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Clustering spatial autoregressive kriging model for climate: A bibliometric analysis approach

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A B S T R A C T

Climate change is caused by temperature, rainfall, and wind variation in locations that last a long time. This change can be described and predicted using a spatial model, one of which is the Clustering Spatial Autoregressive (SAR) Kriging model. Therefore, this research aims to conduct a bibliometric analysis in a spatial and Clustering SAR Kriging model on climate change. It presents a Systematic Literature Review (SLR) with the development of the Clustering SAR Kriging model, incorporating articles from the Google Scholar, ScienceDirect, Dimensions AI, and Scopus databases from 2011-2021. Furthermore, two stages of analysis have been conducted, first, bibliometric analysis was performed for mapping and thematic evolution using VOSviewer software and R-biblioshiny. This analysis generated 185 papers after conducting a duplication check and developed a network of research on evolutionary subject matters at this stage. Second, research subjects were analyzed using the Clustering SAR Kriging model. More screening criteria were followed, and 18 articles were obtained for the SLR analysis. Furthermore, the development of the Clustering SAR Kriging model was observed for the prediction and description of climate change. The results are predicted to benefit applicable businesses to predict climate phenomena in unobserved places.

1. Introduction

Climatology is the study of the atmosphere and weather patterns over time. This subject of technology makes a specialty of recording and analyzing weather patterns at some stage and understanding atmospheric situations (Efe et al., 2022). Variations in patterns are strongly prompted by using climate change (Banzhaf et al., 2022). In many countries, this is appreciably changing diverse environmental variables, which can have effects and significantly threaten the population in addition to agriculture, the environment, the economic system, and industry (McKee, 1993). Changes in precipitation patterns at once affect water source ecosystems, management, hydrology, and agriculture (Pinar Aslantas Bostan, 2006). Meanwhile, some of the impacts of climate change include; monthly and annual precipitation trends (McKee, 1993), thunderstorms (Ghavidel et al., n.d.), hydrological procedures and water quality (Ouyang & Panda, 2022), catastrophic rainfall events (Peirce et al., 2022), air pollution (Masri et al., 2022), and effects on indoor pests (Querner et al., 2022). Based on locations, factors such as rainfall, temperature, wind velocity, sunshine, and many others affect climate change. Therefore, modeling is carried out to reduce the effects on various sectors that may be used to predict climate change. A few statistical-mathematical models for these predictions include the spatial autoregressive model, spatial clustering, and the kriging method.

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Huseyin and Saffet (McKee, 1993) analyze the kriging method for predicting monthly and annual rainfall. Yousef et al. (Ghavidel et al., n.d.) kriging technique predicted thunderstorm danger zonation, and the clustering classified the different areas based on occurrence. Alexandra et al. (Peirce et al., 2022) conducted an SLR of sixteen filtered papers from PubMed, Web of Science, and Scopus, focusing on characterizing the country of research on flooding. Furthermore, Shashi et al. (Shekhar et al., 2011) explored the emerging area of spatial data mining, specializing in special methods to extract patterns from spatial information. Nao et al. (Ohana-Levi et al., n.d.) proposed clustering analysis to characterize the spatial variability of an agricultural field. Yanmei et al. (Li et al., n.d.) Empirical Bayesian Kriging (EBK) were applied to cope with non-Gaussian, reasonably non-stationary data, and a place for analysis became delimited based on a suitable stage of uncertainty within the interpolation maps of water stages. Meanwhile, Manuel et al. (Ribeiro et al., 2016) used regression and ordinary kriging to predict air quality. Orton et al. (Orton et al., n.d.) proposed an approach to deal with such datasets, termed increment-averaged kriging (IAK), which suits a single model using facts from all profiles and all soil depths. Miguel et al. (Gonzalez-Gonzalez & Guertin, 2021) SAR model used to predict dry bean yields. Yuliya et al. (Marchetti et al., n.d.) produce contiguous spatial clusters and preserve the spatial-correlation structure of the data so that the lack of predictive information is minimum. Marcos et al. (Silva et al., 2021) used cluster analysis to delimit homogeneous regions, and the kriging spatial interpolation method offers steady rainfall spatialization. Francesco (Troiani et al., 2017) applied cluster analysis to illustrate the tectonic systems Weeberb et al. (Requia et al., 2019) located that the clusters may also affect the error of the prediction values and especially the proportion of explained variance for the maximum of the PM2.5 components evaluated. Chaosheng et al. (Zhang et al., 2011) investigated the usage of a geographically weighted regression (GWR) technique for the spatial modeling of SOC in Ireland.

Based on this description, spatial modeling of climate change has been carried out. However, no research fully discusses SLR in spatial modeling focusing on the scientific articles in clustering the SAR kriging model to predict and describe these changes in unobserved locations. The SLR contains several steps, such as topic formulation, study design, sampling, data collection, and reporting (Kouchaksaraei & Karl, 2019), as shown in Table 1.

