Progress in the Application of Geostatistics Downscaling Methods in the Field of Public Health

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Abstract. With the continuous development of the two emerging fields of medical geography and spatial epidemiology, Geostatistical downscaling plays an important role in high-precision disease mapping and incidence prediction in a range of public health applications. This article combines the application cases of different diseases and lists a series of geostatistical downscaling methods, including Area-to-point and Area-to-Area Kriging, Area-to-point and Area-to-area Poisson Kriging, Area-to-point and Area-to-Area regression Kriging, Area-to-point and Area-to-Area co-kriging, Area-to-point and Area-to-Area binomial kriging, etc. By introducing the application progress of different methods in the field of public health, the advantages and disadvantages are compared. Finally, trends and some basic questions of methods proposed recently are discussed in the conclusion.

Keywords: Geostatistics, Downscaling, Area-to-point, Area-to-Area, Kriging, public health

1. Introduction

Recently, with the development of the two emerging fields of medical geography and spatial epidemiology, a series of analysis techniques such as resampling, general statistical methods, machine learning, spatial statistical analysis, etc. have become more and more popular in the field of public health. In the field of public health, epidemiological statistics generally use counties as the smallest unit, but when controlling the spread of epidemics, in order to formulate precise control measures, it is necessary to infer the specific incidence of epidemics based on county-level statistics (such as incidence) The point-scale incidence rate of a district such as a township or village. Therefore, obtaining small-scale information from large-scale data has always been an important content of different scale conversion research. Geostatistical downscaling takes into account the changes in the scales of regionalized variables before and after interpolation while interpolating variables, and has an accurate accuracy evaluation of the results of downscaling [1]. Therefore, it is a relatively new interpolation method compared to traditional point interpolation. It has obvious advantages in spatial prediction and uncertainty analysis in the field of public health.
1.1. Data source and search strategy

In order to comprehensively summarize the applied research of geostatistics downscaling in the field of public health, we focused on five databases including CNKI, Wanfang, Web of Science, pubmed and Sciencedirect. We used three core concepts (geostatistics, Standard push down and public health) related topics, titles, abstracts and keywords to search for target documents. At the same time, after a preliminary understanding of the relevant knowledge applied to the field of public health under the scale of geostatistics, the relevant search terms were expanded, and the latter included some previous systematic reviews that were not limited to public health.

| Table 1. Literature search strategy. |
|-------------------------------------|
| Database                     | CNKI, Wanfang, Web of Science, Pubmed, Sciencedirect |
| Search field                  | Title+Abstract+Keywords (Wanfang, CNKI, Sciencedirect), Subject+Title (Web of Science), Full Text (PubMed) |
| Search term                   | (kriging OR interpolation OR geostatic*) AND ("area to point" OR "area to area" OR "polygon to polygon" OR "polygon to point" OR downscal* OR disaggregat*) |

1.2. Data extraction and synthesis

According to the search strategy developed in this article, 1815 records were obtained from 1993 to 2020. The selected literature was analyzed, and the application of different types of geostatistical downscaling methods in public health was used as the screening criteria, and 97 of them were identified as key reading literature. The geostatistical downscaling methods are mainly: Area-to-point and Area-to-Area Kriging, Area-to-point and Area-to-area Poisson Kriging, Area-to-point and Area-to-Area regression Kriging, Area-to-point and Area-to-Area co-kriging, Area-to-point and Area-to-Area binomial kriging, etc.

2. Basic Principles of Geostatistical Downscaling

The core of geostatistics is the Kriging method, an optimal, linear, and unbiased interpolation estimator [2]. Kriging interpolation was first proposed by South African mining engineer Krige in 1951 to estimate mineral reserves. After decades of development, it has been widely used in various fields such as ecology, hydrology, land use, and public health. The essence of the Kriging method is to infer the spatial distribution of the entire regionalized variable based on the observations of a limited number of sampling points of the regionalized variable, that is, use a limited known sample \( (Z) Z_0(i=1,2,\ldots,n) \) to estimate the value of the point to be estimated \( Z_i^* = \sum_{i=1}^{n} \lambda_i Z_i \) \((\lambda_i \) is the weight of known sample Point observations)[3], the conventional Kriging method cannot directly solve the downscaling problem[4].

