第四届“认证杯”数学中国

数学建模国际赛

承　诺　书

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The average temperature of Antarctic

Abstract

Mean surface temperature is an important aspect of reflecting climate changes and global warming. Taking the Antarctic into consideration, we define distract surface average temperature and construct a mathematical framework to calculate, predict, analyze the surface average temperature in the Antarctic.

1. We build up two mathematical framework to solve the mean temperature according to the definition of distract surface average temperature.

1) Using the method of regional optimization to calculate the average temperature series in Antarctic during 1991-2005. Firstly, choose 30 different temperature observation sites in Antarctic to acquire correlation coefficients of temperature of different station with the assistance of covariance model by Haar wavelet function and matrix operator. Then conduct the weighted process plus optimal weights to gain the mean temperature series of the Antarctic, using the pivoting Gauss method.

2) Calculating the mean temperature series of the Antarctic by region interpolation method.30 point spline interpolation is used to measure the surface temperature of the whole Antarctica region using four observation sites to obtain the average temperature.

The analysis of the average temperature of Antarctica is carried out on the two models.

2. Based on the prediction of the average temperature in Antarctic, we established the prediction model based on NAR neural network using the time series network with nonlinear self-binding and the 1991-2015 calculated data. Considering of input, output number and number of convergence, a neural network composed of 1 layers of output layer, 20 hidden layer and 3 lagged variables is established. After 200 training, we are able to obtain the average temperature forecast of the next 3 years.

3. Due to the complexity of the climate of Antarctica, the average temperature of the earth's surface is changed from the following two aspect: the trend of temperature variation in spatial distribution by cluster analysis; the change trend of temperature in the quarter by regression analysis to get the temperature variation trend in Antarctica.

Keyword: mean surface temperature, Haar wavelet function, NAR neural network cluster analysis

1. Introduction

1.1 Background

The average temperature of the surface is a key indicator of climate change and global warming. A region of the average temperature of the surface is affected by many factors, such as latitude, land sea distribution, landform, vegetation coverage rate, surface reflectance, atmospheric circulation, seasons and so on. We need to define the regional surface average temperature and predict the surface average temperature of the next few years by the data from station to analyze the temperature trend and variation. In the past, the study of surface temperature is based on the MODIS or TM data inversion of surface temperature, principal component analysis, the main value analysis method to analyze the regional surface temperature or time, the use of regression analysis or BP neural network to establish the surface temperature prediction model.

1.2 Analysis

According to the purpose of the subject research, the three step is to solve the problem:

Task1: Give the reasonable mathematical definition of the average surface temperature of the area. According to the Meteorological Bureau of Antarctica's surface temperature data, we can calculate the average temperature of the surface of Antarctica.

Task2: According to the calculated surface temperature of Antarctica, the average temperature of the earth's surface can be predicted of the next few years.

Task3: Give comprehensive analysis of the surface temperature in Antarctica to represent the surface temperature characteristics of Antarctica.

2. Assumption

1. The data we use are true and accurate.
2. Assuming that the site temperature change is smooth and continuous, there will not be a big mutation.
3. All the data is apparent to us all.

3 .Symbol Definitions

T (r, t),	Average temperature
ω(i)	weight
-2Λ	Lagrange multiplier
$z(x, y)$	Distance function

4. Task One

In this section we will propose the definition of the regional average temperature, and the two methods for calculating the average temperature of Antarctica ——The method to optimize regional weight and the method of regional interpolation average . Use the temperature data of 30 sites. And then compare the advantages and disadvantages of the two methods.

4.1 The definition of the regional average temperature

The regional average temperature is the useful characterization of regional climate change research and the study of climate system. Suppose the acreage of area Ω is S, T (r, t) is the temperature of r in time t. In ideal state, every r in t has a T (r, t), and the ideal regional average temperature is

$$\overline{T}(t) = \frac{1}{S}\int_{\Omega} T(r,t)d\Omega \tag{1}$$

In actual calculation, the temperature inside Ω is always getting from observation point, we cannot get every point's T(r, t).Suppose that there's N observation points, T (i, t) is temperature of i in t, $\omega(i)$ is the weight in i, 1<i<N, then the actual regional average temperature is

$$\overset{\wedge}{\overline{T}} = \sum_{i=1}^{N} \omega(i)T(i,t) \tag{2}$$

Constraint condition of $\omega(i)$ is

$$\omega(1) + \omega(2) + . . .+ \omega(N) - 1 = 0 \tag{3}$$

4.2Model One

4.2.1 The method to optimize regional weight

According to the definition, calculate the weight with the mechanism of weight optimization. The aim is to minimize the D-value between the ideal regional average temperature and the actual regional average temperature, so mean variance should be as small as possible. The mean variance is

$$\varepsilon^2 = \overline{T}(r,t) - \overline{\hat{T}}(i,t) = \left(\frac{1}{S}\int_\Omega T(r,t)d\Omega - \sum_{i=1}^{N}\omega(i)T(i,t)\right)^2 \tag{4}$$