Table 1
The aspects included in our article

Author	SLR?	Clustering?	SAR?	Kriging?	Climate?	Bibliometric Analysis?
(McKee, 1993)	×	×	×	✓	✓	×
(Ghavidel et al., n.d.)	×	✓	×	✓	✓	×
(Peirce et al., 2022)	✓	×	×	×	✓	×
(Shekhar et al., 2011)	×	✓	✓	×	×	×
(Ohana-Levi et al., n.d.)	×	✓	×	×	×	×
(Li et al., n.d.)	×	×	×	✓	✓	×
(Ribeiro et al., 2016)	×	×	×	✓	✓	×
(Orton et al., n.d.)	×	×	×	✓	×	×
(Gonzalez-Gonzalez & Guertin,	×	×	✓	×	×	×
(Marchetti et al., n.d.)	×	✓	×	×	×	×
(Silva et al., 2021)	×	✓	×	✓	×	×
(Troiani et al., 2017)	×	✓	×	×	×	×
(Requia et al., 2019)	×	✓	×	×	×	×
(Zhang et al., 2011)	×	×	×	✓	×	×
Our article	✓	✓	✓	✓	✓	✓

2. Materials and Methods

2.1 Scientific Article Data

In this study, literature that specializes in clustering the SAR kriging model for climate change was identified and selected for review. The approach used is an SLR consisting of several steps, such as a topic formula, which defines keywords relevant to the subject. The layout determines the database sources, sampling, and data collection, including searching, saving, and merging strategies. The final step is data analysis to decide on the right tools for the data in usability, depth and rigor, helpful format, and replicability (Palmatier et al., 2018). The literature review focuses on clustering the SAR kriging model for climate change. The data used were articles obtained from indexed databases, namely Scopus, ScienceDirect, Dimensions AI, and Google Scholar, published from 2011 to 2021. The Preferred Reporting Items were used for the Systematic Reviews and Meta-Analyses (PRISMA) technique for selecting the data sources from the database. Table 2 shows the four codes of keywords in this research.

Table 2
Four codes of keywords

Code	Keywords
I	"Spatial Analysis" OR "Spatial Model" OR "Spatial Autoregressive" OR "SAR Model"
II	"Kriging" OR "Ordinary Kriging" OR "OK"
III	"Spatial Cluster"
IV	"Climate"

From Table 2, the keywords used in this first search are “Spatial Analysis” OR “Spatial Model” OR “Spatial Autoregressive” OR “SAR Model” as the main model, then the second keyword was added using “Kriging” OR “Usually Kriging” OR “OK”. Furthermore, the third keyword was included using "Spatial Cluster," and "Climate" was added for research related to the model. The number of publications from the database with four codes of keywords can be seen in Table 3 below.

Table 3
Search results from four databases with four codes of keywords

Keywords	Code	Databases			
		Scopus	Science Direct	Dimensions Ai	Google Scholar
Keyword 1	I	59,890	29,064	22,884	13,000
Keyword 2	Keywords 1 AND II	3,076	2,941	711	994
Keyword 3	Keywords 2 AND III	11	287	70	35
Keyword 4	Keywords 3 AND IV	6	158	3	21

2.2 Selection of Relevant Articles

There are several options to save the search result database, and Bibtex format was used because it can be easily merged by text editor or reference manager software. JabRef is the reference manager software to manage and merge the reference database. The merged database may additionally contain similar data or beside the point topics. Therefore, the duplicated articles or merged contents are expected to be removed. After selecting all articles for viewing duplicates, a Scopus article was chosen as a reference. A ScienceDirect and 2 Dimensions AI articles were removed from this process to obtain 185 articles. The next step is a manual selection process with three stages, screened of relevant titles, abstract, and full paper. For the relevant titles, 93 articles were removed from ScienceDirect, 1 from Dimensions AI, and 11 from Google Scholar. From this screening, 80 articles were obtained. For the second screening of relevance abstract, 2, 40, and 6 articles were removed from Scopus, ScienceDirect, and Google Scholar. From this screening, 30 articles were obtained. For the last screen of the relevant full paper, 1, 10, and 1 article were removed from Scopus, ScienceDirect, and Google Scholar. From the last screening, 18 articles were obtained, and the process was carried out using the PRISMA flow chart, as shown in Fig. 1.

