prix de l'or	Verser
5	Russian	Russia	Цена на золото	Депозит
6	Spanish	Spain	Precio de oro	Depositar

After found the cities that were the trend centers of each country, then the distance between the city centers has been calculated. The distance between cities represented the distance between countries. Furthermore, the distance has been sorted from closest to furthest. Based on this

distance, it has been determined that the first-order radius was the closest distance, the second-order radius was the sum of the first-order and second-closest distances, and so on until all countries have been entered by the radius. The radius simulation shown in **Figure 1**.

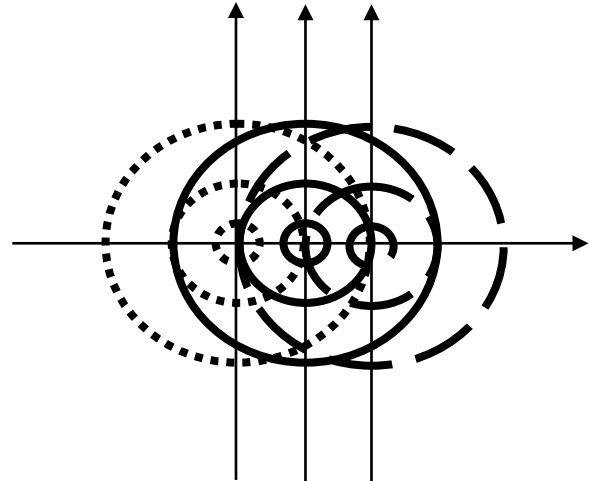


Figure 1. High-order spatial illustration

The classification of each country by radius has been established in the weighting matrix. The matrix has been adopted from the inverse distance matrix which has been raised to the power of its spatial order so that it has been formed in equation 1. Finally, equation 1 has been used for capitals and also some combinations of time (time 1, 2, and 3) and keywords (keywords 1 and 2). So the total simulation that has been tried was 7.

$$W^n = \begin{bmatrix} 0 & \frac{1}{d_{12}^n} & \dots & \frac{1}{d_{1j}^n} \\ \frac{1}{d_{21}^n} & 0 & \dots & \frac{1}{d_{2j}^n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{d_{i1}^n} & \frac{1}{d_{i2}^n} & \dots & 0 \end{bmatrix} \dots (1)$$

where d_{ij}^n is the distance between country i and country j, 0 is the distance between the country and itself, and $\frac{1}{d_{ij}^n} = \frac{1}{d_{ji}^n}$.

RESULT

In general, this research used 7 simulations. Simulation 1 was the center of the country based on the capital.

Furthermore, simulation 2 was google trends data that used the keyword "gold price" on October 13, 2017-October 13, 2019. For simulation 3, the keyword "gold price" on October 13, 2019-October 13, 2021 has been used in the google trends data. Simulation 4 used the same keywords but combined simulation times 2 and 3. This research used also google trends data with

different keywords. Simulation 5 was google trends data that used the keyword "deposit" at the same time as simulation 2. For simulation 6, the same keywords as simulation 5 and the same time as simulation 3 have been used in the google trends data. Simulation 7 used the same keywords but used simulation time 4.

Table 2. Country center by capital and google trend

No	Country	Capital	Time	Country center by trend	
				Keyword "Gold Price"	Keyword "Deposit"
1	Saudi Arabia	Riyadh	(1)	Mecca	Jeddah
			(2)	Najran	Jeddah
			(3)	Jazan	Jeddah
2	China	Beijing	(1)	Beijing	Fujian
			(2)	Guangdong	Beijing
			(3)	Guangdong	Zhejiang
3	United Kingdom	London	(1)	Leicester	Liverpool
			(2)	Hounslow	Hull
			(3)	Hounslow	Hull
4	France	Paris	(1)	Île de France	Centre Val de Loire
			(2)	Alpes Côte d'Azur	Picardy
			(3)	Rhone Alpes	Picardy
5	Russia	Moscow	(1)	Dagestan	Mordovia
			(2)	Khabarovsk Krai	Chuvashia
			(3)	Dagestan	Sakhalin Oblast
6	Spain	Madrid	(1)	Cantabria	Madrid
			(2)	Aragon	Madrid
			(3)	Region of Murcia	Aragon

Note: (1): October 13, 2017-October 13, 2019; (2): October 13, 2019-October 13, 2021; and (3): October 13, 2017-October 13, 2019

The country center based on capital and google trends data shown in **Table 2**. For example, Saudi Arabia, the country center based on capital was Riyadh but it was different if based on google trends data used the keywords "gold price" or "deposit". Time had an effect on determining the center of the country based on the keyword "gold price" during October 13, 2017-October 13, 2019 was Mecca, during October 13, 2019-October 13, 2021 was Najran, and during October 13, 2017-October 13, 2021 was Jazan. However, if used the keyword "deposit" in the google trends data, the center of the country was Jeddah without the influence of time.