Expand this formula

$$\varepsilon^2 = \frac{1}{S^2}\int_\Omega d\Omega \int_\Omega \rho(r,r')d\Omega' - \frac{2}{S}\sum_{i=1}^{N}\omega(i)\int_\Omega \rho(r,i)d\Omega + \sum_{i,j=1}^{N}\omega(i)\omega(j)\rho(i,j) \tag{5}$$

$$\rho(i,j) = T(i,t) * T(j,t) \tag{6}$$

When the weight $\omega(i)$ satisfies condition (3) and (6), it's the best weight. Using the Lagrange multiplier method -2Λ

$$F = \varepsilon^2 - 2\Lambda\left(\sum_{i=1}\omega(i) - 1\right) \tag{7}$$

Since $\frac{\partial F}{\partial \omega_i} = 0$ and $\frac{\partial F}{\partial \Lambda} = 0$, then

$$\begin{cases} \sum \omega_i \rho(r_i, r) - \Lambda = \overline{\rho}(i), i = 0..n \\ \sum \omega_i = 1 \end{cases} \tag{8}$$

$$\overline{\rho}(i) = \frac{1}{S}\int_\Omega d\Omega \rho(r, r_i) \tag{9}$$

Matrix is

$$\begin{bmatrix} \rho_{11}..\rho_{1N} & -1 \\ \cdots\cdots\cdots & \\ \rho_{N1}..\rho_{NN} & -1 \\ 1....1....1 & \end{bmatrix} \begin{bmatrix} \omega(1) \\ ... \\ \omega(N) \\ \Lambda \end{bmatrix} = \begin{bmatrix} \overline{\rho}(1) \\ ... \\ \overline{\rho}(N) \\ 1 \end{bmatrix} \tag{10}$$

Let inverse matrix of ρ_{ij} equals b_{ij}

The solution is

$$\begin{cases} \omega_i = \sum_{j}^{N} b_{ij}(\Lambda + \overline{\rho}(r_j)) \\ \Lambda = \dfrac{1 - \sum_{i}^{N}\sum_{j}^{N} b_{ij}\overline{\rho}(r_j)}{\sum_{i}^{N}\sum_{j}^{N} b_{ij}} \end{cases} \quad (11)$$

When the temperature is standardized, ρ means the correlation coefficient between i and j, and the importance in the whole area. The question is turned to be solving $\overline{\rho}$.

4.2.2 Haar wavelet and matrix integral operator

According to the definition

$$\overline{\rho}(i) = \frac{\mathrm{cov}(i,j)}{\sqrt{D(i)D(j)}} \quad (12)$$

$$\mathrm{cov}(i,j) = \frac{1}{m-1}\sum_{k=1}^{m}((T(i,t_k) - \frac{1}{m}\sum_{k=1}^{m}T(i,t_k)(T(j,t_k) - \frac{1}{m}\sum_{k=1}^{m}T(j,t_k))) \quad (13)$$

In the formula, m represents the time region of the i, j temperature data. After analysis, there is a functional relationship between the D-value and the distance between two points.

$$\psi(|r_i - r_j|) = a_1 + a_2 \exp(a_3|r_i - r_j|) \quad (14)$$

$$\overline{\rho}(i) = \frac{1}{S}\int_{\Omega}\Psi(|r_i - r_j|)d\Omega \quad (15)$$

In order to solve (15) with Haar wavelet, transform the definition domain and formula. [-π, π]、 [-π/2,0] transform to [0,1]、[0,1],then

$$\overline{\rho}(i) = \frac{\pi}{2}\int_0^1\int_0^1 z(x,y)dxd \quad (16)$$

$$z(x,y) = \sin\frac{\pi x}{2}(a_1 + a_2\exp(a_3 R\arccos(\sin x_i \sin x_j \cos(y_i - y_j) + \cos x_i \cos x_j))) \quad (17)$$

Haar wavelet is

$$h_0 = \frac{1}{\sqrt{m}}$$

$$h_i(t) = \frac{1}{\sqrt{m}}\begin{cases} 2^{\frac{j}{2}}, \frac{k-1}{2^j} & t < \frac{k-\frac{1}{2}}{2^j} \\ -2^{\frac{j}{2}}, \frac{k-\frac{1}{2}}{2^j} & t < \frac{k}{2^j} \end{cases} \tag{18}$$

i=0, 1…m-1, i= $2^j + k$.

The steps of using Harr wavelet to calculate $\overline{\rho}$ and T are as follows:

1. According to the definition of the Harr wavelet function, the t is discredited by the equal step, and then the discrete form of the Haar wavelet bases is obtained. The matrix H is calculated.

$$\boldsymbol{H} = \begin{bmatrix} \vec{\boldsymbol{h}}_0^T \\ \vec{\boldsymbol{h}}_1^T \\ \vdots \\ \vec{\boldsymbol{h}}_{m-1}^T \end{bmatrix} = \begin{bmatrix} h_{0,0} & h_{0,1} & \cdots & h_{0,m-1} \\ h_{1,0} & h_{1,1} & \cdots & h_{1,m-1} \\ \cdots & \cdots & \cdots & \cdots \\ h_{m-1,0} & h_{m-1,1} & \cdots & h_{m-1,m-1} \end{bmatrix} \tag{19}$$