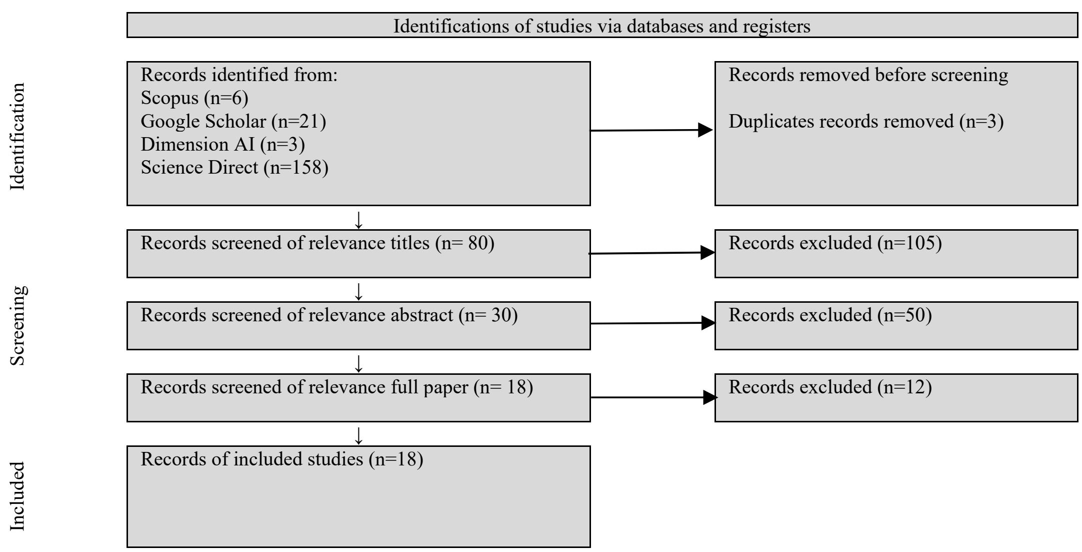

Fig. 1. PRISMA systematic literature review procedure

2.3 Bibliometric Analysis

Bibliometric analysis was conducted using a filtered database with 80 and 30 articles as “Dataset 1” and “Dataset 2”. This approach is often used for literature analyses on attaining bibliographic overviews of clinical selection of incredibly referred to publications. It can recover a list of productions, national or subject bibliographies, or other specialized subject patterns (Ellegaard & Wallin, 2015). Furthermore, VOSviewer and R-biblioshiny were used for bibliometric analysis to obtain the visualization and thematic evolution. It is a software tool for constructing and visualizing bibliometric networks, including journals or individual publications, and can be constructed based on citation, bibliographic coupling, co-citation, or co-authorship (Van Eck & Waltman, 2019). R-biblioshiny for R-bibliometrix (Aria & Cuccurullo, 2017; Massimo & Corrado, 2020) is a Java software program application developed using Massimo Aria from the University of Naples Federico. It combines the capability of the R-bibliometrix bundle with the ease of use of internet apps and the usage of the bright bundle surroundings. R-bibliometrix is a bundle from the open-source R software program with a sparkly net interface able to carry out comprehensive analyses and medical mapping of records with entire bibliographic data (Aria & Cuccurullo, 2017). Dataset 1 was analyzed using VOSviewer to obtain the visualization mapping and clustering from co-authorship and co-occurrence.

3. Results

3.1 *Results from Bibliometric Analysis*

Topics inside climate change and spatial analysis models are highlighted. Furthermore, VOSviewer software creates a network of co-authorship-author and co-occurrence-word terms with the aid of the title and abstract fields. Comparable means phrases are grouped with the aid of the VOSviewer glossary. The network creates clusters shown in different colors, each representing a cluster using one color.

3.1.1 Mapping and Clustering

Co-authorship-author network on a clustering analysis, SAR model, and kriging method is created by obtaining bibliographic information, as shown in Fig. 2. There are six clusters of collaboration, indicated by using specific colors with connected lines, and particular keywords in the search process can cause this. It implies that every cluster has similar themes in their papers, and in this case, the maximum effective author on the topic beneath observe becomes Zhao, Y, with five articles, followed by Weijun and Yongfu with four each.

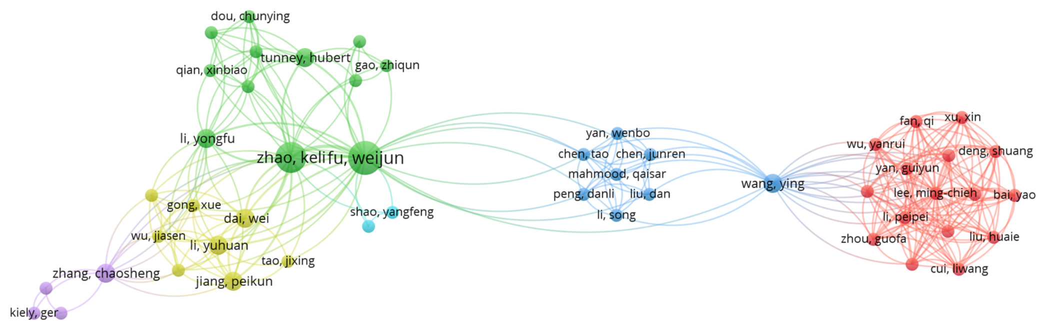

Fig. 2. Co-authorship-author network for Dataset 1

The behavior of a co-occurrence word network in Dataset 1 can be shown in Fig. 3. It may be visible that there are several colors to suggest each cluster and node with special sizes and distances. The identical color approach is in one cluster, and the node's size means the number of words mentioned. The nodes are directly proportional to the terms within the database. The distance from one node to another indicates the power of the connection between the words. The climate change node appears small, and the distance between the "climate change" and the "spatial analysis" node is quite similar. This suggests that spatial analysis of climate change prediction was rarely conducted.