The distances between countries for all simulations shown in **Table 3**. In the column captions, (1) Saudi Arabia, (2) China, (3) United Kingdom, (4) France, (5) Russia, and Spain (6). The * in the table was the distance between the country and itself. For example, if taken the distance between Saudi Arabia and other countries, the distance between Saudi Arabia and China was 6595.66 km. Furthermore, the distance between Saudi Arabia and the United Kingdom was 4943.46 km. Likewise, the distance between Saudi Arabia and France was 4681.95 km. In addition, the distance between Saudi Arabia and Russia was 3532.58 km. Lastly, the distance between Saudi Arabia and Spain was 4963.52 km.

Table 3. Distance between countries (km)

	Country	Center	(1)	(2)	(3)	(4)	(5)	(6)
Simulation 1	Saudi Arabia (1)	Riyadh	*	6595.66	4943.46	4681.95	3532.58	4963.52
	China (2)	Beijing	6595.66	*	8138.09	8213.60	5790.40	9218.89
	United Kingdom (3)	London	4943.46	8138.09	*	342.74	2500.81	1262.61
	France (4)	Paris	4681.95	8213.60	342.74	*	2486.34	1052.76
	Russia (5)	Moscow	3532.58	5790.40	2500.81	2486.34	*	3440.17
	Spain (6)	Madrid	4963.52	9218.89	1262.61	1052.76	3440.17	*

Table 3 Continued...

Table 3 Continued...								
Simulation 2	Saudi Arabia (1)	Mecca	*	6595.66	5049.17	4665.03	2020.08	5019.55
	China (2)	Beijing		6595.66	*	8098.75	8219.16	5580.95
	United Kingdom (3)	Leicester		5049.17	8098.75	*	508.97	3726.13
	France (4)	Île de France		4665.03	8219.16	508.97	*	3507.42
	Russia (5)	Dagestan		2020.08	5580.95	3726.13	3507.42	*
	Spain (6)	Cantabria		5019.55	9010.85	1077.47	794.92	4131.12
Simulation 3	Saudi Arabia (1)	Najran	*	7184.03	5424.86	4614.55	8808.98	5091.23
	China (2)	Guangdong		7184.03	*	9544.88	9549.33	4172.65
	United Kingdom (3)	Hounslow		5424.86	9544.88	*	962.76	7672.21
	France (4)	Alpes Côte d'Azur		4614.55	9549.33	962.76	*	8234.27
	Russia (5)	Khabarovsk Krai		8808.98	4172.65	7672.21	8234.27	*
	Spain (6)	Aragon		5091.23	10286.34	1187.14	737.96	8810.60
Simulation 4	Saudi Arabia (1)	Jazan	*	7372.35	5382.11	4732.88	2925.35	4877.80
	China (2)	Guangdong		7372.35	*	9544.88	9568.95	6362.98
	United Kingdom (3)	Hounslow		5382.11	9544.88	*	762.030	3681.85
	France (4)	Rhone Alpes		4732.88	9568.95	762.03	*	3402.47
	Russia (5)	Dagestan		2925.35	6362.98	3681.85	3402.47	*
	Spain (6)	Region of Murcia		4877.80	10431.36	1499.88	971.35	4133.50
Simulation 5	Saudi Arabia (1)	Jeddah	*	7942.94	5020.40	4433.98	3682.39	4540.63
	China (2)	Fujian		7942.94	*	9542.91	9683.00	6662.27
	United Kingdom (3)	Liverpool		5020.40	9542.91	*	717.60	3051.09
	France (4)	Centre Val de Loire		4433.98	9683.00	717.60	*	3039.81
	Russia (5)	Mordovia		3682.39	6662.27	3051.09	3039.81	*
	Spain (6)	Madrid		4540.63	10512.65	1445.90	907.63	3850.39
Simulation 6	Saudi Arabia (1)	Jeddah	*	7433.44	4887.38	4784.28	3837.74	4540.63
	China (2)	Beijing		7433.44	*	7974.67	8570.33	5222.07
	United Kingdom (3)	Hull		4887.38	7974.67	*	664.61	2999.52
	France (4)	Picardy		4784.28	8570.33	664.61	*	3481.10
	Russia (5)	Chuvashia		3837.74	5222.07	2999.52	3481.10	*
	Spain (6)	Madrid		4540.63	9218.89	1503.31	851.310	4025.27
Simulation 7	Saudi Arabia (1)	Jeddah	*	8042.57	4887.38	4784.28	9502.63	4405.49
	China (2)	Zhejiang		8042.57	*	9179.76	9757.28	3330.94
	United Kingdom (3)	Hull		4887.38	9179.76	*	664.61	8125.09
	France (4)	Picardy		4784.28	9757.28	664.61	*	8789.66
	Russia (5)	Sakhalin Oblast		9502.63	3330.94	8125.09	8789.66	*
	Spain (6)	Aragon		4405.49	10220.83	1439.25	811.20	9518.40