2. Q_H for the matrix H of the integral operator matrix

$$Q_H = H \bullet Q_B \bullet H^T \tag{20}$$

$$\boldsymbol{Q}_{B_m} = \frac{1}{m}\begin{bmatrix} \frac{1}{2} & 1 & 1 & \cdots & 1 \\ 0 & \frac{1}{2} & 1 & \cdots & 1 \\ 0 & 0 & \frac{1}{2} & \cdots & 1 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & \frac{1}{2} \end{bmatrix} \tag{21}$$

3. According to Z formula find Z matrix, C function integral coefficient matrix, the formula is

$$C = H \bullet Z \bullet H^{-1} \tag{22}$$

$$Z_i(x,t) = H^T \bullet C \bullet H \tag{23}$$

4. Solve $\overline{\rho}$

$$\bar{\rho}(i) = \frac{\pi}{2}\int_0^1\int_0^1 z_i(x,y)\mathrm{d}x\mathrm{d}y = \frac{\pi}{2}H^T \cdot Q_H \cdot C \cdot Q_H \cdot H \tag{24}$$

5. According to the formula (6) calculate ρ matrix.

6. According to the formula (10) calculate the best weight.
7. According to the formula (2) calculate the temperature.

4.3Model Two

Based on the definition of regional surface mean temperature, the average temperature of the surface of Antarctica is solved by using the method of regional interpolation. Among them, the interpolation function uses the triangle linear interpolation method, the three spline interpolation method, the neighbor interpolation method and the four point spline interpolation method. After operation, the three time spline interpolation results are not convergent. The results of the linear interpolation and the neighbor interpolation are not smooth, and the results are in the infinite value. The results of the four spline interpolation method are smooth and reasonable. So the operation of the four spline interpolation function is chosen.

Take 1991 as an example, the calculation steps of the average temperature of Antarctica in 1991 are as follows:

1. According to the Antarctica 30 meteorological observation stations, in order to measure surface temperature data, interpolate the temperature of 30 sites each month of Antarctica Area.
2. Measure the mean value of all the temperature after the interpolation.
3. Measure average temperature of the surface of the 12 months.

Temperature values in other years are also used to find out the above steps.

4.4 Model solving

The average temperature curve obtained by using the method of region optimization is shown below.

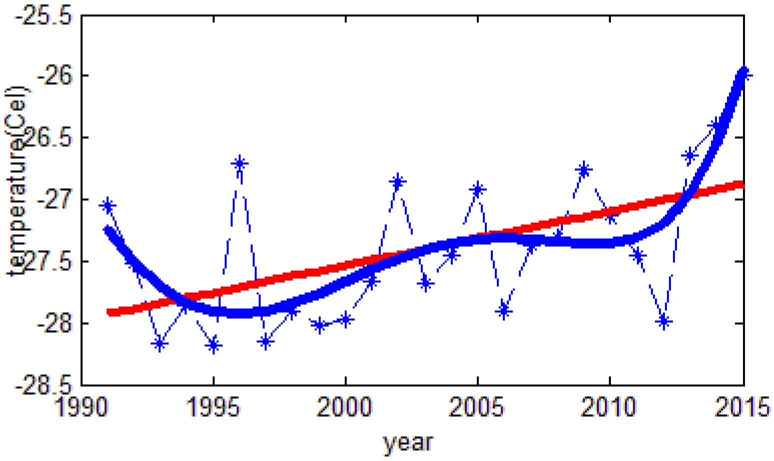

Fig.1 The average temperature
calculated by the method to optimize regional weight

According to the method of regional interpolation average, the average temperature of the surface is obtained as shown in Table 1:

Table 1: average surface temperature in Antarctica

Year	Temp	Year	Temp	Year	Temp	Year	Temp	Year	Temp
1991	-27.903	1996	-27.033	2001	-27.211	2006	-27.932	2011	-27.422
1992	-28.535	1997	-28.104	2002	-26.644	2007	-27.374	2012	-27.883
1993	-28.463	1998	-27.690	2003	-27.565	2008	-26.892	2013	-26.349
1994	-28.323	1999	-27.829	2004	-27.384	2009	-26.682	2014	-27.016
1995	-28.229	2000	-27.752	2005	-26.750	2010	-27.117	2015	-28.942

According to the value of the surface of Antarctica, the average temperature of the surface of Antarctica is plotted

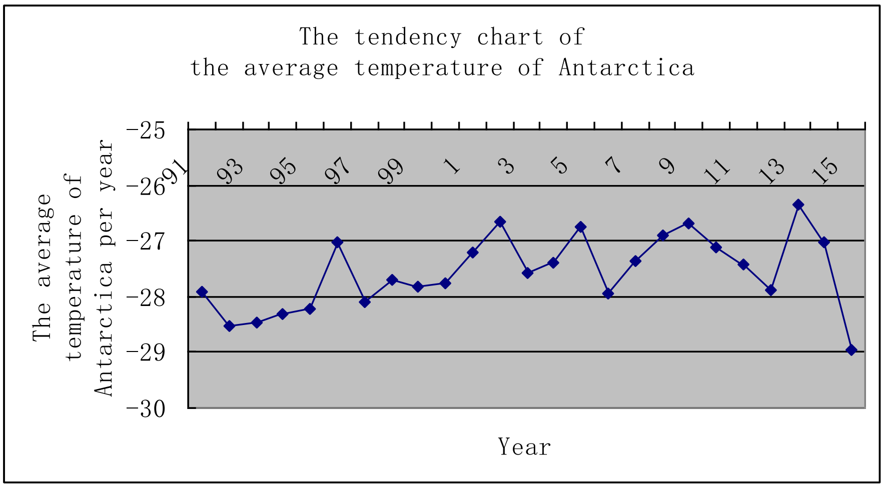

Fig.2 The average temperature calculated by the method of regional interpolation average

