Spatio-temporal interpolation: Current Practices and Future Prospects

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Abstract

Decision making, risk management in environmental management and justified interpretations are needed to accurate spatio-temporal continuous data over the interesting area. However, Geographical data of the environmental phenomena is usually acquired by sampling points in rugged areas especially the deep ocean area and mountainous region. Thus, spatio-temporal interpolation methods are generating the spatially continuous layers using sampling points in different time frames. Most of existing spatio-temporal interpolation methods of geographical data are roughly based on two approaches, namely reduction approach, and extension approach. The main purpose of this paper is reviewing recent used spatio-temporal interpolation methods, discussing the advantages and limitations of these methods, also providing some novel ideas for defining the roadmap of the future state for the spatio-temporal interpolation techniques.

Keywords: *Spatio-temporal interpolation, reduction approach, extension approach, AI techniques.*

1. Introduction

Interpolation is a process of estimating data values when and/or where no data values were measured [1], [2]. Geographic Information Systems (GIS) provide many powerful models for addressing the problem of interpolation for the geographical data which changes over the time.

The spatial interpolation is defined as the process of intelligent guesswork, in which the investigator and the GIS attempt to estimate the values of a continuous field at places where the field has not been measured [3]. The common spatial interpolation techniques were classified into three categories, which are the geostatistical interpolation, non-geostatistical interpolation and combined methods [4].

There are also many techniques are used to interpolate missing values for time series data. Temporal interpolation is the processes of estimating a missing value in a specific time with values calculated using time series data values (statistics for spatio-temporal data).

Although the Pharos started to document their events on the wall of the temples and obelisks, Spatio-temporal research in geography date back to the late 1960s and early 1970s when the scientists reported and modeled the spatio-temporal pattern of human behaviors [2], [5], [6].

It's generally accepted that Spatio-temporal data has a vital role in planning, analyzing and risk management of any geographical phenomena. Geographical data of the environmental phenomena is usually acquired by sampling from mountainous regions and deep ocean areas. Decision-making in environmental management and justified interpretations are needed to accurate spatio-temporal continuous data over the interesting area.

The spatio-temporal interpolation methods can estimate the unknown values of a continuous field at places and/or time when the field has not been measured using other known values. In other words, the spatio-temporal interpolation methods estimate the geometric and/or attribute data changes of the geographical phenomena over time. Most of existing spatio-temporal interpolation methods of geographic data are roughly based on two approaches; reduction approach and extension approach [7], [8]. Reduction spatio-temporal interpolation was defined as "*the spatio-temporal interpolation approach that treats time as an independent dimension, which could be convenient only if the sample was taken in the same locations at the same times*". In this method, researchers handle the spatio-temporal interpolation as a series of spatial interpolation. On the other hand, extension spatio-temporal

interpolation was defined as "*the spatio-temporal interpolation approach that treats time as another dimension, which handles the spatio-temporal interpolation as a one higher dimension spatial interpolation*" [7], [8].
The main purpose of this paper is reviewing the current state of the spatio-temporal interpolation methods and having an overview of the advantages and limitations of each method, also describing the roadmap of the future state for the spatio-temporal interpolation techniques.

2 Spatio-temporal interpolation methods: Current practices

There are two different spatio-temporal interpolation methods; namely reduction and extension [7], [8]. In this section, a variety of reduction and extension spatio-temporal interpolation methods are introduced as proposed in Figure 1, also novel artificial intelligence methods were developed for spatio-temporal interpolation are briefly discussed, and then a comparison of the advantages and limitations are reviewed.

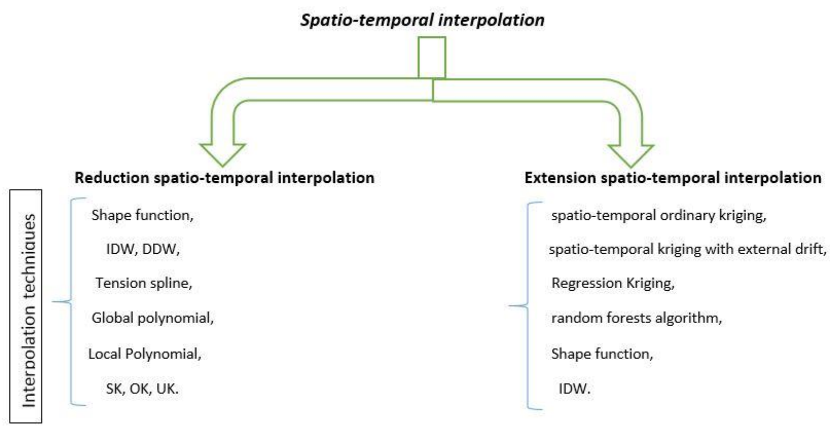

Figure 1: Proposed Classification of Spatio-temporal interpolation methods

2.1 Reduction spatio-temporal interpolation

Reduction spatio-temporal interpolation also known as spatial interpolation primitive is an interpolation strategy that solves the spatio-temporal interpolation problem as a sequence of spatial interpolation problems occurred in different time series [8]–[10], then the temporal interpolation cloud be calculated based on the spatial interpolation results on each location [8], [10], [11]. This view of the spatio-temporal interpolation problem cloud be true if the researchers sampled the dataset in the same location with a regular time frame, such as measuring the air temperature at 6 am every day using fixed station. Some applications using reduction spatio-temporal interpolation are reviewed below. Table 1 lists the reduction spatio-temporal interpolation methods discussed in this sub-section.