Table 4. Formation of spatial order (km)

Order	Simulation 1 (max d=9218.89)		Simulation 2 (max d=9010.85)		Simulation 3 (max d=10286.34)		Simulation 4 (max d=10431.36)	
	Distance	Radius	Distance	Radius	Distance	Radius	Distance	Radius
1	342.74	342.74	508.97	508.97	737.96	737.96	762.03000	762.03000
2	1052.76	1395.50	794.92	1303.89	962.76	1700.72	971.35000	1733.38000
3	1262.61	2658.11	1077.47	2381.36	1187.14	2887.86	1499.88000	3233.26000
4	2486.34	5144.45	2020.08	4401.44	4172.65	7060.51	2925.35000	6158.61000
5	2500.81	7645.26	3507.42	7908.86	4614.55	11675.06	3402.47000	9561.08000
6	3440.17	11085.43	3726.13	11634.99			3681.85000	13242.93000

Order	Simulation 5 (max d=10512.65)		Simulation 6 (max d=9218.89)		Simulation 7 (max d=10220.83)	
	Distance	Radius	Distance	Radius	Distance	Radius
1	717.60	717.60	664.61	664.61	664.610	664.610
2	907.63	1625.23	851.31	1515.92	811.20	1475.81
3	1445.90	3071.13	1503.31	3019.23	1439.25	2915.06
4	3039.81	6110.94	2999.52	6018.75	3330.94	6246.00
5	3051.09	9162.03	3481.10	9499.85	4405.49	10651.49
6	3682.39	12844.42				

All orders that have been formed from 7 simulations shown in **Table 4**. For example, if simulation 1 has been selected, the first closest distance between 2 countries was 342.74 km, so the radius for the first order that has been formed was 342.74 km. Furthermore, the second closest between the two countries was 1052.76 km so that the

radius formed for the second order was 1395.50 km. The result of the radius was the sum of the first closest distance to the second closest distance between 2 countries. Finally for the sixth order which has been formed from the sixth distance between 2 countries was 3440.17 km so that the sixth order had a radius of 11085.43 km which

was the result of the sum of the first, second, and sixth closest distances between the 2 countries. The last order that formed order the sixth because the farthest distance between 2 countries was 9218.89 km while the radius of the sixth order was 11085.43 km. Likewise with simulations 3, 6, and 7 which had the highest spatial order 5. Where this has indicated that all countries have entered the existing radius.

Based on the radius in **Table 4**, the distances between countries in **Table 3** have been classified in **Table 5**. If taken the example of the distance between Saudi Arabia and Russia, it is not only the center of the country that was different but also the classification of the spatial order. In simulation 1, when the center of Saudi Arabia was Riyadh and the center of Russia was Moscow, the distance between these two countries has been classified as spatial order 4. While in simulation 2 between Saudi Arabia where the center was Mecca

and Russia where the center was Dagestan, the distance has been classified as spatial order 3. Furthermore, in simulation 3, between Saudi Arabia with its center Najran and Russia with its center Khabarovsk Krai entered the classification of spatial order 5. In simulation 4, when the center of Saudi Arabia was Jazan and when the center of Russia was Dagestan, the distance between the 2 countries have been classified as spatial order 3. In simulations 5 and 6, the distance between Saudi Arabia and Russia has been classified as spatial order 4 although in simulation 5 Saudi Arabia the center was Jeddah and Russia the center was Mordovia while in simulation 6 Saudi Arabia the center was Jeddah and Russia the center was Chuvashia. Finally, in the last simulation, the distance between Saudi Arabia, whose center was Jeddah and Russia, whose center was Sakhalin Oblast, has been classified as spatial order 5.