4.5 Conclusion and analysis

4.5.1 Conclusion of results

From the surface of Antarctica, the average temperature of the whole surface of Antarctica during 1991 to 2015 was found to be between -29 and -26, and the fluctuation range is not particularly large. The rising trend of the fluctuation of the surface temperature shows that the surface temperature of Antarctica is increasing year by year.

4.5.2 Analysis of the two methods

The common characteristic of the two method is using discrete observation data in time and space to simulate the integral of temperature by Antarctic land area and time, then work out the average temperature.*The regional interpolation method is simple than Regional optimization method, in terms of the academic Algorithms and ideas. And the key of the Interpolation algorithm can be realized by MATLAB. But in the situation of this question, observation stations are sparse and uneven distribution. There while be huge error compute only by using the interpolation of the adjacent points. But Regional optimization method introduces covariance and matrix integral operator, taking into consideration connection and restriction of weight because of geographical distribution of observation stations is much appropriate than region interpolation method in logic and correlation test.

There is another key to the model, which is on the using of data from abundant of observation times. In theory, the weight of temperature from different observation stations are changes with time. So computing every time's average value with corresponding weight will be closer to the true value.

5. Task Two

In this paper, a NAR neural network based on dynamic neural network time series is selected to establish the model of the earth's surface temperature prediction in Antarctica. The networking is trained and tested by the data calculated by Model 1 to obtain the trend of annual average temperature. Using this to analyze its variation direction, and provide reliable data for the study of environmental management.

5.1 The Foundation of Model

NAR model, which is composed of input layer, hidden layer, input delay layer and output layer, is a special form of NARMA model. The output of each NAR in the Y model, which is used to adjust the parameters of the neural network, and complete the adjustment of the neural network, is a kind of neural network with the ability of memory. When the measured data is a time series, the NAR model can be defined as:

$$y_n = F(y_{n-1}, \cdots, y_{n-k}) + k\varepsilon_n \qquad (25)$$

In the formula: F—nonlinear function; k—constant; ε_n —random variable that obeys Gauss distribution. The structure of the network is shown in Figure

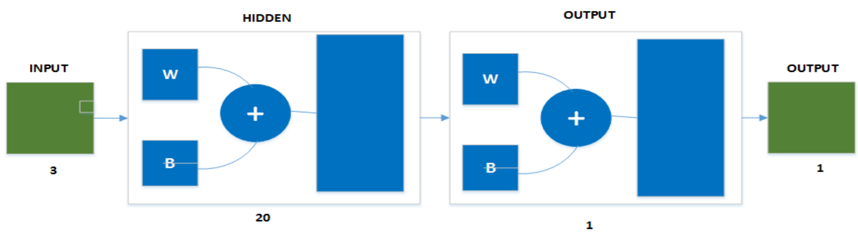

Fig3.The structure of NAR

Prediction step of NAR model:

1. Set the time delay between the input and output layers and the number of neurons in the hidden layer. The output delay of NAR neural network is 3, the number of hidden layer neurons is 20.

2. Import the historical time corresponding data, and set up the corresponding training validation, test set of the percentage. The training set is used to train the data of the prediction model; the validation set is used to verify the feasibility of the network; the test set is used to evaluate the data of the model's prediction ability. In this paper, the training set is 70%; the validation set is 15%; the testing set is 15%.

3. Conduct NAR network training. The network uses LM (LevenbergMarquardt) training algorithm for neural network learning

4. MSE (Mean Error Squared) is chosen to judge the network performance. According to the error curve, the error curve can determine whether the network is good or not, and determine which is the optimal network for prediction.

5. Prediction output and detection of network

5.2 The result of model:

Take the forecast sample into the average temperature model of NAR neural network. Although the prediction results show that the local estimate of the phenomenon, but the overall simulation and the measured values are basically the same. The mean square error MSE=10e-19, which shows that the average value of the NAR neural network can predict the average temperature of the next 3 years perfectly.