Table 1: Reduction spatio-temporal interpolation techniques

Process	*Methods*	*Findings*	*Ref.*
Developing a map of House Prices	Shape function, IDW	Shape function is much better than IDW.	[8]
Assessing seven interpolation methods	Tension Spline, Global polynomial, Local Polynomial, IDW, SK, OK, UK	SK is the optimal techniques for spatial interpolation. The average decline rate of groundwater level from 2007 to 2013 was increased compared with 2001-2006.	[12]

Interpolate meteorological data	cubic spline function for temporal interpolation Linear Regression was used for spatial interpolation	The mean temperature was low in the high regions. Precipitation was reached to 1,400 mm during the summer season in the Alpine. Precipitation was reached to 800 mm during the summer season in the northern part of the basin receives. The net radiation was between 400 and 500 kWh/a/ m^2. Snowfall above 200 mm was only in the Alpine.	[13]
Comparing DDW with IDW	IDW, DDW	IDW was much better than the DDW. DDW was not recommended for modeling the environmental application.	[14]

Shape function is one of the regular interpolation methods which can be used as a spatio-temporal interpolator. Lixin Li et al. (2004) adopted three dimensions shape functions from finite element methods based on the linear approximation for the spatio-temporal interpolation. This 3-D shape function was implemented as two dimensions for the spatial data and one dimension for temporal data; they also developed a novel spatio-temporal interpolation using 4-D shape function which treated 3-D for representing spatial data and 1-D as temporal data. In order to implement the reduction shape function interpolation method for 2-D space and 1-D time problems, two steps should be carried out by implementing two interpolation functions; one function for spatial interpolation and other function for temporal interpolation. The spatial interpolation by shape functions for triangles should be calculated first, and then the spatio-temporal approximation is implemented by combining a time shape function with the space function. Similarly to the reduction approach to 2-D space and 1-D time problems, 3-D space and 1-D time problem is solved by using 3-D spatial interpolation by shape functions for tetrahedra or hexahedral sub-domains and approximation in space and time [8] Lixin Li et al. (2004) applied the reduction shape functions interpolation and compared it with IDW (Inverse Distance Weighting) method using a set of real estate data with house prices obtained from the Lancaster county assessor's office in Lincoln, Nebraska. 126 residential houses were selected from a quarter of a section of a township, which covers an area of 160 acres since 1990 to 2002. The results reported Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values of the shape function are better than IDW based [8].

Another case study which deals with the reduction spatio-temporal interpolation problem as a sequences of the spatial interpolation was conducted by Yong Xiao et al. (2016), when seven interpolation methods were used for interpolating groundwater level (tension spline interpolation, global polynomial interpolation, inverse distance weighted interpolation, local polynomial interpolation, simple Kriging interpolation, ordinary Kriging interpolation, and universal Kriging interpolation) using 30 observation wells located in the piedmont plain in west of Beijing, China from 2001 to 2013 [12]. Yong Xiao et al. (2016) started to implement the spatial interpolation every year in order to interpolate the mean annual groundwater level, then the temporal variation of groundwater level for different land use was analyzed. The Mean error and the Root-mean-square error results considered that the simple Kriging is the optimal spatial interpolation method for interpolating groundwater level, also temporal studies indicated that the average decline rate of groundwater level from 2007 to 2013 was increased compared with the average decline rate of groundwater level from 2001 to 2006 [12].

Similarly, Wolfram Mauser et al. (2016) was investigated the spatial and temporal Interpolation of the meteorological data by collecting the air temperature, air humidity, the wind, short and long wave radiation and precipitation three times every day at 7:30, 14:30 and 21:30 from 1970 to 2006 in GLOWA-Danube [13]. Temporal interpolation for every 1-h time step of 288 available stations was processed using a cubic spline function as an interpolator for all parameters except precipitation, the precipitation measurements were temporally disaggregated. Then the temporally interpolated values for each hour were transferred to the stations' area. Finally, the spatial interpolation was performed based on hourly regressions of elevation gradients and a DEM and inverse square distance weighting of the regression residuals [13]. The results indicated that precipitation was reached to peak values of up to 1,400 mm during the summer season in the Alpine region and 800 mm in the north of the Danube basin. Also, the net radiation was between 400 and 500 kWh/a/ m^2, while the air temperature was correlated with the

terrain elevation, in other words, the mean temperature was low in the high regions such as the Central Alps, the Alpine foothills and the low mountain ranges [13].
Ferry Susanto et al. (2016) proposed Distribution-based Distance Weighting algorithm as a new improvement of Inverse Distance Weighting (IDW) algorithm. Distribution-based Distance Weighting is a reduction spatio-temporal interpolation used to interpolate the air temperature variables in the northeast of Tasmania, Australia from Jan. 2013 to Dec. 2013 [14]. The result of the comparison between new DDW and the tradition was very interesting; the result showed that IDW was much better than the DDW. Ferry Susanto et al. (2016) recommended that the proposed DDW was unlikely used for modeling the environmental application [14].

2.2 Extension spatio-temporal interpolation

Extension spatio-temporal interpolation or the temporal-interpolation primitive is an interpolation strategy that deals with the temporal part of the spatio-temporal interpolation problem as another dimension in space, which handles the spatio-temporal interpolation as a one higher dimension spatial interpolation [7], [8]. Extension spatio-temporal interpolation used to interpolate irregular datasets which measured in different time frames or collected by mobility sensors [8]. For the huge spatio-temporal datasets, the extension spatio-temporal interpolation is very complex and expensive to implement because temporal interpolation functions need to be calculated for every spatial location with at least one measurement in time [10]. In the next part of this subsection, many applications that use extension spatio-temporal interpolation are reviewed as listed in Table 2.