2.1. Principle

Gotway, Kyriakidis, and Young proposed the Kriging method to predict from surface data to point data in 2002, 2004, and 2005, respectively. The method was finally determined by Kyriakidis as (Area-to-Point Kriging ATPK) [5]. This method allows mapping the variability within geographic units while determining the consistency of the prediction, so that the sum or average of the estimated values after downscaling is equal to the original datum [6]. At this stage, the general methods for pushing down on the geostatistical scale include Area-to-Point Kriging (ATPK), Area-to-Area Kriging (ATAK), and other interpolation methods based on this. This section introduces the principle of ATPK/ATAK method in detail, and focuses on the analysis of the key and difficult points in the use of this method.

2.1.1. Area-to-Point Kriging (ATPK). ATPK essentially uses known surface (can be continuous surfaces of various shapes) data (continuous or discrete) to interpolate unknown points (which can be inside or outside known surfaces). The estimated value of the unknown point is the linear weighted sum of the data on the area and its nearby area.
\( \nu_i \) is the known area, where \( i = 1, 2, \ldots, k \), \( Z(\nu_i) \) is the observation value, where \( i = 1, 2, \ldots, k \), \( x \) is the estimated point, and the observation value is \( Z^*(x) \), and the estimation equation:

\[
Z^*(x) = \sum_{i=1}^{k} \lambda_i(\nu_i) Z(\nu_i)
\]  

(1)

\( \lambda_i(\nu_i) \) is the weight of \( Z(\nu_i) \), calculated according to the Kriging equation \( Z(\nu_i) \)

\[
\sum_{j=1}^{K} \lambda_x(\nu_i) \bar{C}(\nu_i, \nu_j) + \mu_x = \bar{C}(\nu_i, x)
\]

(2)

\[
\sum_{j=1}^{K} \lambda_x(\nu_j) = 1
\]

(3)

Estimated variance:

\[
\sigma^2 = C(x, x) - \sum_{i=1}^{K} \lambda_x(\nu_i) \bar{C}(\nu_i, x) - \mu_x
\]

(4)

\( \mu_x \) is the Lagrangian multiplier, \( \bar{C}(\nu_i, x) \) is the covariance of area and point, and \( \bar{C}(\nu_i, \nu_j) \) is the covariance of area and area.

Given area \( \nu_i \), discretize area \( \nu_i \) into \( N(v_i) \) points \( s_j, \ j = 1, 2, \ldots, N(v_i) \), denoted as \( \nu_i = \{s_j | j = 1, 2, \ldots, N(v_i)\} \), then the covariance function of area \( \nu_i \) and point \( x \) is:

\[
\bar{C}(\nu_i, x) \approx \frac{1}{|\nu_i|} \int_{s \in \nu_i} Cov[z(s), z(x)] \, ds
\]

\[
\approx \frac{1}{N(v_i)} \sum_{j=1}^{N(v_i)} C(s_j, x), s_j \in \nu_i
\]

(5)

Given area \( \nu_i = \{s_k | k = 1, 2, \ldots, N(v_i)\} \), \( \nu_j = \{s_l | l = 1, 2, \ldots, N(v_j)\} \), then the covariance function of area \( \nu_i \) and area \( \nu_j \) is [5]:

\[
\bar{C}(\nu_i, \nu_j) \approx \frac{1}{|\nu_i|} \frac{1}{|\nu_j|} \int_{s_e \in \nu_i} \int_{s_r \in \nu_j} Cov[z(s), z(s')] \, ds \, ds'
\]

\[
\approx \frac{1}{N(v_i)} \frac{1}{N(v_j)} \sum_{k=1}^{N(v_i)} \sum_{l=1}^{N(v_j)} C(s_k, s_l)
\]