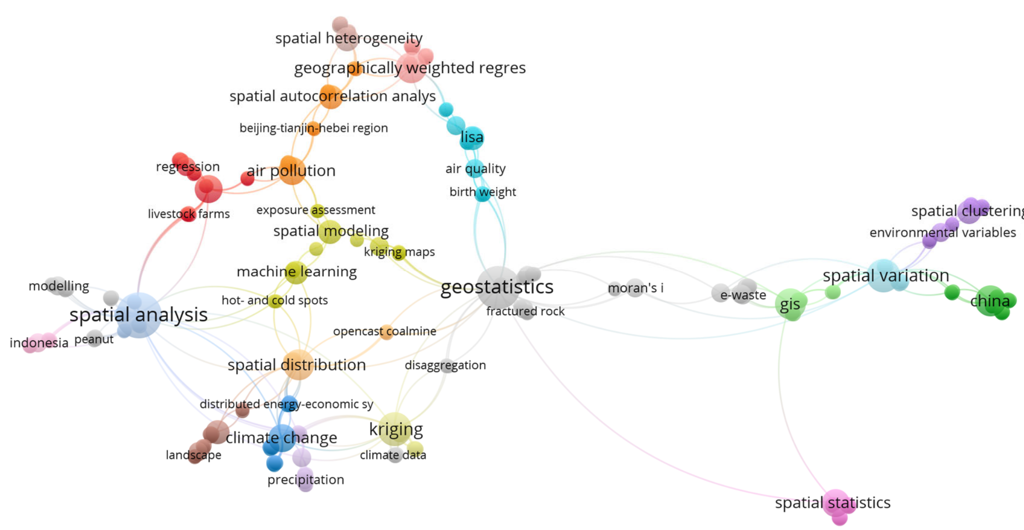

Fig. 3. Co-occurrence-word network for Dataset 1

Here, the spatial analysis concept was linked to various concepts, especially cluster, SAR model, kriging method, and climate change, as shown in Fig. 4.

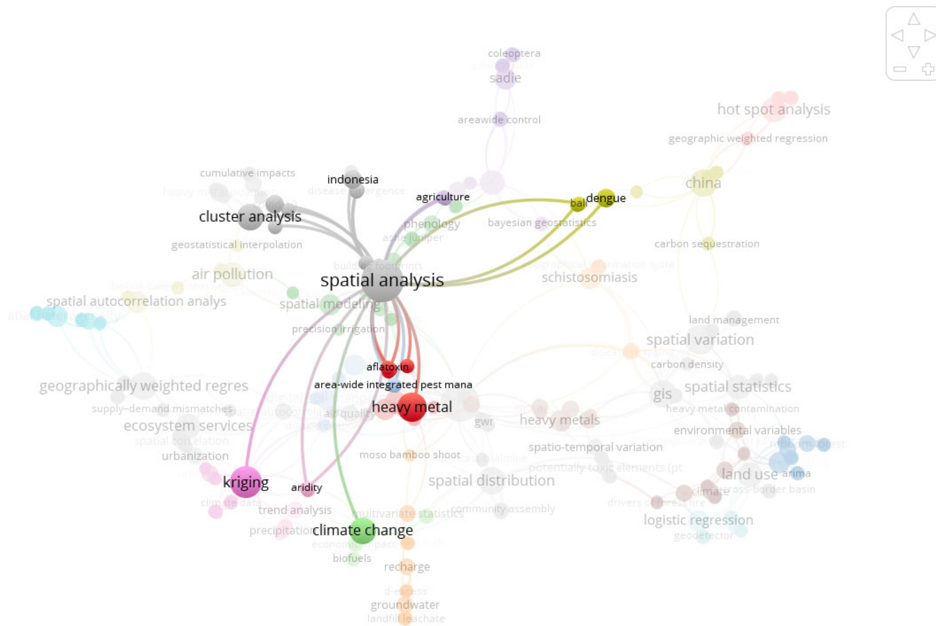

Fig. 4. Spatial Analysis model title and abstract network terms

3.1.2 Thematic Evolution

This section summarizes research on clustering the SAR kriging model for climate change. Using R-biblioshiny, the result shows 30 papers from 10 publishers, and the average publication per year is 4.27. Meanwhile, the average citation per paper is 25.37, with 133 authors involved. From Dataset 2, the number of papers per year was obtained based on databases shown in Fig. 5 below.