Table 2: Extension spatio-temporal interpolation methods

process	***Methods***	***Findings***	***Ref.***
Evaluating two spatio-temporal Kriging algorithms	spatio-temporal ordinary Kriging and spatio-temporal Kriging with external drift	Ordinary Kriging needs only to prepare the spatio-temporal semivariogram. Kriging with external drift requires preparing the secondary information as and the spatio-temporal semivariogram well. The spatio-temporal interpolation results were improved using the ST Kriging with external drift.	[15]
Comparing two spatio-temporal Kriging algorithms	spatio-temporal ordinary Kriging and spatio-temporal Kriging with external drift	The results indicate an advantage to 3-D estimation. The Kriging with external drift led to significantly lower prediction errors.	[16]
Interpolating the daily mean, maximum and minimum air temperatures	Regression Kriging	The average accuracy for predicting mean, maximum, and minimum daily air temperatures is RMSE = ±2C for areas covered with stations. The average accuracy between ± 2C and ± 4C for areas with a lower number of stations. The lowest prediction accuracy was observed at high altitudes over than 1km.	[17], [18]
Investigating several spatio-temporal methods	Regression Kriging and Random Forests algorithm	The spatio-temporal regression Kriging was much better than Random Forests algorithm. Both the Kriging model and the Random Forests model failed for estimating water content and electrical conductivity. Kriging model was most successful at predicting soil temperature.	[19]

Developing a map	Shape function, IDW, Kriging	The shape function was the optimal interpolation methods. Kriging was much better than IDW.	[8]
	Shape function		[10]
Comparing two spatio-temporal interpolation	Shape function, IDW	The shape function interpolation was performing better than IDW.	[20]
Enhancing IDW	Parallel IDW	IDW using the k-d tree took 190s with the single-threaded approach. IDW using the k-d tree took 58s using the multi-threaded approach.	[21]

Kriging is a group of popular geostatistical algorithms for estimating the continuous attribute which is based on least-squares regression algorithms [4]. Kriging is used as a spatio-temporal interpolator for many applications. Two spatio-temporal Kriging algorithms of soil water content were compared. Snepvangers et al. (2003) compared the spatio-temporal ordinary Kriging and spatio-temporal Kriging with external drift. In ordinary Kriging used only the information of the soil water content and ignored the relationship between soil water content and precipitation, while the Kriging with external drift interpolator used the relationship between net precipitation and soil water content as secondary information to improve the interpolation results. An irrigation experiment data on 60*60 m grasslands in the south of the Netherlands in a 30-day monitoring period (August 16–September 14, 2000) were used as a dataset of the interpolation. The soil water content data were measured with vertically installed 10-cm Time Domain Reflectometry probes. One of the most important differences between the spatio-temporal ordinary Kriging and spatio-temporal Kriging with external drift was the external data which needed to prepare. In other words, the ST ordinary Kriging needs only to prepare the ST Semivariogram, while the ST Kriging with external drift requires a trend model in order to incorporate the semivariance model and the secondary information. In this application linear and logarithmic models were used for the net precipitation as secondary information. However the ST ordinary Kriging is a simpler interpolator, the results were improved using the ST Kriging with external drift based on the logarithmic model [15]. Another application was interpolating the rainfall data using the Kriging with external drift such as the rainfall event of March 1973 in the north of Tunisia and the extreme event of September 1986 recorded in the north-eastern part of Tunisia [16]. In this application, the elevation data was used as secondary information of the Kriging with external drift. Kebaili et al. (2009) suggested a three dimensions interpolation of the variogram, instead of the two dimensions approach for spatio-temporal rainfall analysis. The novel 3-D approach was developed based on extended traditional geographical location (x, y) to (x, y and duration). In this study, the elevation was used as secondary information for the spatio-temporal Kriging with external drift interpolation and a comparison between Spatio-temporal ordinary Kriging and Kriging with external drift based on the 3-D approach was conducted. The results reported that the Kriging with external drift led to significantly lower prediction errors.

The spatio-temporal Regression Kriging is a different Kriging algorithm was used to interpolate the daily mean, minimum and maximum air temperatures at a ground resolution of 1 km for the global land mass observed from 2000 to 2011 by Milan Kilibarda et al (2014; 2015). A global station data set included more than 9000 stations was produced by merging the European Climate Assessment and Dataset (ECA&D) and the Global Surface Summary of Day (GSOD) data set. In order to improve the spatial interpolation of mean, maximum and minimum daily temperature, the Moderate Resolution Imaging Spectroradiometer (MODIS) images of the Terra and Aqua Earth were used after fitting the missing pixels using Automated Geoscientific Analyses Geographic Information System (SAGA GIS) function Close Gaps. The spatio-temporal interpolation was applied using R environment for statistical computing which provides many packages to support the Kriging interpolation. The root-mean-square error (RMSE) was used for evaluating the accuracy of the spatio-temporal Regression Kriging results, also a comparison with the Global Historical Climatology Network-Monthly (GHCN-M) temperature data set. Milan Kilibarda et al. (2014) believed that the average accuracy for estimating the mean, minimum and maximum daily air temperatures is RMSE = ±2C for areas with a higher number of stations and between ± 2C and ± 4C for areas with a minimal number of stations. The results also reported that the lowest accuracy was observed at high elevation areas over than 1000 m and in Antarctica with RMSE almost 6C [17], [18].