(6)

2.1.2. Area-to-Area Kriging (ATAK). \( \nu_i \) is the known area, where \( i = 1, 2, \ldots, k \), \( Z(\nu_i) \) is the observation value, where \( i = 1, 2, \ldots, k \), \( \nu_0 \) is the estimated area, and the estimated value of the observation is \( Z^*(\nu_0) \), the estimation equation is:

\[
Z^*(\nu_0) = \sum_{i=1}^{k} \lambda_i(\nu_0) Z(\nu_i)
\]

(7)

Kriging equation:

\[
\sum_{j=1}^{K} \lambda_j(\nu_0) \bar{C}(\nu_i, \nu_j) + \mu(\nu_0) = \bar{C}(\nu_i, \nu_0)
\]

(8)
Estimated variance:

\[ \sigma^2(v_0) = C(v_0, v_0) - \sum_{i=1}^{K} \lambda_i(v_0)C(v_i, v_0) - \mu(v_0) \]  

Compared with ATPK, the right end of the ATAK estimation equation replaces the known points with the known area, that is, replace \( C(v_i, x) \) with \( C(v_i, v_0) \) and \( C(x, x) \) with \( C(v_0, v_0) \).

According to the principles of ATPK and ATAK, it can be seen that when downscaling is performed, these two methods can perform downscaling on the basis of factors such as the shape, size and spatial relationship of area-scale data, while retaining the influence of the original data to the maximum. Regarding this point, Kyriakidis [5] and Goovaerts [6] proved in detail that ATPK has an important feature of coherence (interpolation down to the average of the sum of all point values in an arbitrary known surface is equal to the original value of the known area).

2.1.3. Deconvolution. In the downscaling process, the availability of the point-scale covariance function is important for obtaining small-scale information. In practical applications, considering the second-order stationary assumptions, the point scale variation function is generally used instead of the point scale covariance function. Therefore, in the absence of point-scale data, how to accurately infer the point-scale variogram downscaling based on the acquired area-scale data is an important research content.

In geostatistics, inferring the point-scale variogram based on the empirical variogram of the area-scale data is called deconvolution. Including: analysis method [4], iterative weighted generalized least squares method [7] and iterative empirical process method [6], etc. [8, 9]. The steps of deconvolution are as follows:

1. According to the known area scale data, use the variation function of the geometric center as the empirical variation value of the known area.
2. Select the variation function model (such as spherical model, Gaussian model, power function model or logarithmic model, etc.), use generalized least squares method or maximum likelihood estimation method to fit the variogram, and give the best model parameter.
3. Initialize the variogram of a point scale, and transform it into a variogram of the area scale through regularization.
4. Adjust the point scale variation function to minimize the difference between the regularized model and the fitted model.

At this point, it can be considered that the point-scale variation model can truly reflect the spatial variation structure at the point-scale, and is applied to ATPK or ATAK.

3. The development of geostatistics downscaling in the field of public health

In 1991, French scholar Christian [46] first proposed the application of geostatistics tools to the analysis of disease incidence, opening up a new direction of combining geostatistics with public health. At present, in the process of using geostatistical methods for downscaling, according to whether auxiliary data is used or not, the scale is pushed down into two categories: downscaling without auxiliary data and downscaling with auxiliary data [10, 11].

3.1. Downscaling without auxiliary data

In the field of geostatistics, when small-scale auxiliary information is not integrated, downscaling methods include area-to-point kriging (ATPK) and area-to-area kriging (ATPK), area-to-point Poisson kriging (ATPPK) and area-to-area Poisson kriging etc.
3.1.1. Area-to-Point kriging (ATPK) and area-to-area kriging (ATAK). At present, the application of ATPK, ATAK is commonly used in high-precision mapping on the scale of population density and soil properties. As shown in Table 2:

| Time  | Author      | Research Area               | Downscaled Data          | Citations |
|-------|-------------|-----------------------------|--------------------------|-----------|
| 2004  | 신정엽       | Erie County, New York, USA  | Population data          | 29        |
| 2008  | Yoo         | Ann Arbor, USA              | Population data          | 40        |
| 2012  | Schirrmann M| Eastern Germany             | Phosphorus sample data   | 43        |
| 2012  | Kerry R     | Northern Ireland            | Soil organic carbon data | 21        |
| 2014  | Brus DJ     | North Brabant               | Soil organic matter content data | 27    |
| 2014  | Lu B        | London, England             | London house price data  | 22        |