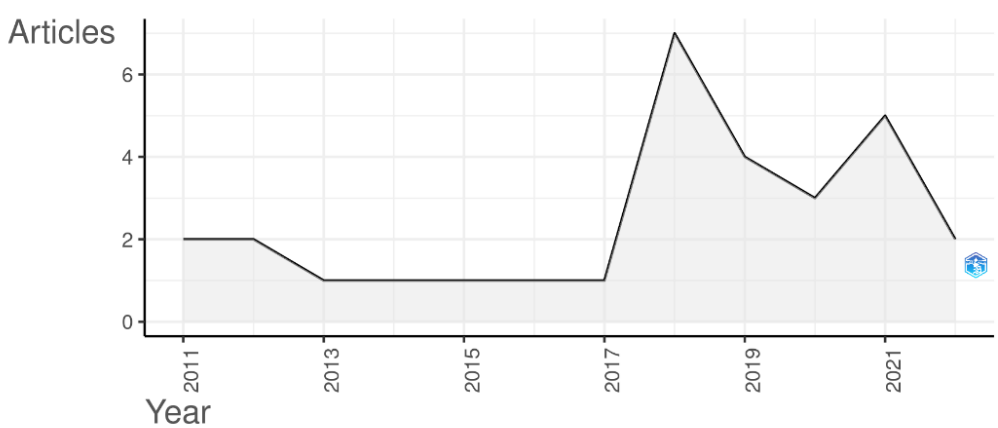

Fig. 5. Number of papers from four databases published between 2011 and 2021

Based on Fig. 5, the number of publications on clustering analysis, SAR model, and kriging method on climate change increased between 2017 and 2018. Furthermore, the number of publications decreased between 2018 and 2020 and then increased from the beginning of 2020 until the end of 2021. Several journals published some articles on clustering analysis, the SAR model, and the kriging method on climate change. There are 30 journals in this database, and Table 5 presents the top 10 on these topics.

Table 4
Top 10 journal publishing

Journal Publishing	Papers
Science of The Total Environment	4
Geoderma	2
Journal of Hydrology	2
Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery	2
Agricultural Water Management	1
Annual Review of Sociology	1
Applied Geochemistry	1
Arabian Journal of Geosciences	1
Bmc Emergency Medicine	1
Computational Statistics and Data Analysis	1

The R-biblioshiny tool for visualization can analyze the conceptual structure of themes, namely thematic map and evolution. The literature most often discussed themes are portrayed and mapped as clusters plotted in the grid diagram, including the four quadrants. Furthermore, the clusters are depicted in circles of various sizes and colors. The coloring circles clusters of associated keywords are the size indicating the number of papers. The thematic map produces the associated keywords of spatial analysis on climate change, shown in Fig. 6.

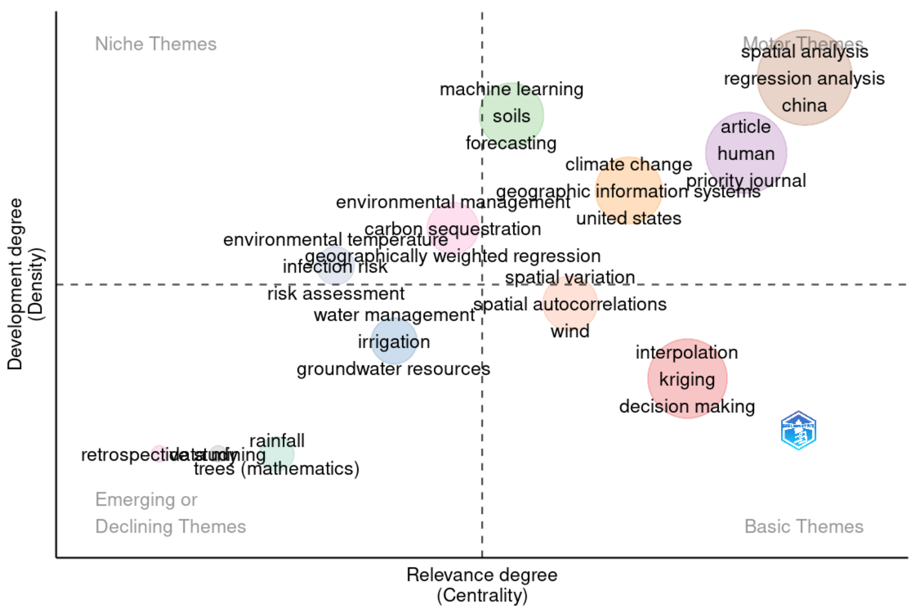

Fig. 6. Thematic map of Dataset 2

Figure 6 shows that the topics discussed in Dataset 2 are presented in a circle color, indicating four clusters. The spatial analysis topic is in the motor themes quadrant and is different from climate factors in the emerging or declining themes. This indicates that spatial analysis strongly links climate factors. The topic of spatial analysis has not been frequently studied and is open to further research in connection with climate change.

3.2 Clustering SAR Kriging model for Climate Change

The spatial analysis techniques include a strategy and the characteristics of point, line, and polygon data sets (Paramasivam & Venkatramanan, 2019). Climate is an important spatial data, and the system's numerical models are needed to produce change projections (Greasby & Sain, 2011). Many climate change impact studies can be modeled using clustering analysis (Yokoi et al., 2011; Hennon et al., 2013; Carvalho et al., 2016; Mahlstein & Knutti, 2010), SAR model (Samrat & Alok, 2017; Mojiri et al., 2018; Sadiq et al., 2019), and kriging method (McKee, 1993; Mojiri et al., 2018; Yang et al., 2015). Table 5 summarizes the model used to analyze climate change.