Regression Kriging and Random Forests algorithm were used as two different Spatio-temporal interpolation approaches to model dynamic soil properties in 3-dimensions (x, y and depth) and time by Caley K. Gasch et al. (2015). Volumetric water content, temperature, and bulk electrical conductivity measurements were collected for three years by a total of 210 sensors were installed at 42 locations with 5 different depths (0.3, 0.6, 0.9, 1.2, and 1.5 m depths) on the R.J. Cook Agronomy Farm. This farm is a research site operated by Washington State University, located near Pullman, Washington, USA. Also, 11 Level 3A RapidEye satellite images were acquired from 2011 to 2013 to incorporate vegetation patterns on the farm. The random forest algorithm has many advantages such as the target variable does not need to assume specific distributions [19], [22], [23], also random forest algorithm is very powerful for fitting a predictive model for a multivariate dataset. On the other hand, random forest algorithm has some drawbacks such as overfitting the datasets that are mostly noisy. Also, the random forest algorithm can be a limitation as dataset complexity increased [19], [24]. All the implementation and analyzing of the models were conducted using R statistical with many libraries and packages which supported the spatio-temporal data analysis. The results reported that the predictive power of both the Kriging model and the Random Forests model decreased, especially for water content and electrical conductivity, however the Kriging model was most successful at predicting soil temperature. In other words, the spatio-temporal regression Kriging predictions provide a more spatiotemporally smoothed representation of the response soil variables, compared with the Random Forests model [19].

In a comprehensive study conducted by Lixin Li et al. (2003), the shape function based extension spatio-temporal interpolation was adapted to treat the time as a third regular dimension. In other words, the shape function based extension spatio-temporal interpolation extends the 2-D problem to 3-D. The implementation of the shape function based extension spatio-temporal interpolation likes the implementation of linear approximation by three dimensions shape functions based reduction interpolation for tetrahedra with one modification which is changing the z dimension to time dimension [8]. In order to solve the three dimensions space and one dimension time problem a novel linear four dimensions shape function was developed. By using the new 4-D shape function, it will be easy to interpolate un-sampled values at location (x, y, and z) and with time stamp t. The new linear 4-D shape function was implemented based on four dimensions Delaunay tesselation, that can be represented by five tuples of indices to the data points [8].

In one well-known recent experiment implemented by Lixin Li et al. (2011), the shape functions based extension spatio-temporal interpolation was applied to particle pollution which known as particulate matter PM2.5 data set to investigate the relations between the air pollution and population health outcomes. PM2.5 data was collected in 2009 by monitoring sites spread over the contiguous U.S. to interpolate 3,109 counties in U.S. In shape function based spatio-temporal interpolation the time scale should be decided, so the time scale was divided into four categories (one time of the original scale, 5 times of the original scale, 10 times of the original scale and 15 times of the original scale). The data was divided into two classes: the sample data and the check data; the sample data was used to interpolate the points in check data. The estimated data and the original data of the check data class were compared using MBE (Mean Biased Error), RMSE (Root Mean Squared Error) and MAPE (Mean Absolute Percentage Error) as three different accuracy assessments [10]. Lixin Li et al. (2011) used the accuracy assessments to define suitable time scale for the spatio-temporal interpolation instead of testing the accuracy of the interpolator. The findings concluded that more than 108 million persons were residing in the US with PM2.5 exceeding 35ug/m^3 for at least a day in 2009 and more than 27 million persons were residing in the US with annual PM2.5 exceeding the national standard [10].

Using the same data set of PM2.5, the data was used to interpolate 207,630 census block groups in U.S. In this application the researchers applied the data set on two different spatio-temporal interpolation methods and selected the scale time (5 times of the original scale) for the shape function based spatio-temporal interpolation while the scale time for the IDW was different (10 times of the original scale). The time scales were selected based on the error statistics MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error) and MARE (Mean Absolute Relative Error). The results reported that the SF-based is performing better than the IDW- based interpolator [20].It is important to bear in mind that comparing two spatio-temporal interpolation methods (SF, IDW) using two different time scale (5 times of the original scale, 10 times of the original scale) cloud affected on the interpolation output and the comparison results.

In another major study, Lixin Li et al. (2014) adapted the traditional spatial IDW method to formulate the spatiotemporal interpolation based on the extension approach. Parallel programming techniques and a k-d tree data structure were used to improve the computational cost of IDW based on extension spatio-temporal interpolation [21]. The same data set of PM2.5, the data was used to interpolate 207,630 censuses using the new adaptive IDW based on extension spatio-temporal interpolation. Interestingly, Lixin Li et al (2014) reported that the IDW interpolation using the k-d tree spent 190s using the single-threaded, while it spent only 58s using the multi-threaded on the same computer [21].

2.3 Comparison between Reduction approach and Extension approach

A comprehensive study was designed to compare between mean over time method, Spacetime product, and tetrahedral method as three different spatio-temporal interpolation methods based on the shape function [7]. The mean over time methods and spacetime product method are two examples of reduction spatio-temporal interpolation which treat the time as a separate dimension. On the other hand, the tetrahedral method is an example of the extension spatio-temporal interpolation which deals with the time as a regular third dimension [7]. The comparison was carried out based on four criteria which were the accuracy, the storage, the Error-Proneness to Time Aggregation and the query complexity using the dataset of house prices obtained from the Lancaster county assessor's office in Lincoln [7]. Although, the results reported that the tetrahedral method produced less error than the Spacetime product method and Mean over time method according to the error measures of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). However, The Spacetime product method needed less storage space than the tetrahedral method. The findings suggested that the tetrahedral method was overall better than the Space Time product method and the Mean over time method. In other words, the shape function based on extension spatio-temporal interpolation was much better accurate, needed less error-proneness to time aggregation and less query complexity than the shape functions based on the reduction spatio-temporal interpolation [7]. Another experiment using the same dataset of the houses prices was conducted to compare the IDW based on the reduction approach and extension approach, and also compare the extension 3-D shape function and 4-D shape function based on the accuracy of each approach. Surprisingly, the results indicated that IDW based on the reduction approach is much better than the extension approach. Also, the 4-D extension shape function results were worse than the 3-D extension shape function [8], [25].