ATPK has achieved a lot of results in population data processing related to public health issues. 신정엽 [12] applied ATPK to the census area data of Erie County, New York, and proved that ATPK has higher accuracy than area-weighted interpolation, scale method, and density method. Yoo[13,14], compares Tobler's Pycnophylactic interpolation method with ATPK, which is used to process the population distribution data collected in the 1970 Ann Arbor 18 population census area, and achieve population density downscaling in this area. The results show that the predicted population density surfaces of the two are almost the same, and both have coherence. The significant advantage of ATP is that it can give the accuracy evaluation of the downscaling results, which is very important for the uncertainty propagation in the spatial analysis operation. Yoo [15] further developed the ATPK method to explain inequality constraints. And Lu B [16] applies ATPK to the downscaling of housing prices.

In addition, ATPK is more used in data processing of the earth's environment. In the process of phosphorus sample mapping, Schirrmann M [17] et al. used ATPK to downscale the phosphorus sampling areas of different sizes and shapes, and used the area of the site to synthesize the samples of the sampling point set, which greatly reduced the workload. At the same time, the smoothing effect of general interpolation and the aggregation effect of synthetic samples are reduced. Based on soil samples and legacy soil data from 6862 Northern Ireland regions (The 1:250000 digital map provided by the local soil association and the related typical organic carbon concentration percentage), Kerry R [18] et al. used the ATPK method to draw a soil organic carbon map in Northern Ireland..Brus D[19] selected all soil sample data collected from Noord-Brabant province (5051 square kilometers) in four periods (2008-2011) in the BLGG database (total sample size is 23272), and used ATPK to this area's farmland surface The organic matter content in the soil was statistically analyzed, and these area data were used for spatial mapping.

In summary, there are few specific examples of the application of a single ATPK or ATAK method in public health. The main reason is that the data source used in the calculation is relatively single and lacks the combination with other auxiliary information, resulting in low accuracy of downscaling results. However, the mature application of ATPK and ATAK in soil properties and population density analysis has laid a good theoretical foundation for the promotion of geostatistical downscaling methods to the field of public health.

3.1.2. Area-to-Point Poisson kriging (ATPPK) and area-to-area Poisson kriging (ATAPK). Ali [20] and others used Poisson Kriging to draw a map of the incidence of dysentery and cholera based on the data of the relative family population of the paternal line. This is the first application of Poisson Kriging in the field of public health, which realizes the spatial interpolation of Poisson Kriging applied to the local disease rate, and obtains the predicted disease incidence and related prediction variance. Later, Monestiez P introduced this method into experiments describing the spatial distribution of wild species [21, 22]. Goovaerts proposed an improved method based on ATPK and ATAK [23, 24] called Area-to-Point Poisson Kriging (ATPPK), and Area-to-Area Poisson Kriging (ATAPK), which is used to predict
the incidence of lung cancer, cervical cancer and other diseases. After that, the specific development process of ATPPK, ATAPK is as follows:

Table 3. ATPPK/ATAPK application examples

| Time | Author       | Research Area                  | Downscaled Data                                      | Citations |
|------|--------------|--------------------------------|------------------------------------------------------|-----------|
| 2006 | Goovaerts P  | Indiana, Arizona, California, Nevada, Utah | Incidence of lung cancer and cervical cancer          | 32        |
| 2013 | Asmarian NS  | Iran                           | Incidence of esophageal cancer                        | 9         |
| 2016 | Asmarian NS  | Iran                           | Incidence of gastric cancer                           | 19        |
| 2017 | Jiaxin Wang  | Shandong Province              | Incidence of hand, foot and mouth disease             | 19        |
| 2018 | Kou K        | Shandong Province              | Incidence of esophageal cancer                        | 28        |