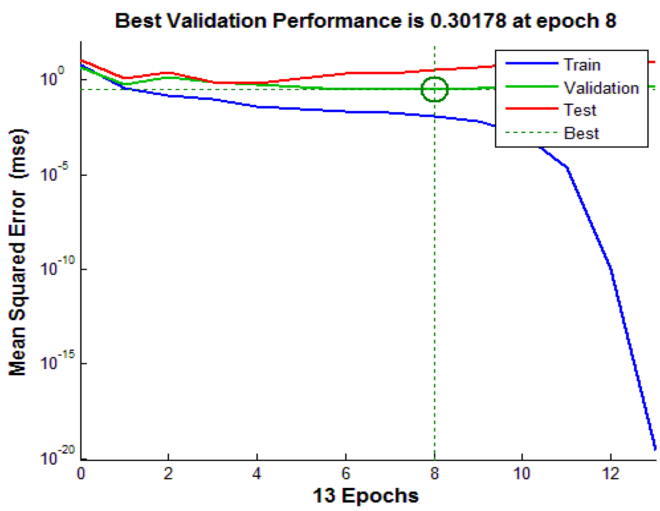

Fig4. Error curve

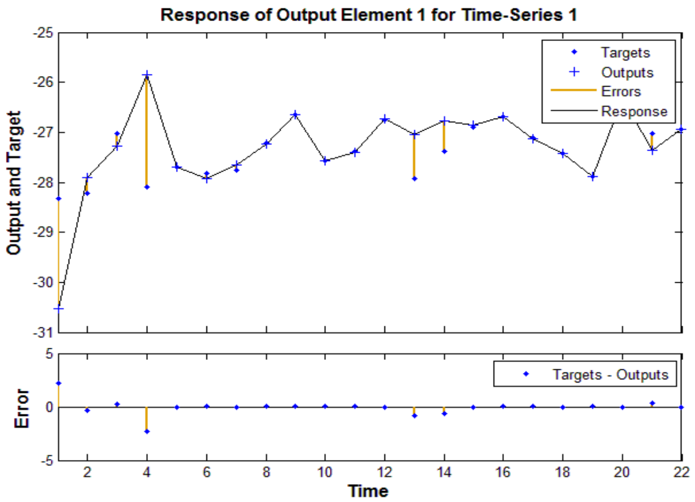

Fig5.Output and targets

Error autocorrelation analysis is to examine the correlation degree of the error of the detection time series and can be used to define strength and weakness of model. From the Figure.5 , we can see that the prediction error of NAR model is nonlinear and the correlation degree in the range of confidence is small. So the NAR model is not due to the error of the prediction point.

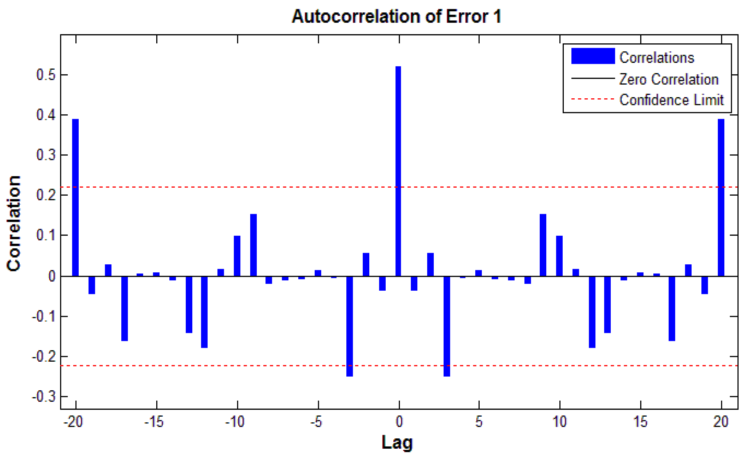

Fig6.Autocorrelation of error

Prediction of the next 3 years the average temperature is [-27.5235, -27.2722, -26.9317], the temperature sequence as shown in Figure:

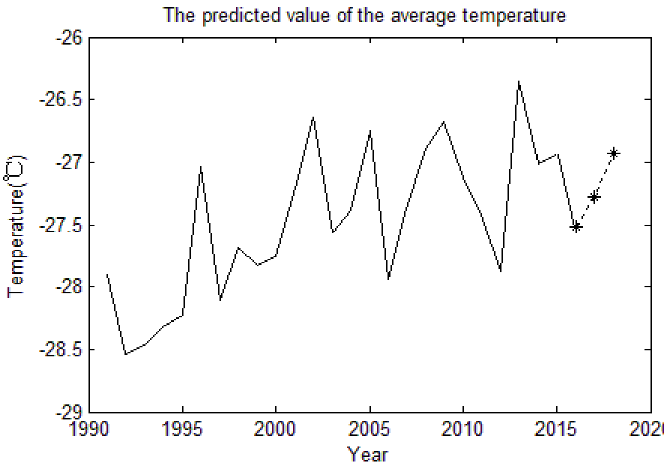

Fig7.Prediction

6. Task Three

The trend of temperature change in the space was obtained by cluster analysis, and the trend of seasonal temperature variation was obtained by regression analysis.

6.1 The foundation of model

1. The temperature change trend of the Antarctic continent is different because of the vast area, the long coastline of Antarctica, different regions within the wide dimension. In this paper, the annual average temperature of 30 stations in Antarctica is analyzed by SPSS cluster analysis. According to the classification results, we analyzed the characteristics of temperature variation in different regions of Antarctica.

2. The average surface temperature is affected by the season, and the average surface temperature is different in different seasons. In this paper, a linear regression method is used to simulate the variation of surface temperature in different seasons.