Table 5. Spatial order classification

	Negara	Pusat	(1)	(2)	(3)	(4)	(5)	(6)
Simulation 1	Saudi Arabia (1)	Riyadh	*	5	4	4	4	4
	China (2)	Beijing	5	*	6	6	5	6
	United Kingdom (3)	London	4	6	*	1	3	2
	France (4)	Paris	4	6	1	*	3	2
	Russia (5)	Moscow	4	5	3	3	*	4
	Spain (6)	Madrid	4	6	2	2	4	*
Simulation 2	Saudi Arabia (1)	Mecca	*	5	5	5	3	5
	China (2)	Beijing	5	*	6	6	5	6
	United Kingdom (3)	Leicester	5	6	*	1	4	2
	France (4)	Île de France	5	6	1	*	4	2
	Russia (5)	Dagestan	3	5	4	4	*	4
	Spain (6)	Cantabria	5	6	2	2	4	*
Simulation 3	Saudi Arabia (1)	Najran	*	5	4	4	5	4
	China (2)	Guangdong	5	*	5	5	4	5
	United Kingdom (3)	Hounslow	4	5	*	2	5	2
	France (4)	Alpes Côte d'Azur	4	5	2	*	5	1
	Russia (5)	Khabarovsk Krai	5	4	5	5	*	5
	Spain (6)	Aragon	4	5	2	1	5	*
Simulation 4	Saudi Arabia (1)	Jazan	*	5	4	4	3	4
	China (2)	Guangdong	5	*	5	6	5	6
	United Kingdom (3)	Hounslow	4	5	*	1	4	2
	France (4)	Rhone Alpes	4	6	1	*	4	2
	Russia (5)	Dagestan	3	5	4	4	*	4
	Spain (6)	Region of Murcia	4	6	2	2	4	*
Simulation 5	Saudi Arabia (1)	Jeddah	*	5	4	4	4	4
	China (2)	Fujian	5	*	6	6	5	6
	United Kingdom (3)	Liverpool	4	6	*	1	3	2
	France (4)	Centre Val de Loire	4	6	1	*	3	2
	Russia (5)	Mordovia	4	5	3	3	*	4
	Spain (6)	Madrid	4	6	2	2	4	*
Simulation 6	Saudi Arabia (1)	Jeddah	*	5	4	4	4	4
	China (2)	Beijing	5	*	5	5	4	5
	United Kingdom (3)	Hull	4	5	*	1	3	2
	France (4)	Picardy	4	5	1	*	4	2
	Russia (5)	Chuvashia	4	4	3	4	*	4
	Spain (6)	Madrid	4	5	2	2	4	*

Simulation 7	Saudi Arabia (1)	Jeddah	*	5	4	4	5	4
	China (2)	Zhejiang	5	*	5	5	4	5
	United Kingdom (3)	Hull	4	5	*	1	5	2
	France (4)	Picardy	4	5	1	*	5	2
	Russia (5)	Sakhalin Oblast	5	4	5	5	*	5
	Spain (6)	Aragon	4	5	2	2	5	*

Based on the distance between countries in **Table 3** and the spatial order classification in **Table 5**, the high-order spatial weighting matrix has been shown in equations 2 to 8. Equation 2 was the high-order spatial weighting matrix from simulation 1 where the center of the country based on the capital. The spatial order weighting matrix in equation 3 from simulation 2 where the country center that has been used comes from google trends data with the keyword "gold price" on October 13, 2017-October 13, 2019. Simulation 3 where the keyword was "gold price" on October 13, 2019-October 13, 2021 on google trends data formed a high-order spatial weighting matrix in equation 4. Equation 5 was a high-order spatial

weighting matrix from simulation 4 where the center of the country from google trends data with the keyword "gold price" on October 13, 2017-October 13, 2021. The spatial order weighting matrix in equation 6 from simulation 5 where the country center that has been used from google trends data with the keyword "deposit" on October 13, 2017-October 13, 2019. Simulation 6 where the keyword was "deposit" on October 13, 2019-October 13, 2021 on google trends data formed a high-order spatial weighting matrix in equation 7. The last one, equation 8 was the matrix the high-order spatial weighting from simulation 7 where the center of the country from google trends data with the keyword "deposit" on October 13, 2017-October 13, 2021.