During the development of ATPPK, high-precision mapping of disease incidence has developed rapidly abroad. Goovaerts [24] et al. selected two comparison regions: 92 counties in Indiana (with equivalent geometric shapes); 118 counties in four western states (larger geometrical differences) of lung cancer and cervical cancer incidence rates were downscaled in the process. Comparing the two methods of ATPPK and Poisson Kriging, the results show that the former has better precision results. And the greater the difference in geometry and size of county data, the more obvious the accuracy advantage of ATPPK. Goovaerts [6, 25] In 2008, the problem of deconvolution of semi-variance graphs was improved and the feasibility of ATPK was improved.

Asmarian et al. [26, 27] used ATAPK to down-scale and interpolate the incidence data of esophageal cancer in 233 counties in Iran from 2003 to 2007, draw a map of the incidence of esophageal cancer and give an estimated map of the incidence of esophageal cancer in the region. The results of the study show that ATAPK will reduce its prediction accuracy in sparsely populated areas.

After that, Asmarian NS [27] further analyzed the gastric cancer incidence data in Iran from 2003 to 2010, and used the ATAPK and BYM spatial models to smooth the standardized incidence rates of gastric cancer in 373 surveyed counties, and compared the accuracy of the two methods in identifying high-risk areas. The results show that the interpolation results of ATAPK and BYM models are basically the same, but the former is less smooth and the accuracy is better than the latter.

Kou K [28] used the ATAPK method to smooth the esophageal cancer mortality of 140 county-level units in Shandong Province in the process of spatial analysis of esophageal cancer mortality among high-risk populations in China. Wang Jiaxin[29] used ATAPK to downscale and interpolate the incidence data of hand, foot and mouth disease at district level in Shandong Province in 2010, and obtained a high-precision map of the incidence of hand, foot and mouth disease in the region, and explored the spatial distribution pattern of hand, foot and mouth disease on the township scale. The health department formulates prevention and control measures and allocates medical resources more accurately to provide reference.

In addition to the field of public health, at the same time, Liu [30] applied ATPPK to the downscaling of population health data, expanding the scope of application of geostatistics in the field of public health. In general, the Poisson expansion of ATPK is of great significance to the development of geostatistics [31]. It can consider the shape and size of the administrative unit at the same time, it has coherence, and reduces the weight of unreliable value. However, ATPPK and ATAPK still use a single data source, and the accuracy needs to be improved.

3.2. Downscaling with auxiliary data

In many cases, only a single data cannot be used to push down the small-scale target geographic variables well. In the downscaling process, you can consider introducing auxiliary data, using auxiliary information to explain the unknown temporal or spatial changes of the target geographic variables, and using small-scale auxiliary information to explore the spatial distribution characteristics of smaller attributes. At present, in the field of geostatistics, the main methods for scale-down in the case of fusion...
of small-scale auxiliary information include: Area-to-Point/Area Regression Kriging (ATPRK/ATARK), Area-to-Point/Area Binomial Kriging (ATPBK/ATABK), Co-Kriging, Area and Point Kriging, etc. These are widely used in the field of public health, and are of great significance for the prediction and prevention of the incidence and space of major diseases and infectious diseases.