6.2 The result of model

Spatial distribution characteristics

The temperature variation characteristics are not the same in the polar and the adjacent sea area, but can partly reflect the change of the temperature of Antarctica. In order to divide the space distribution of the temperature variation in Antarctica, we have carried out the cluster analysis of the 30 stations.

Table 2. Examples of 30 sites’ temperature departure

	1994	1995	1996	1997	1998	1999	2000
Amundsen	-0.8158	4.6842	0.9842	1.4842	-0.5158	-0.5158	0.184
Arturo	-5.885	-4.0857	-3.5857	-2.1857	-1.98571	-0.9857	-0.685

Belgian	-7.7	-6	-5.4	-4.8	-4.3	-3.6	-3.5
Casey	0.0895	-6.9105	2.8895	-7.2105	-0.5105	-4.3105	1.089
Davis	-7.341	-5.3418	-4.8418	-4.5418	-3.6418	-3.5418	-3.541
Dumont	-4.358	-3.8586	-3.6586	-3.5586	-3.3586	-3.3586	-3.258
Esperanza	-7.605	-6.6057	-6.1057	-4.6057	-4.5057	-4.3057	-4.105

Of the following is the section of the site of temperature range

Table 3. The results of classification

Code	Category	Distance	Code	Category	Distance	Code	Category	Distance
1	4	14.137	11	4	15.685	21	1	0
2	4	8.485	12	4	18.886	22	2	9.434
3	4	10.459	13	4	7.683	23	2	8.432
4	4	13.616	14	3	4.963	24	2	10.947
5	3	8.265	15	4	13.798	25	5	0
6	4	8.805	16	3	3.727	26	2	7.311
7	3	5.731	17	2	18.298	27	2	5.468
8	3	12.523	18	3	6.944	28	2	8.422
9	4	8.118	19	2	9.081	29	2	6.546
10	4	6.770	20	3	7.580	30	2	13.020

The clustering results of 30 site distribution and temperature variation are given from Figure 8

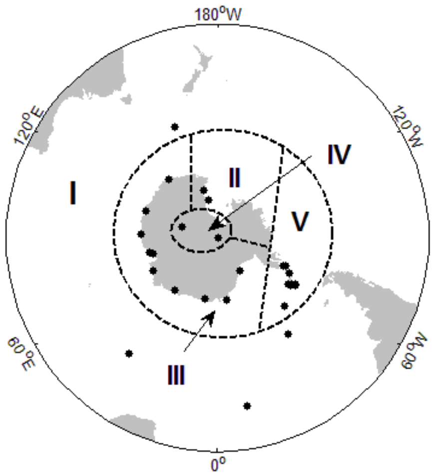

Fig8. The results of classification

This shows that there are 5 different regions of temperature change. The cluster analysis is classified into the same class. In the same region, the average distance of each station is less than the critical distance and the correlation coefficient is large with the consistent change. The average distance from other regions is greater than the critical distance of the less correlation coefficient. Each region can independently reflect changes in temperature in Antarctica.

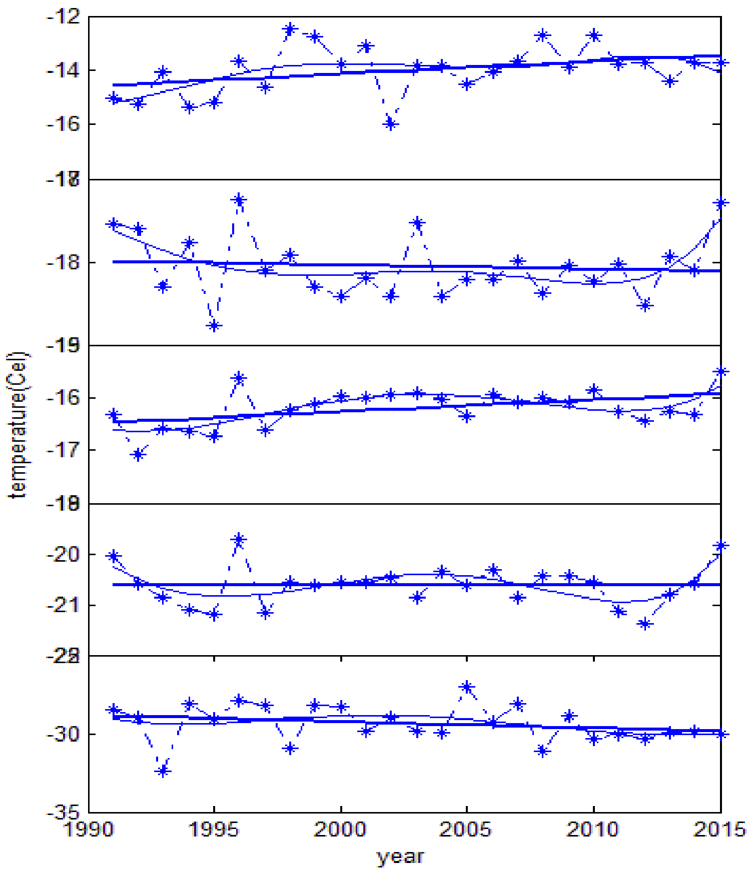

Fig9.Different sites' temperature features

The variation curves of the average temperature series in each region of the 1990-2015 are given from Figure.9 respectively.