Table 5
Summary of the Clustering SAR Kriging model

No	Author	Titles	Research Object
1	(McKee, 1993)	*Spatial Analysis of Monthly and Annual Precipitation Trends in Turkey*	Prediction and characterization of the magnitude of observed locations at OK, IDW, and CRS interpolation methods
2	(Yokoi et al., 2011)	*Application of Cluster Analysis to Climate Model Performance Metrics*	Group the performance metrics that are mutually linked with aspects of the climate used cluster analysis
3	(Carvalho et al., 2016)	*Regionalization of Europe based on a K-Means Cluster Analysis of the climate change of temperatures and precipitation*	Analysis of the K-Means Cluster Method is used to classify climate data sets of temperature and rainfall
4	(Samrat & Alok, 2017)	*Climate sensitivities and farmland values in Nepal: A spatial panel Ricardian approach*	The impact of climate change on agricultural land by comparing the SAR and SEM models
5	(Mojiri et al., 2018)	*Comparison of Predictions by Kriging and Spatial Autoregressive Models*	Comparing the prediction accuracy of Spatial Autoregressive models with Kriging predictions using simulation studies and real data
6	(Sadiq et al., 2019)	*Ricardian analysis of climate change–agriculture linkages in Pakistan*	Predictions to determine the impact of climate change on agriculture through Ricardian Regression and SAR model specifications
7	(Yang et al., 2015)	*Spatial Interpolation over Greater Sydney Region*	Comparison of ANUDEM, Spline, IDW, and Kriging spatial interpolation techniques to rainfall data
8	(Felix et al., 2019)	*K-Means Cluster Using Rainfall and Storm Prediction in Machine Learning Technique*	Application of K-Mean Cluster analysis to divide regional domains based on climate change using rainfall simulation, maximum and minimum temperature

4. Discussions

4.1 The State-of-the-Art

The results of the bibliometric analysis described the relationship between topics obtained from the literature review (Dataset 3), totaling 18 articles. From four databases, the results provided in the form of 188 articles after filtering redundancies have increased based on the number of publications from 2011 to 2021. Table 5 shows that the state of the art was completed with the objectives, method, and object. Clustering analysis, SAR model, and kriging method are used to predict climate change, but there is no combination between these variables.

4.2 Research Development of Clustering SAR Kriging model for Climate Change

Research on spatial modeling for climate change prediction in the last ten years has developed quite significantly. Several studies on this topic with spatial modeling have been carried out, including cluster analysis, SAR modeling, and the kriging method. First, cluster analysis is used to group the performance metrics mutually linked with aspects of the climate (Yokoi et al., 2011), classify climate data sets of temperature and rainfall (Carvalho et al., 2016), and define regions encompassing a similar mean climate and similar projected changes (Mahlstein & Knutti, 2010). Second, the SAR model determines the proximity value of a location, such as analyzing the impact of climate change on farmland values (Samrat & Alok, 2017), predictions to determine the impact on agriculture (Sadiq et al., 2019), and analyzing urban spatial growth (Qiu et al., 2022). Third, the kriging method is used to predict values at unobserved locations, such as predicting the magnitude of observed changes at unobserved locations (McKee, 1993), predicting daily rainfall data for local climate impact (Yang et al., 2015), and using kriging estimators to compared the accuracy using the weather station data (Kuo et al., 2021). In predicting climate change, the role of spatial modeling is influential in determining the prediction and description of the effects of climate change (Zomer et al., 2008). These papers work on individual models, and no finding has combined the three variables. Furthermore, there is an opportunity to develop this model by combining the clustering analysis, SAR model, and kriging method into a SAR Kriging Clustering model that can predict and describe climate change.

5. Conclusions

This research provided an SLR on clustering the SAR kriging model for climate change. Furthermore, three steps were used to obtain 188 articles from Scopus, ScienceDirect, Dimensions AI, and Google Scholar between 2011 to 2021. All of the articles were analyzed using PRISMA methods, and VOSviewer and R-biblioshiny programs were employed to obtain bibliometric visualization. After screening duplicate, title, abstract, and full papers, 18 articles for the SLR analysis were selected. This research summarizes the finding on clustering the SAR kriging model. It presents a bibliographic mapping of the topics, the network of co-authorships, and thematic evolution. Meanwhile, the bibliometric analysis shows that many subjects on clustering SAR kriging model can be studied. In conclusion, the clustering SAR kriging model associated with climate and its prediction procedure is very open for research improvement.

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References

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Banzhaf, E., Bulley, H. N., Inkoom, J. N., & Elze, S. (2022). *Mapping Open Data and Big Data to Address Climate Resilience of Urban Informal Settlements in Sub-Saharan Africa*. 1–13.

Carvalho, M. J., Melo-Gonçalves, P., Teixeira, J. C., & Rocha, A. (2016). Regionalization of Europe based on a K-Means Cluster Analysis of the climate change of temperatures and precipitation. *Physics and Chemistry of the Earth*, *94*, 22–28. https://doi.org/10.1016/j.pce.2016.05.001

Efe, B., Gözet, E., Özgür, E., Lupo, A. R., & Deniz, A. (2022). Spatiotemporal Variation of Tourism Climate Index for Türkiye during 1981–2020. *Climate*, *10*(10), 1–32. https://doi.org/10.3390/cli10100151

Ellegaard, O., & Wallin, J. A. (2015). The bibliometric analysis of scholarly production: How great is the impact? *Scientometrics*, *105*(3), 1809–1831. https://doi.org/10.1007/s11192-015-1645-z