3.2.1. Area-to-point Regression kriging (ATPPK) and Area-to-area Poisson kriging (ATAPK). ATPRK is essentially based on ATPK using a single data source, adding auxiliary data, using regression equations, and obtaining scale-down results. The specific principles Ge Y[32], Hu M[33], Wang Q[34-37], etc. are explained in detail. Generally speaking, ATPRK or ATAPRK includes two major steps: 1) Regression modeling. 2) Scale down based on ATPK. The details of the process are as follows:

1. Extract relevant, full-coverage auxiliary data based on existing area-scale data;
2. Based on the dependent variable (existing area-scale data) and independent variables (correlation auxiliary data), establish a regression equation to obtain the regression coefficient and the residual of the area-scale;
3. Calculate the overall trend of the target variable based on auxiliary data and regression equation;
4. Use ATPK or ATAK to scale down the surface scale residuals;
5. The sum of the overall trend and the area-scale residuals is the result of scaling down.

Table 4. ATPRK/ATARK application examples

| Time  | Author    | Research Area       | Results                                | Citations |
|-------|-----------|---------------------|----------------------------------------|-----------|
| 2008  | Liu XH    | California, USA     | Population density scale down          | 33        |
| 2008  | Kerry R   | Northern Ireland    | Soil organic carbon prediction map     | 33        |

Liu XH [38] used regression equation and residual Kriging method to estimate population density. Compared with the traditional co-kriging method, the ATPRK method clearly explained all the scale differences between the source data and the target value, which can significantly increase the scale. Push down accuracy. Kerry R, Goovaerts P, etc. introduced the principle of ATPRK18 in detail, and used two auxiliary data sets (aeronautical radiation measurement and a digital elevation model of topography in Northern Ireland) as covariates [39], and used GIS spatial connection program to connect each soil sampling observations are linked to their most recent airborne radiation measurement observations and altitude, and are used to predict soil organic carbon. The results show that the accuracy of the prediction map obtained by ATPRK is much higher than that of ATPK alone.

Generally speaking, from small-scale auxiliary data, the results obtained by using ATPRK to scale down are better than a single ATPK or ATAK, but it involves regression trends and other issues, so this method has not coherence.

3.2.2. Area-to-point Binomial kriging (ATPBK) and Area-to-area Binomial kriging (ATABK)

Table 5. ATPBK/ATABK application examples

| Time  | Author     | Research Area        | Results                               | Citations |
|-------|------------|----------------------|---------------------------------------|-----------|
| 1993  | Oliver     | West Midlands, England| Childhood cancer incidence             | 10        |
| 2005  | Goovaerts  | United States        | Lung cancer mortality                  | 43        |
| 2009  | Goovaerts  | Michigan, United States| Breast Cancer Incidence Forecast       | 39        |
| 2008  | Goovaerts  | North Florida        | Prostate cancer risk estimation        | 40        |

Oliver [40, 41] used the binomial kriging method to introduce small-scale coastal ward statistics to draw a children's cancer risk map in Midlands, 2 km west of England. Goovaerts [42, 43] used the same method to map the nationwide lung cancer mortality rate. Goovaerts [44] incorporated individual-level data (patient residence) and region-based data (incidence rate in the census area) into the mapping of advanced cancer incidence using the ATPBK method, and applied it to three of Michigan The county’s
breast cancer incidence rate forecast. Research has shown that ATPBK has higher accuracy than methods that only deal with residential data (kernel density estimation and index kriging). In order to reduce the error caused by the small-scale missing geocoding information in the process of pushing down the disease data scale, Goovaerts [45] uses the binomial Kriging method to combine the two-dimensional diagnosis rate of advanced cancer in the postal code area and the census area. The data, combined into a North Florida advanced prostate cancer risk map. The experimental results improve the accuracy of theoretical risk estimation, and have a smaller variance of prediction errors, which is better than using single-scale data to do ATPBK.

3.2.3. Other geostatistical downscaling methods. In addition to the above methods, other methods of pushing down on geostatistical scales have emerged in the field of public health. Goovaerts [46] proposed the Area-And-Point Kriging (AAPK) method. Unlike the traditional point Kriging method, the estimated and predicted variance calculated by the AAPK method depends on the distance to the point data. It also depends on the proximity to the centroid and edge of the geographic unit. Compared with ATPK and ATAK, AAPK does not require a deconvolution process, which proves that in the case of sparse sampling, the addition of area data is beneficial to improve the prediction accuracy, and the accuracy of area data reduces the smoothness of the interpolation surface. In addition, Downscaling Cokriging (DSCK) is also a commonly used method of downsampling. However, due to the complexity of the calculation process, the DSCK method is currently only applied to remote sensing data, and only one auxiliary data is used for downsampling.