2.4 Spatio-temporal interpolation based on AI techniques

The spatio-temporal interpolation methods based on the Artificial Intelligence techniques cloud also classify as extension or reduction approach, however, these methods were listed in an individual section in order to emphasize the AI model used in each study. These methods were briefly described in

Table 3

Table 3: AI models for spatio-temporal interpolation

Process	***Methods***	***Findings***	***Ref.***
Proposing and AI model	Feed Forward Neural Network	The feed forward neural network model provided a reliable estimation.	[26]
Developing a novel spatio-temporal interpolation model	Cellular automata	The developed model was executed correctly with a high accuracy outputs.	[27]
Developed a new hybrid spatio-temporal model	ANN, Kriging and Fuzzy logic system	The proposed model was a successfully handle the Geographical spatio-temporal prediction problems with a high level of accuracy.	[28]
Evaluating a new hybrid model	Artificial Neural Network and Genetic Algorithm	The model was successfully predicting the medium and high groundwater levels, but it was overestimating for predicting the low groundwater level	[29]

Developing a new model	SANN and HBI	HBI using spatio-temporal covariance line with considering the environmental covariates was the most accurate model for interpolating the precipitation.	[30]
Comparing two spatio-temporal interpolation methods	GAM and ordinary space-time Kriging	GAM was successfully interpolate the amount of PM10 GAM got less root mean square error than OK.	[31]

A significant key study by Oleg Antonic et al. (2001) described how to implement a spatio-temporal interpolation of the climatic variables using the neural networks (Antonic, Krizan, Marki, & Bukovec, 2001). In order to conduct the spatio-temporal interpolation, the monthly mean of air temperature, minimum and maximum air temperature, precipitation, relative humidity, global solar irradiation and potential evapotranspiration were collected from 127 weather stations in the Republic of Croatia (Antonic et al., 2001). In this case study, Oleg Antonic et al. (2001) used the feed-forward Neural Network as empirical functions in order to model the spatio-temporal interpolation. The inputs of this model were the month name, the station location as latitude and longitude, the station elevation, the value of the climatic variable observed at the Hvar and Zagreb stations as Anchorage stations. While the output was an estimation of value climatic variable value at other stations (Antonic et al., 2001). However, Oleg Antonic et al. (2001) reported that this spatio-temporal interpolation model based on the feed-forward neural network provided a reliable estimation; a comparison between this model and other spatio-temporal interpolation algorithms should be conducted.

According to Sharolyn Anderson (2002), Daid model was a novel developed spatio-temporal interpolation model. This new model consisted of three main processors; namely, the calibration processor, the temporal processor and the spatial processor. The inputs of the daid model were the temporal dataset and the spatial dataset independently. In the first processor which was the calibration processor, a relationship between the given spatial data and the temporal data were defined, then the spatial data and the temporal data were integrated together to produce the spatio-temporal data using a cellular model. The input of the temporal processor was the temporal dataset; this processor was used to interpolate the missing temporal information at the unknown surface using the regression analysis. The spatial processor was used to produce the final interpolated spatio-temporal surface; while the inputs of this processor were the output of the calibration processor and any other external data cloud used in the interpolation function. The spatial processor used the cellular automata which used as an artificial technique as an interpolator [2]. The daid spatio-temporal interpolation model was used to interpolate the air temperature, the population density and land use in the Phoenix Arizona from 1985 to 2000. 36 weather stations were used in the study area to collect the air temperature, these data was input for the temporal processor the calibration processor. While 5 satellite images were captured to the study area in 1985, 1988, 1990, 1990 and 2000. These satellite images were used as the spatial dataset and were inserted to a spatial processor and the calibration processor. Also, a polygon shapefile was created to store the population density from 1990 to 2000. The outputs of the daid spatio-temporal model were a complete surface temperature and land cover land use of the Phoenix Arizona from 1985 to 2000. Based on the model validation results, the daid model was executed correctly with a high accuracy outputs [2].

Likewise, Tapoglou et al. (2014) developed a new hybrid spatio-temporal model to predict the hydraulic changes in the south of Germany from the first of November 2008 to end of October 2012. This model consisted of three main parts, which were the Artificial Neural Network (ANN), Kriging algorithm and the Fuzzy logic system. The ANN was used to interpolate the temporal data, while the Kriging algorithm was used to interpolate the spatial data, and the Fuzzy logic system was used to combine the ANN and Kriging [28]. A total of 64 wells, 7 weather stations, and 5 observation points were used to collect data about the hydraulic head, temperature, rainfall and surface water elevation. An ANN with eight inputs parameters (4 rainfall, 1 temperature, and 3 surface water elevation points) and two hidden layers (20 nodes for the first hidden layer and 11 nodes for the second hidden layer) was developed for each well to model the hydraulic head in Bavaria, Germany. 80% of the observational data was used for training the ANN, while the 20% remained was used for testing the ANN performance. The fuzzy logic was used to define the nearest wells to the prediction points and with the smallest error before running the Kriging. The fuzzy logic system divided the wells into small, average and large classes based on the distance between the prediction point and the observational point and the average of the ANN performance error.