Felix, A. Y., Vinay, G. S. S., & Akhik, G. (2019). K-Means cluster using rainfall and storm prediction in machine learning technique. *Journal of Computational and Theoretical Nanoscience*, *16*(8), 3265–3269. https://doi.org/10.1166/jctn.2019.8174

Ghavidel, Y., Baghbanan, P., & Farajzadeh, M. (n.d.). *The spatial analysis of thunderstorm hazard in Iran*. *10*(5). https://doi.org/10.1007/s12517-017-2902-7

Gonzalez-Gonzalez, M. A., & Guertin, D. P. (2021). Seasonal bean yield forecast for non-irrigated croplands through climate and vegetation index data: Geospatial effects. *International Journal of Applied Earth Observation and Geoinformation*, *105*(November), 102623. https://doi.org/10.1016/j.jag.2021.102623

Greasby, T. A., & Sain, S. R. (2011). Multivariate Spatial Analysis of Climate Change Projections. *Journal of Agricultural, Biological, and Environmental Statistics*, *16*(4), 571–585. https://doi.org/10.1007/s13253-011-0072-8

Hennon, C. C., Papin, P. P., Zarzar, C. M., & ... (2013). Tropical cloud cluster climatology, variability, and genesis productivity. In *Journal of …*. journals.ametsoc.org. https://journals.ametsoc.org/view/journals/clim/26/10/jcli-d-12-00387.1.xml?tab_body=abstract-display

Kouchaksaraei, H. R., & Karl, H. (2019). Service function chaining across openstack and kubernetes domains. *DEBS 2019 - Proceedings of the 13th ACM International Conference on Distributed and Event-Based Systems*, 240–243. https://doi.org/10.1145/3328905.3332505

Kuo, P. F., Huang, T. E., & Putra, I. G. B. (2021). Comparing kriging estimators using weather station data and local greenhouse sensors. *Sensors*, *21*(5), 1–15. https://doi.org/10.3390/s21051853

Li, Y., Hernandez, J. H., Aviles, M., Knappett, P. S. K., Giardino, J. R., Miranda, R., Puy, M. J., Padilla, F., & Morales, J. (n.d.). *Empirical Bayesian Kriging method to evaluate inter-annual water-table evolution in the Cuenca Alta del Río Laja aquifer, Guanajuato, México*. *582*, 124517. https://doi.org/https://doi.org/10.1016/j.jhydrol.2019.124517

Mahlstein, I., & Knutti, R. (2010). Regional climate change patterns identified by cluster analysis. *Climate Dynamics*, *35*(4), 587–600. https://doi.org/10.1007/s00382-009-0654-0

Marchetti, Y., Nguyen, H., Braverman, A., & Cressie, N. (n.d.). *Spatial data compression via adaptive dispersion clustering*. *117*, 138–153. https://doi.org/https://doi.org/10.1016/j.csda.2017.08.004

Masri, S., Jin, Y., & Wu, J. (2022). Compound Risk of Air Pollution and Heat Days and the Influence of Wildfire by SES across California, 2018–2020: Implications for Environmental Justice in the Context of Climate Change. *Climate*, *10*(10), 2018–2020. https://doi.org/10.3390/cli10100145

Massimo, A., & Corrado, C. (2020). *Bilionshiny biliomertrix*. https://www.bibliometrix.org/biblioshiny/

Mojiri, A., Waghei, Y., Sani, H. R. N., & Borzadaran, G. R. M. (2018). Comparison of predictions by kriging and spatial autoregressive models. *Communications in Statistics: Simulation and Computation*, *47*(6), 1785–1795. https://doi.org/10.1080/03610918.2017.1324980

Ohana-Levi, N., Bahat, I., Peeters, A., Shtein, A., Netzer, Y., Cohen, Y., & Ben-Gal, A. (n.d.). *A weighted multivariate spatial clustering model to determine irrigation management zones*. *162*, 719–731. https://doi.org/https://doi.org/10.1016/j.compag.2019.05.012

Orton, T. G., Pringle, M. J., Bishop, T. F. A., Menzies, N. W., & Dang, Y. P. (n.d.). *Increment-averaged kriging for 3-D modelling and mapping soil properties: Combining machine learning and geostatistical methods*. *361*, 114094. https://doi.org/https://doi.org/10.1016/j.geoderma.2019.114094

Ouyang, Y., & Panda, S. S. (2022). Linking Climate-Change Impacts on Hydrological Processes. *Climate*, *10*(7), 1–5. https://doi.org/10.3390/cli10070096

Palmatier, R. W., Houston, M. B., & Hulland, J. (2018). Review articles: purpose, process, and structure. *Journal of the Academy of Marketing Science*, *46*(1), 1–5. https://doi.org/10.1007/s11747-017-0563-4

Paramasivam, C. R., & Venkatramanan, S. (2019). An introduction to various spatial analysis techniques. *GIS and Geostatistical Techniques for Groundwater Science*, *June*, 23–30. https://doi.org/10.1016/B978-0-12-815413-7.00003-1

Peirce, A. M., Espira, L. M., & Larson, P. S. (2022). Climate Change Related Catastrophic Rainfall Events and Non-Communicable Respiratory Disease: A Systematic Review of the Literature. *Climate*, *10*(7). https://doi.org/10.3390/cli10070101

Pinar Aslantas Bostan, Z. (2006). *Exploring the Mean Annual Precipitation and Temperature Values Over Turkey By Using Environmental Variables*. *June 2014*, 1–6.