3.3. Analysis

Since its development in the 1960s, geostatistics has been used by more and more disciplines to analyze data distributed in space or time[43-47]. Based on a series of research results in the field of public health in the field of geostatistics scaling down in recent years, this article summarizes the methods of geostatistics scaling down, and gives examples of the applicable scope, advantages and disadvantages of each method. The specific list is as follows:

| Table 6. Application and comparison of geostatistics downscaling methods |
|---------------------------------------------------------------|
| **Type of data** | **Method** | **Advantage** | **Disadvantage** |
|------------------|------------|---------------|------------------|
| area-scale       | ATPK, ATAK | Coherence and a certain smoothing effect | The data source used in the calculation is relatively single, lacking in combination with other auxiliary information, and the accuracy is low. |
| area-scale and point-scale | ATPRK, ATARK, AAPK | High accuracy | When it comes to issues such as regression trends, this method has not coherence |
| Two area scale data with different attributes and different scales | ATPCK, ATACK | Coherence and high accuracy. | The variogram and interaction variogram of the point scale must be calculated through deconvolution, which requires a large amount of calculation. |
| Two area-scale data with the same attributes and different scales | Binomial Kriging | Coherence and high accuracy. | Small application range |

In the process of geostatistical scale downscaling, the presence or absence of auxiliary data has an important impact on the efficiency and accuracy of the downscaling results. At the same time, different methods can be used to downscale the data for different data types: if only area scale data is available, choose ATPK, ATAK and other methods; there are area scale and some scale data, ATPRK, ATARK, AAPK, etc. can be used; there are area scale data with different attributes and different scales, DSCK
can be used (currently this method is only used for remote sensing image processing); Two area-scale data with the same attributes and different scales can use the binomial kriging method. In practical applications, various methods can be compared with each other, and the one with higher prediction accuracy can be selected for scaling down.

4. Conclusions
In recent years, the development trend of geostatistics can be summarized by crossover and synthesis, and a series of crossover research results such as medical geography and health GIS have been produced. The cross-fusion of these results once again reflects to a certain extent that geostatistics is expanding the scope of using spatial information. Looking at the development of Kriging valuation theory, the inclusiveness of the new estimation method to spatial information can be said to be a very distinctive feature. And every breakthrough in the original hypothesis and the use of new information means another innovation in theoretical methods.

Although the geostatistical scale-down method is gradually improved, there are still some basic issues that need to be further discussed:

(1) The degree of discretization.
In the process of pushing down on the geostatistical scale, the area-scale data must be discretized, but there is no clear indication of the degree of discretization. Discretization to a smaller resolution will increase the amount of calculation, and discretization to a larger resolution will ignore the smaller-scale area data. At the same time, the degree of discretization also affects the inference of the point scale variogram.

(2) The extent of pushdown.
Due to the limited information of the acquired data, it is impossible to push down to an infinite scale based on the limited information. The larger the push down, the lower its reliability. In view of the existing geostatistical scale-down methods, the future development trend should be to ensure that the shape and size of the data are comprehensively considered in the downscaling process, to ensure that the results of the downscaling are of coherence, and to be compatible with as much auxiliary information as possible. In order to improve the accuracy of the downscaling. In addition, the geostatistical downscaling should be oriented to time series data, and it should be developed to the temporal-spatial geostatistical scale to provide continuous scaling results in time and space.

All the studies mentioned in this article show that the geostatistical pushdown technology has great development potential in the field of public health, and the field of geographic health still needs professional exploration. In the future, research that combines geospatial scale conversion technology with public health may provide further technical support for preventing public health diseases and reducing the incidence of public health.

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