After defining the best wells for each prediction point, the variogram was computed. Linear variogram, Exponential variogram, and power law variogram were calculated as three different models for fitting the spatial interpolation problem, the cross validation recommended that power law variogram which had the lowest error. Finally, the Kriging was running for each prediction point at every time step [28]. The results reported that the proposed hybrid spatio-temporal model was a successful model to handle the Geographical spatio-temporal predication problems with a high level of accuracy [28].
In the same track, a hybrid model using Artificial Neural Network and Genetic Algorithm was developed to solve the problem of groundwater level prediction in Mahanadi river basin of Orissa State, India [29]. A total of 26 meteorological stations were used to collect the groundwater level from 1993 to 2002, while the data from 1993 to 1999 were used for training the ANN model and the other data from 2000 to 2002 were used for testing the performance of the hybrid model. This case study was mainly motivated to predict the groundwater level in November and January months of the year with a lead time of one week, also the groundwater level was divided into three categories low (from 0m to 1.5m), medium (from 1.5m to 3m) and high (greater than 3m). An ANN model was developed based on three input parameters, one hidden layer, and one output variable. The GA used to optimize the prediction solution from a group of potential solutions. This hybrid GA-ANN model was compared with Levenberg Marquardt, back-propagation, and Bayesian regularization as three different ANN models. The correlation coefficient (R), the index of agreement (IOA), the Nash-Sutcliffe coefficient (E), the mean absolute error (MAE) and the root mean square error (RMSE) were used as a performance indicator of the models. The results reported that the hybrid new model using the Artificial Neural Network and the Genetic Algorithm was successfully predicting the medium and high groundwater levels, but it was overestimating for predicting the low groundwater level [29].
I.Hussain et al. (2012) proposed a generalized additive model (GAM) with Gaussian link function which divided the space-time model into two parts: trend component and residual component in order to interpolate the precipitation in Pakistan taking in account the environmental covariates such as humidity, temperature, elevation, wind speed, latitude and longitude. A total of 51 stations were used to collect the annual precipitation for the monsoon seasons from 1947 to 2000. The trend component was modeled using a spatial artificial neural network (SANN) with optimal control parameter ranging from 1.3 to 1.5 and the optimal number of nearest neighborhood equal 6. SANN consisted of an input layer, two hidden layers, and the output layer. One of the hidden layers was used for Gaussian Kernel Function, while the other used as summation layer. In order to model the residual component, four different methods were compared: Kriging with external drift using spatio-temporal covariance and using the environmental covariates as secondary information, hierarchical Bayesian interpolation (HBI) using spatio-temporal covariance line with considering the environmental covariates, HBI using spatial covariance with considering the environmental covariates and transformed HBI using spatial covariance without considering the environmental [30]. The findings reported that the hierarchical Bayesian interpolation (HBI) using spatio-temporal covariance line with considering the environmental covariates was the most accurate model for interpolating the precipitation during the monsoon seasons in Pakistan.
With the same manner, I.Hussain et al. (2013) compared between GAM and ordinary space-time Kriging in order to interpolate the particulate matter (PM10) in the north of U.S. The logarithm of area source emissions of PM10, wind speed, temperature, and precipitation were considered the environmental covariates. Monthly measurements of particulate matter data were collected using 61 stations from 1998 to 2000. In this study, the residual components were performed using the ordinary space-time Kriging and the covariance function was fitted using PSO algorithm, while the trend component was modeled using SANN [31]. The results indicated that GAM was successfully interpolated the amount of PM10 better than the ordinary space-time Kriging even if the values of the environmental covariates were unknown with a small root mean square error, also the amount of PM10 was very low in the winter season from December to April while it got higher during the summer season [31].

3 Current practices problems

In observational studies, Kriging provided accurate prediction results as a spatio-temporal interpolator, however, one major drawback of Kriging is that the computational cost especially the time complexity for using the large dataset [32]. A significant study on reducing the computational cost of spatio-temporal interpolation using Kriging was presented by Srinivasan et al. (2010), a graphical processing unit (GPU) using a fast algorithm was proposed to reduce the time complexity of Kriging interpolation method [32]. IDW is not only like Kriging in weighting the neighboring known values to obtain the prediction for unmeasured locations but also, they spent a lot of time to handle the big datasets [21], [32].

Although the extension Shape function has much better results than the IDW and Kriging, it based on the linear approximation which cannot be fitted for all models [7], [8], [10], [20].

There are many applications which investigating the role of the Artificial Intelligence techniques and Machine Learning approaches to solve spatial interpolation problem. For example, developing a model to interpolate and predict the digital elevation model (DEM) using the ANN and GA [33]. The results found that the ANN model had the high level of accuracy to interpolate the elevation. Another example of integrating ANN, GA and fuzzy system in order to interpolate the rainfall data, a new model was developed. The results reported that the purposed model based on the ANN, GA and fuzzy system had acceptable accuracy for interpolating the rainfall data [34]. Also, ANN was used to configure a high accurate spatial interpolation model of air temperature [35]. However, a comprehensive study of the usage of the ANN in GRASS GIS as a spatial interpolation reported that the ordinary Kriging and IDW were much better than the ANN; also the ANN required more long time for the interpolation [36]. Also, J. Li et al. (2011) established a new starting points for solving spatial interpolation problem, when comparing the performance of 23 spatial interpolation methods using mud content in the south-west Australian, including Non-geostatistical spatial interpolation, Geostatistical, Machine Learning, Combination of Statistical and Geostatistical methods, Combination of Machine Learning and Non-geostatistical spatial interpolation method and Combination of Machine Learning and Geostatistical spatial interpolation methods [37]. On the other hand, there is a lack of studies which investigate how the artificial intelligence techniques or the Machine Learning methods affect the results of spatio-temporal interpolation.

4 Spatio-temporal interpolation: Future prospects

During the recent years, there are many attempts to solve the problem of the current practices of spatio-temporal interpolation using the new technology especially the data structure models, Machine Learning techniques and artificial intelligence approaches [21], [22], [28], [32]. However, there are a few studies that investigate the Machine Learning for spatial analysis of the environmental phenomena, while the fundamental goals of the Machine Learning systems are modeling the spatio-temporal dependencies, increasing the prediction accuracy and reducing the training time [38]–[42].