As it is seen from the picture, in the past 25 years, different degrees of significant warming trends occur in various regions. The II and V regions were increased most obviously (0.168℃ and 0.36℃), but the IV region was less than 0.12℃. Generally speaking, the average temperature in I region range -6℃ from -2℃, and temperature of 2015 dropped to -7.5℃; there is a warming trend in II region; temperature fluctuation in III region is not big, but of slightly cooling trend; IV regional changes in temperature is more obvious, but there is no sudden changes of temperature in 2015; there also exists a warming trend in V region. According to the analysis of Figure.9, I, II and V region are warming significantly because of offshore and the impact of global warming with melting glaciers,; the temperature change is mainly caused by local temperature changes while the global warming has little effect on Region IV in Antarctic Circumpolar.

Time changing trend:

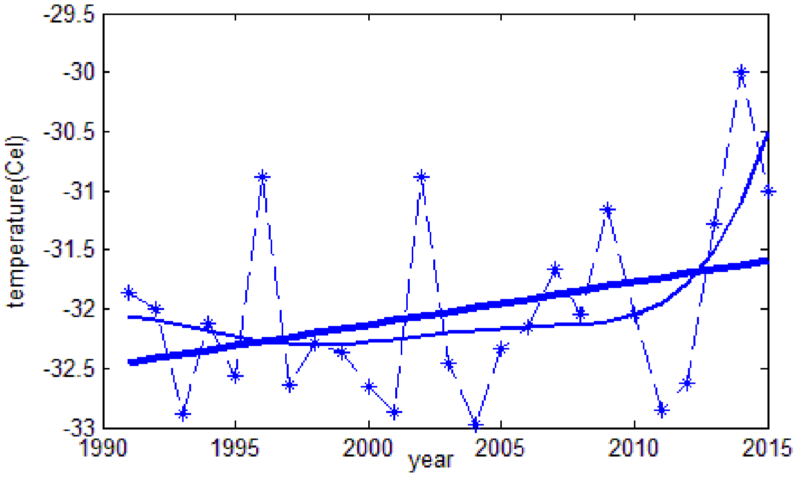

Fig10.Winter temperature

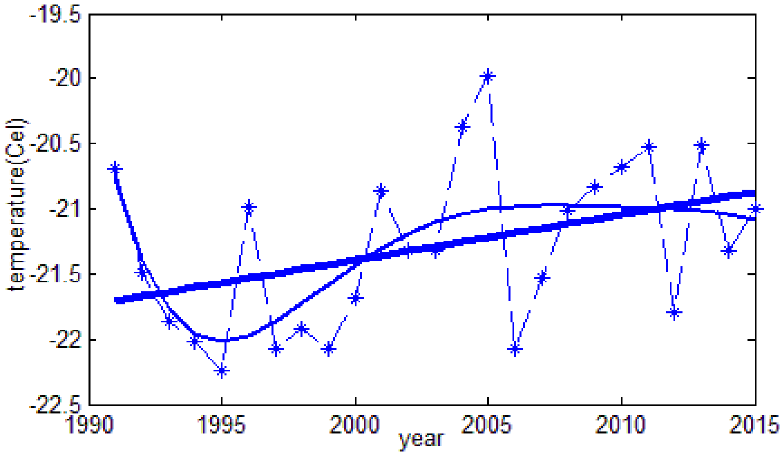

Fig11.Summer temperature

The picture shows the average temperature of Antarctica in (summer January) and July (Antarctica's winter). We can learn that the summer temperature rise in Antarctica in the last 20 years, showing a warming trend. But the trend of winter temperature, may be related to the cold air into the Antarctic cycle has a stable temperature change.

7. Conclusion

7.1 Strengths

1. Establishing models aiming at problems and the structure is simple and easy to be realized
2. Model 1 is the solution of the covariance model, which avoids the problem that the application of the inverse matrix, and it can improve the regional optimization method
3. The training speed of model 2 is faster than BP neural network with the longer forecast period and the higher forecast precision
4. The credibility is high to use the mathematical theory to establish the model. It is easy to popularize the model with the professional software calculation

7.2 Weakness

1. Only consider the different time temperature data, dislodging the wind speed, pressure and other columns as a perturbation term
2. Model 1 still needs to be optimized, because the results are affected by the spatial distribution of sample points.
3. The error of model 2 will accumulate as the forecast increases

7.3 Improvement

All of the temperature data are derived from British Antarctic Survey website. We choose 30 observation sites of more abundant data, because some of data cannot be obtained. Actually, in order to predict the average temperature accurately, the observation data should cover the entire Antarctic continent. This means there are still some errors between the model value and the actual value. We still need a lot of data to optimize the model.

Different generating functions correspond to different wavelet transform, such as Haar wavelet, Shannon wavelet, etc. To achieve multi-resolution analysis of wavelet, it is necessary to select the appropriate wavelet generating function. Because of the limitation of data, we choose the most simple one-Haar wavelet in the model. In addition, the resolution is not high with the low speed of generating function to zero. In theory, the best model is when the approaching speed achieving the most with the best resolution.