$$W_1^1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_1^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1262.61^2 & 0 \\ 0 & 0 & 0 & 0 & 1052.76^2 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1262.61^2 & 1052.76^2 & 0 & 0 & 0 \end{bmatrix}, W_1^3 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 2500.81^2 & 0 \\ 0 & 0 & 0 & 0 & 2500.81^2 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 2500.81^2 & 2500.81^2 & 0 & 0 & 0 \end{bmatrix}$$

$$W_1^4 = \begin{bmatrix} 0 & 0 & 1 & 1 & 1 \\ 0 & 4943.46^4 & 4681.95^4 & 3532.58^4 & 4963.52^4 \\ 4943.46^4 & 0 & 0 & 0 & 0 \\ 4681.95^4 & 0 & 0 & 0 & 0 \\ 3532.58^4 & 0 & 0 & 0 & 1 \\ 4963.52^4 & 0 & 0 & 1 & 3440.17^2 & 0 \end{bmatrix}, W_1^5 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 6595.66^5 & 0 & 0 & 0 & 1 & 0 \\ 6595.66^5 & 0 & 0 & 0 & 5790.40^3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 5790.40^3 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\text{and } W_1^6 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 8138.09^6 & 8213.60^6 & 0 & 0 & 9218.89^6 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 8138.09^6 & 0 & 0 & 0 & 0 & 0 \\ 8213.60^6 & 0 & 0 & 0 & 0 & 0 \\ 9218.89^6 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \dots (2)$$

$$W_2^1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_2^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1077.47^2 & 0 \\ 0 & 0 & 0 & 0 & 794.92^2 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1077.47^2 & 794.92^2 & 0 & 0 & 0 \end{bmatrix}, W_2^3 = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 2020.08^3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$W_2^4 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 3726.13^4 & 0 \\ 0 & 0 & 0 & 1 & 3507.42^4 & 0 \\ 0 & 1 & 1 & 0 & 4131.12^4 & 0 \\ 0 & 3726.13^4 & 3507.42^4 & 0 & 4131.12^4 & 0 \end{bmatrix}, W_2^5 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 6595.66^5 & 5049.17^3 & 4665.03^3 & 0 & 5019.33^3 & 0 \\ 6595.66^5 & 0 & 0 & 0 & 5580.95^3 & 0 \\ 5049.17^3 & 0 & 0 & 0 & 0 & 0 \\ 4665.03^3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 5580.95^3 & 0 & 0 & 0 & 0 \\ 5019.33^3 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\text{and } W_2^6 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 8098.75^6 & 8219.16^6 & 0 & 9010.85^6 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 8098.75^6 & 0 & 0 & 0 & 0 & 0 \\ 8219.16^6 & 0 & 0 & 0 & 0 & 0 \\ 9010.85^6 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \dots (3)$$

$$W_3^1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_3^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 962.76^2 & 1187.14^2 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_3^3 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$W_3^4 = \begin{bmatrix} 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 5424.86^4 & 4614.55^4 & 4172.65^4 & 0 & 5091.23^4 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 5424.86^4 & 0 & 0 & 0 & 0 & 0 \\ 4614.55^4 & 0 & 0 & 0 & 0 & 0 \\ 0 & 4172.65^4 & 0 & 0 & 0 & 0 \\ 5091.23^4 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\text{and } W_3^5 = \begin{bmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 7104.03^5 & 0 & 0 & 0 & 8808.98^5 & 0 \\ 1 & 1 & 9544.88^5 & 9549.33^5 & 0 & 10286.34^5 \\ 0 & 1 & 0 & 0 & 7672.21^5 & 0 \\ 0 & 9544.88^5 & 0 & 0 & 1 & 8234.27^5 \\ 1 & 0 & 1 & 1 & 0 & 8810.60^5 \\ 8808.98^5 & 0 & 7672.21^5 & 8234.27^5 & 1 & 8810.60^5 \\ 0 & 10286.34^5 & 0 & 0 & 0 & 8810.60^5 \end{bmatrix} \dots (4)$$