Future researchers should therefore concentrate on the investigation of the following points:

- Developing a reduction spatio-temporal interpolation based on geostatistical spatial interpolation methods such as Kriging and Machine Learning temporal interpolation, while many Machine Learning approaches were used for time series prediction.
- Developing a reduction spatio-temporal interpolation based on non-geostatistical spatial interpolation methods such as IDW and Machine Learning temporal interpolation.
- Developing a new reduction model for spatial interpolation based on the Machine Learning algorithms and calculate the temporal interpolation using the statistical methods; while there are no any Machine Learning techniques developed to investigate spatial interpolation.
- Developing a novel hybrid model using meta heuristic algorithms and Machine Learning techniques for solving the extension spatio-temporal interpolation problems; while there were many publication that investigate the PSO as an optimizing techniques for the spatial interpolation and for time series analysis as well [43]–[47].
- Developing a novel hybrid model using Machine Learning algorithms for solving the extension spatio-temporal interpolation problems.
- Evaluating the above spatio-temporal interpolation methods for defining the higher accuracy interpolator with less amount of time complexity

References

[1] C. J. Willmott and S. M. Robeson, “Climatologically aided interpolation (CAI) of terrestrial air temperature,” *Int. J. Climatol.*, 1995.

[2] S. J. Anderson, "Design and implementation of a spatio-temporal interpolation model," Arizona State University, 2002.

[3] P. A. Longley, Goodchi, M. F. Ld, D. J. Maguire, and D. W. Rhind, *Geographical Information Systems and Science*, vol. 83, no. 3. 2011.

[4] J. Li and A. D. Heap, "Spatial interpolation methods applied in the environmental sciences: A review," *Environ. Model. Softw.*, vol. 53, pp. 173–189, 2014.

[5] T. Hägerstrand, "Innovation diffusion as a spatial process," *Innov. Diffus. as a Spat. Process*, 1967.

[6] T. Hägerstrand, "Reflections on ``what about people in regional science?'\'," *Pap. Reg. Sci. Assoc.*, vol. 66, no. 1, pp. 1–6, 1989.

[7] L. Li and P. Revesz, "A Comparison of Spatio-temporal Interpolation Methods," *Geogr. Inf. Sci.*, no. 2478, pp. 145–160, 2002.

[8] L. Li and P. Revesz, "Interpolation methods for spatio-temporal geographic data," *Comput. Environ. Urban Syst.*, vol. 28, no. 3, pp. 201–227, 2004.

[9] D. Liao *et al.*, "GIS approaches for the estimation of residential-level ambient PM concentrations," *Environ. Health Perspect.*, 2006.

[10] L. Li, X. Zhang, J. B. Holt, and R. Piltner, "Spatiotemporal Interpolation Methods for Air Pollution Exposure," pp. 75–81, 2011.

[11] J. S. Borak and M. F. Jasinski, "Effective interpolation of incomplete satellite-derived leaf-area index time series for the continental United States," *Agric. For. Meteorol.*, 2009.

[12] Y. Xiao *et al.*, "Geostatistical interpolation model selection based on ArcGIS and spatio-temporal variability analysis of groundwater level in piedmont plains, northwest China.," *Springerplus*, vol. 5, p. 425, 2016.

[13] W. Mauser and M. Prasch, "Regional Assessment of Global Change Impacts," pp. 19–27, 2016.

[14] F. Susanto, P. De Souza, and J. He, "Spatiotemporal interpolation for environmental modelling," *Sensors (Switzerland)*, vol. 16, no. 8, pp. 1–20, 2016.

[15] J. J. J. C. Snepvangers, G. B. M. Heuvelink, and J. A. Huisman, "Soil water content interpolation using spatio-temporal Kriging with external drift," *Geoderma*, vol. 112, no. 3–4, pp. 253–271, 2003.

[16] Z. Kebaili Bargaoui and A. Chebbi, "Comparison of two Kriging interpolation methods applied to spatiotemporal rainfall," *J. Hydrol.*, vol. 365, no. 1–2, pp. 56–73, 2009.

[17] M. Kilibarda *et al.*, "Spatio-temporal interpolation of daily temperatures for global land areas at 1 km resolution," *J. Geophys. Res. Atmos.*, 2014.

[18] M. Kilibarda, M. P. Tadić, T. Hengl, J. Luković, and B. Bajat, "Global geographic and feature space coverage of temperature data in the context of spatio-temporal interpolation," *Spat. Stat.*, vol. 14, pp. 22–38, 2015.

[19] C. K. Gasch, T. Hengl, B. Gr??ler, H. Meyer, T. S. Magney, and D. J. Brown, "Spatio-temporal interpolation of soil water, temperature, and electrical conductivity in 3D + T: The Cook Agronomy Farm data set," *Spat. Stat.*, vol. 14, pp. 70–90, 2015.

[20] L. Li, X. Zhou, M. Kalo, and R. Piltner, "Spatiotemporal interpolation methods for the application of estimating population exposure to fine particulate matter in the contiguous U.S. and a real-time web application," *Int. J. Environ. Res. Public Health*, vol. 13, no. 8, 2016.

[21] L. Li, T. Losser, C. Yorke, and R. Piltner, "Fast inverse distance weighting-based spatiotemporal interpolation: A web-based application of interpolating daily fine particulate matter PM2.5 in the contiguous U.S. using parallel programming and k-d tree," *Int. J. Environ. Res. Public Health*, vol. 11, no. 9, pp. 9101–9141, 2014.

[22] S. Ahmad, A. Kalra, and H. Stephen, "Estimating soil moisture using remote sensing data: A Machine Learning approach," *Adv. Water Resour.*, 2010.

[23] M. Kuhn and K. Johnson, "An Introduction to Feature Selection," in *Applied Predictive Modeling*, 2013.