The neural network, which can be different from the learning style and content has the ability of self-adaption and self-organization. In fact, the selection of the number of time delay and the number of hidden neurons are determined by many factors. There is no mature theoretical basis, and can only be determined by the experience of the designer. Each training process will get a different prediction results. It will be the perfect NAR neural model to be at the state of the minimum mean square error and the decisive factor.

8. References

[1] Cong Wang, Ning Huang, Bao Yang. Improvement of regional optimization method and its application in calculation of average temperature Gansu: LanZhou University, 2014.2

[2] Wanhai Gen, Yiming Chen, Yufeng Liu, Xiaojuan Wang. Using Haar wavelet and the operator matrix to determine the approximate value of definite integral [A] Hebei: College of science, Yanshan University, 2012.4

[3] Xiang Wang, Jixiang He, Lie She, Jing Zhang. Research on the prediction model of water nitrite in aquaculture water based on NAR neural network Anhui: Hefei, 2015.8

[4] Longhua Lu, Lingen Bian, Pengqun Jia. Temporal and spatial variation of temperature in the South Pole and adjacent regions [D]Beijing: Chinese Academy of Meteorological Sciences, 1997.6

9. Appendix

Code:

```
1.% Clustering analysis plot
load n_axi.mat  % draw observation stations in Antarctic map
addpath D:\2013 MATLAB\toolbox\m_map
addpath(genpath('D:\2013 MATLAB\toolbox\m_map'))
m_proj('stereographic','latitude',-90,'radius',60,'rotagnle',180);
m_coast('patch',[.7 .7 .7], 'edgecolor', 'none');
m_grid('xaxislocation','top');
for n = 1:30;

m_line(n_axi(3,n),n_axi(2,n),'marker','.','markersize',15,'color','bl
ack');
end
```

2.%Haar

```
clear;
load dot_stop.mat;
T = -[  …  ];
```

```
m = 46;R = 6371.004;a1 = 0.076;a2 = 0.842;a3 = -0.100;%3¸öa
for i = 0:45
   for  j = 0:5
       k = i-2^j+1;
       if ((k-1)/2.^j>=0)&&(k/2.^j<=1)
           jk(i+1,1) = j;
           jk(i+1,2) = k;
       end;
   end;
end;
jk = jk';
jk = jk(jk>0)';
jk = [0,0,0,jk];
jk = reshape(jk,2,46);
n_ = linspace(0,1,47);
n = n_(1:46);
for i = 1:46;
    H_( (n>=0&n<(jk(2,i)-1)/2.^jk(1,i)) | ( n>=jk(2,i)/2.^jk(1,i)&n<=1 ) )
= 0;
    H_( (n>=(jk(2,i)-1)/2.^jk(1,i) & n<(jk(2,i)-1/2)/2.^jk(1,i)) ) =
2.^(jk(1,i)/2);
    H_( (n>=(jk(2,i)-1/2)/2.^jr(1,i) & n<jk(2,i)/2.^jk(1,i)) ) =
-2.^(jk(1,i)/2);
    H(i,:) = H_;
end
H(1,:) = 1/m^(1/2);
Qb = 1/m*(triu(ones(m,m),0)- diag( 1/2*ones(1,m) ));
Qh = H.*Qb.*(H');
dot_stop(1,:) = dot_stop(1,:)/90;        %
dot_stop(2,:) = (dot_stop(2,:)+180)/360;
for i = 1:46;
    for j = 1:46;
    Z(i,j) =(a1 + a2...
        *exp(a3*R*acos(sin(dot_stop(2,j))*sin(dot_stop(2,i))*...
        cos(dot_stop(1,j) - dot_stop(1,i)) +
cos(dot_stop(2,j))*cos(dot_stop(2,i)) )));   %
sin(pi*dot_stop(2,j)/2)*
    end;
end;
C =  H.*Z.*H^(-1);
p = H'*Qh*C*Qh*H;
p = [p;1];
P = T'*T;  P = [P,(-ones(46,1))]; P = [P;ones(1,47)]; P(47,47) = 0;
w = p*P^-1;
```

```
3.% the method of regional interpolation average
clear;
clc;
for n = 1:30;
 eval(['load NUM',num2str(n),'.mat;']);
 for i = 1:12
 eval(['NUM_',num2str(n),'(:,i) =
mean(NUM',num2str(n),'(:,(1+(i-1)*4):(i*4) ),2 );']);
 end;
 eval(['save NUM_',num2str(n),'.mat']);
 eval(['NUM_ALL(:,:,',num2str(n),') = NUM_',num2str(n),';']);
end;
save NUM_ALL.mat
load n_axi.mat
x = -(90+n_axi(2,:)).*cos( n_axi(3,:)*pi/180 )*10.5+338;
y = (90+n_axi(2,:)).*sin( n_axi(3,:)*pi/180 )*10.5+337;


for i = 1:25;
    for j = 1:12;
       t(1,:) =  NUM_ALL(i,j,:);
       [X,Y,T] =
griddata(x,y,t,linspace(min(x),max(x)),linspace(min(y),max(y))','near
est');
       maen_month_year(i,j) = mean(mean(T));
    end;
end;
```