$$\begin{aligned}
 W_1^1 &= \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_2^1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_3^1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\
 W_4^1 &= \begin{bmatrix} 0 & 0 & 1 & 1 & 0 & 1 \\ 5382.11^4 & 0 & 0 & 0 & 4877.80^4 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 4732.80^4 & 0 & 0 & 3681.85^4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 4877.80^4 & 0 & 0 & 0 & 4133.50^4 & 0 \end{bmatrix}, W_5^1 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 7372.35^4 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 9544.88^4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 6362.98^4 & 0 & 0 & 0 & 0 \end{bmatrix}, \text{and } W_6^1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \dots (5) \\
 W_1^2 &= \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_2^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_3^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\
 W_4^2 &= \begin{bmatrix} 0 & 0 & 1 & 1 & 1 & 1 \\ 5020.40^4 & 4433.90^4 & 3682.39^4 & 4540.63^4 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 5020.40^4 & 0 & 0 & 0 & 0 & 0 \\ 4433.90^4 & 0 & 0 & 0 & 0 & 0 \\ 3682.39^4 & 0 & 0 & 0 & 3850.39^4 & 0 \\ 4540.63^4 & 0 & 0 & 0 & 3850.39^4 & 0 \end{bmatrix}, W_5^2 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 7942.94^4 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 6662.27^4 & 0 & 0 & 0 & 0 \end{bmatrix}, \text{and } W_6^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \dots (6) \\
 W_1^3 &= \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_2^3 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_3^3 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\
 W_4^3 &= \begin{bmatrix} 0 & 0 & 1 & 1 & 1 & 1 \\ 4887.38^4 & 4784.28^4 & 3837.74^4 & 4540.63^4 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 4784.28^4 & 0 & 0 & 0 & 0 & 0 \\ 3837.74^4 & 5222.07^4 & 0 & 3481.10^4 & 0 & 4025.27^4 \\ 4540.63^4 & 0 & 0 & 0 & 4025.27^4 & 0 \end{bmatrix}, \text{and } W_5^3 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 7433.44^4 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 7974.67^4 & 8570.33^4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \dots (7) \\
 W_1^4 &= \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_2^4 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, W_3^4 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\
 W_4^4 &= \begin{bmatrix} 0 & 0 & 1 & 1 & 0 & 1 \\ 4887.38^4 & 4784.28^4 & 0 & 4405.49^4 & 0 & 0 \\ 1 & 0 & 0 & 3330.94^4 & 0 & 0 \\ 4784.28^4 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3330.94^4 & 0 & 0 & 0 & 0 \\ 4405.49^4 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \text{and } W_5^4 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 8042.57^4 & 0 & 0 & 0 & 9502.63^4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 9179.76^4 & 0 & 0 & 8125.09^4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 9502.63^4 & 8125.09^4 & 8789.66^4 & 0 & 9518.40^4 \end{bmatrix} \dots (8)
 \end{aligned}$$

For example, W_1^1 in equation (2) described the first-order spatial weighting matrix of simulation 1 where the center of the country based on the capital. In the simulation, the distance between the United Kingdom and France was 342.74 km according to **Table 3**. The distance raised to the power of 1 because it was first order according to **Table 5**. Besides the distance between the United Kingdom and France, the matrix element was 0 because it was not first order.

CONCLUSION AND DISCUSSION

The form of the high-order spatial weighting matrix that has been influenced

strongly by the selection of the country center used, both based on the country's capital and the keywords and times that have been used in the google trends data. Based on the center of the country, the distance between countries and different spatial order classifications has been shown. In simulations 1, 2, 4, and 5 the highest spatial order formed was 6. In contrast to simulations 3, 6, and 7 the highest spatial order was 5. This happened because the furthest distance between countries entered the radius. the highest order so that the next highest order was no longer needed or in other words it had only formed a matrix of 0. Google trends data become an alternative

to choosing the center of the country, especially if to do research that focuses more on certain objects or keywords without having to continue to make the capital country as the center of the country.

This research still had potential for further development. The use of more keywords also needs to be considered in the spatial order for each distance between countries. In fact, it is also necessary to consider using all registered countries officially in order to see how much the spatial order classification changes for each country. This research used the manual method to obtain data from Google Trends data. Next, it is hoped that a programming package can be developed to be able to directly retrieve data from Google Trends based on the various keywords needed.

Acknowledgement: None

Conflict of Interest: None

Source of Funding: None

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How to cite this article: Mubarak F, Aslanargun A, Sıklar I. High order spatial weighting matrix using google trends. *International Journal of Research and Review*. 2021; 8(11): 388-396. DOI: <https://doi.org/10.52403/ijrr.20211150>