[24] A. Statnikov *et al.*, "A comprehensive comparison of Random Forests and support vector machines for microarray-based cancer classification," *BMC Bioinformatics*, 2008.

[25] L. Li, "SPATIOTEMPORAL INTERPOLATION METHODS IN GIS," 2003.

[26] O. Antonic, J. Krizan, A. Marki, and D. Bukovec, "Spatial-Temporal Interpolation of Climatic Variables over Large Region of Complex Terrain using Neural Networks," *Ecol. Modell.*, vol.

138, pp. 255–263, 2001.
[27] S. Anderson, “Design and implementation of a spatio-temporal interpolation model,” 2002.
[28] E. Tapoglou, G. P. Karatzas, I. C. Trichakis, and E. A. Varouchakis, “A spatio-temporal hybrid neural network-Kriging model for groundwater level simulation,” *J. Hydrol.*, 2014.
[29] N. B. Dash, S. N. Panda, R. Remesan, and N. Sahoo, “Hybrid neural modeling for groundwater level prediction,” *Neural Comput. Appl.*, 2010.
[30] I. Hussain, G. Spöck, J. Pilz, M. Faisal, and H. L. Yu, “Spatio-temporal interpolation of precipitation including covariates: During monsoon periods in Pakistan,” *Pakistan J. Stat.*, vol. 28, no. 3, pp. 351–365, 2012.
[31] I. Hussain and F. Muhammad, “Spatio-temporal modeling of particulate matter concentrations including covariates,” *Desalin. Water Treat.*, vol. 25, no. 1, pp. 15–21, 2013.
[32] B. V. Srinivasan, R. Duraiswami, and R. Murtugudde, “Efficient Kriging for real-time spatio-temporal interpolation Linear Kriging,” *20th Conf. Probablility Stat. Atmos. Sci.*, pp. 228–235, 2010.
[33] C. Vi and W. G. Vi, “EXPLORING THE ROLE OF GENETIC ALGORITHMS AND ARTIFICIAL NEURAL NETWORKS FOR INTERPOLATION OF ELEVATION IN GEOINFORMATION MODELS,” vol. II, no. November, pp. 27–29, 2013.
[34] J. Kajornrit, K. W. Wong, and C. C. Fung, “An Integrated Intelligent Technique for Monthly Rainfall Spatial Interpolation in the Northeast Region of Thailand,” *Adv. Intell. Syst. Comput.*, vol. 265 AISC, pp. 53–62, 2014.
[35] J. P. Rigol, C. H. Jarvis, and N. Stuart, “Artificial neural networks as a tool for spatial interpolation,” *Int. J. Geogr. Inf. Sci.*, vol. 15, no. 4, pp. 323–343, 2001.
[36] V. Nevtipilova, “Testing Artificial Neural Network (ANN) for Spatial Interpolation,” *J. Geol. Geosci.*, vol. 03, no. 02, pp. 1–9, 2014.
[37] J. Li, A. D. Heap, A. Potter, and J. J. Daniell, “Application of Machine Learning methods to spatial interpolation of environmental variables,” *Environ. Model. Softw.*, vol. 26, no. 12, pp. 1647–1659, 2011.
[38] M. Jiang, Y. Ding, B. Goertzel, Z. Huang, C. Zhou, and F. Chao, “Improving machine vision via incorporating expectation-maximization into Deep Spatio-Temporal learning,” *Proc. Int. Jt. Conf. Neural Networks*, pp. 1804–1811, 2014.
[39] C. Shang and Y. Zhang, “Combining Newton interpolation and deep learning for image classification,” *Electron. Lett.*, vol. 51, no. 1, pp. 40–42, 2015.
[40] I. Arel, D. Rose, and T. Karnowski, “A deep learning architecture comprising homogeneous cortical circuits for scalable spatiotemporal pattern inference,” *... Work. Deep Learn. ...*, 2009.
[41] T. P. Karnowski, I. Arel, and D. Rose, “Deep Spatiotemporal Feature Learning with Application to Image Classification,” *2010 Ninth Int. Conf. Mach. Learn. Appl.*, pp. 883–888, 2010.
[42] I. Arel, D. C. Rose, and T. P. Karnowski, “Deep Machine Learning — A New Frontier in Artificial Intelligence Research,” *IEEE Comput. Intel. Mag.*, vol. 5, no. November, pp. 13–18, 2010.
[43] D. Ping, L. Jia, and L. H. Yang, “Variation function fitting method based on particle swarm optimization,” vol. 91, pp. 1–4.
[44] D. Alba-Cuellar, A. E. Munoz-Zavala, A. Hernandez-Aguirre, E. E. Ponce-De-Leon-Senti, and E. Diaz-Diaz, “Time Series Forecasting with PSO-Optimized Neural Networks,” *2014 13th Mex. Int. Conf. Artif. Intell.*, pp. 102–111, 2014.
[45] J. Serrà and J. L. Arcos, “Particle swarm optimization for time series motif discovery,” *Knowledge-Based Syst.*, vol. 92, pp. 127–137, 2016.
[46] F. S. D. A. Filho and F. Madeiro, “TIME-SERIES FORECASTING OF POLLUTANT CONCENTRATION LEVELS USING PARTICLE SWARM OPTIMIZATION AND ARTIFICIAL NEURAL NETWORKS,” vol. 36, no. 6, pp. 783–789, 2013.
[47] E. Hadavandi, a. Ghanbari, and S. Abbasian-Naghneh, “Developing a Time Series Model Based on Particle Swarm Optimization for Gold Price Forecasting,” *Bus. Intell. Financ. Eng. (BIFE), 2010 Third Int. Conf.*, no. June, pp. 10–14, 2010.