Qiu, B., Zhou, M., Qiu, Y., Liu, S., Ou, G., Ma, C., Tu, J., & Li, S. (2022). An Integrated Spatial Autoregressive Model for Analyzing and Simulating Urban Spatial Growth in a Garden City, China. *International Journal of Environmental Research and Public Health*, *19*(18). https://doi.org/10.3390/ijerph191811732

Querner, P., Sterflinger, K., Derksen, K., Leissner, J., Landsberger, B., Hammer, A., & Brimblecombe, P. (2022). Climate Change and Its Effects on Indoor Pests (Insect and Fungi) in Museums. *Climate*, *10*(7), 1–10. https://doi.org/10.3390/cli10070103

Requia, W. J., Coull, B. A., & Koutrakis, P. (2019). The influence of spatial patterning on modeling PM2.5 constituents in Eastern Massachusetts. *Science of the Total Environment*, *682*, 247–258. https://doi.org/10.1016/j.scitotenv.2019.05.012

Ribeiro, M. C., Pinho, P., Branquinho, C., Llop, E., & Pereira, M. J. (2016). Geostatistical uncertainty of assessing air quality using high-spatial-resolution lichen data: A health study in the urban area of Sines, Portugal. *Science of the Total Environment*, *562*, 740–750. https://doi.org/10.1016/j.scitotenv.2016.04.081

Sadiq, S., Saboor, A., Mohsin, A. Q., Khalid, A., & Tanveer, F. (2019). Ricardian analysis of climate change–agriculture linkages in Pakistan. *Climate and Development*, *11*(8), 679–686. https://doi.org/10.1080/17565529.2018.1531746

Samrat, B. K., & Alok, K. B. (2017). Climate sensitivities and farmland values in Nepal: A spatial panel Ricardian approach. *Journal of Development and Agricultural Economics*, *9*(6), 145–161. https://doi.org/10.5897/jdae2017.0822

Shekhar, S., Evans, M. R., Kang, J. M., & ... (2011). Identifying patterns in spatial information: A survey of methods. *Reviews: Data Mining …*. https://onlinelibrary.wiley.com/doi/abs/10.1002/widm.25

Silva, M. V. da, Pandorfi, H., Jardim, A. M. da R. F., Oliveira-Júnior, J. F. de, Divincula, J. S. da, Giongo, P. R., Silva, T. G. F. da, Almeida, G. L. P. de, Moura, G. B. de A., & Lopes, P. M. O. (2021). Spatial modeling of rainfall patterns and groundwater on the coast of northeastern Brazil. *Urban Climate*, *38*(February). https://doi.org/10.1016/j.uclim.2021.100911

McKee, T. B., Doesken, N. J., & Kleist, J. (1993). Analysis of Standardized Precipitation Index (SPI) data for drought assessment. *Water (switzerland)*, *26*(2), 1-72. https://doi.org/10.1088/1755-1315/5

Troiani, F., Piacentini, D., Della Seta, M., & Galve, J. P. (2017). Stream Length-gradient Hotspot and Cluster Analysis (SL-HCA) to fine-tune the detection and interpretation of knickzones on longitudinal profiles. *Catena*, *156*(March), 30–41. https://doi.org/10.1016/j.catena.2017.03.015

Van Eck, N. J., & Waltman, L. (2019). Manual for VOSviwer version 1.6.10. *CWTS Meaningful Metrics*, *January*, 1–53. https://www.vosviewer.com/documentation/Manual_VOSviewer_1.6.10.pdf

Yang, X., Xie, X., Liu, D. L., Ji, F., & Wang, L. (2015). Spatial Interpolation of Daily Rainfall Data for Local Climate Impact Assessment over Greater Sydney Region. *Advances in Meteorology*, *2015*. https://doi.org/10.1155/2015/563629

Yokoi, S., Takayabu, Y. N., Nishii, K., Nakamura, H., Endo, H., Ichikawa, H., Inoue, T., Kimoto, M., Kosaka, Y., Miyasaka, T., Oshima, K., Sato, N., Tsushima, Y., & Watanabe, M. (2011). Application of cluster analysis to climate model performance metrics. *Journal of Applied Meteorology and Climatology*, *50*(8), 1666–1675. https://doi.org/10.1175/2011JAMC2643.1

Zhang, C., Tang, Y., Xu, X., & Kiely, G. (2011). Towards spatial geochemical modelling: Use of geographically weighted regression for mapping soil organic carbon contents in Ireland. *Applied Geochemistry*, *26*(7), 1239–1248. https://doi.org/10.1016/j.apgeochem.2011.04.014

Zomer, R. J., Trabucco, A., Bossio, D. A., & Verchot, L. V. (2008). Climate change mitigation: A spatial analysis of global land suitability for clean development mechanism afforestation and reforestation. *Agriculture, Ecosystems and Environment*, *126*(1–2), 67–80. https://doi.org/10.1016/j.agee.2008.01.014