Solar radiation modeling based on stepwise regression analysis in China

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Abstract: In this paper, new solar radiation modeling based on stepwise regression analysis are put forward for estimating global solar radiation from common climate variables (such as sunshine duration, cloud cover, vapor pressure) and geographical elements (altitude, latitude), which simplify the simulation process, improve the operational efficiency under the similar precision. Based on these models and the observation data of common meteorological elements at more than 730 stations in China, the resulting 1km×1km resolution solar radiation distribution show that in the whole country, the annual solar radiation energy on the land surface is about 52.4×10¹⁸ J, and the average annual solar radiation lies between 2780—7560MJ·m⁻²·a⁻¹. There are regional distribution characteristics of global solar radiation in China; it declines from northwest to southeast. The highest value (≥6700 MJ·m⁻²·a⁻¹) areas of solar radiation is in the Tibet Autonomous Region, the northeastern of Qinghai Province and the west border of Gansu Province; their total area is about 1300000km². The lowest value (≤4200 MJ·m⁻²·a⁻¹) area of solar radiation is in the Sichuan Basin and the gorge area of the Yarlung Zangbo Grand Canyon in the south of Tibetan Plateau; their total area is about 750000km².

Key words: global solar radiation, multiple stepwise regression, spatial interpolation, China

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1 INTRODUCTION

Solar radiation, the fundamental source of energy for life on our planet is the primary influencing factor for ecoclimatic environment. On one hand it is an important parameter of the models in carbon cycle, hydrology, meteorology, energy-saving and emission reduction study areas (Robaa, 2009; Xu et al., 2008); on the other hand, 90%—95% of the dry matter in plants are synthesized by photosynthesis process utilized solar energy which is the only energy source of organic nutrients (Yue et al., 2008; Tmka et al., 2007). However, compared with common meteorological elements (such as air temperature, humidity and precipitation); solar radiation observations are too costly to be measured continuously in many climate stations located in the remote areas. Based on a few observation data of the global solar radiation, it is difficult to reveal the spatial distribution characteristics of global solar radiation, so it is the fundamental work to develop models based on multiple regression analysis to estimate solar radiation for data sparse regions in China with extensive weather records such as sunshine duration, cloud cover, vapor pressure.

In this paper, new solar radiation modeling based on stepwise regression analysis are put forward for estimating global solar radiation from common climate variables (such as sunshine duration, cloud cover, vapor pressure) and geographical elements (altitude, latitude). These models are developed using C# and Matlab mixed programming technique (Yue et al., 2007); and the AO component from ESRI was used to visualize the simulation results. Based on Microsoft Dot NET platform the whole system is integrated and deployed without Matlab and ArcGIS desktop. Based on these models and the observation data of common meteorological elements at more than 730 stations in China, the resulting 1km×1km resolution solar radiation distribution is generated and analyzed in the end.

2 MATERIALS AND METHODS

2.1 Data

Meteorological data about monthly solar radiation covering

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First author biography: LU Yimin (1973— ), male, doctoral candidates. He is now doing his PhD research in Chinese Academy of Sciences, focusing on resource & environmental modelling. E-mail: luym@lreis.ac.cn
the period from 1957 to 2001 observed in 122 stations and common meteorological elements covering the period from 1951 to 2002 observed in 735 stations were obtained from National Meteorological Information Center in China. The data about sunshine percentage observed in 603 stations were obtained from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences. The 1km DEM data of study area were obtained from GTOPO30 dataset provided by United States Geological Survey.

There were some discontinuous periods in meteorological data records, such as the period of monthly solar radiation data records ranging from 10 to 44 years and common meteorological element records ranging from 10 to 50 years; especially some individual new stations having only 1 to 2 years observed records. After rejecting the abnormal value, there were monthly solar radiation data observed in 122 stations, cloud cover data observed in 733 stations and vapor pressure, sunshine duration data observed in 735 stations. The focus of this paper is modeling the annual amount of solar radiation in China, so the key to processing data is how to obtain the most representative annual amount of solar radiation in stations. Monthly mean meteorological data were calculated from every month record in the past years. Then we accumulated monthly mean solar radiation and sunshine duration value and calculated the weighted mean value of cloud cover and vapor pressure in 12 months a year.

2.2 Methodology

2.2.1 Traditional methods

At present, there are mainly three kinds of methods on the global solar radiation estimation. The first one is to estimate the global solar radiation based on the spatial interpolation methods. It is one of the simplest ways, however, the simulation results are difficult to satisfy for practical application for solar radiation observation data sparse regions in China. The second is the remote sensing retrieval of solar radiation at the surface (Wei et al., 2003; He et al., 2004). The third is a numerical climatological method. Although it is mature, the method is rather complicated as it is, the Stepwise Regression is an ideal method to overcome multicollinearity. Thus, it is widely used in geology (Tian et al., 2005; Fu et al., 2009), ecology (Petersen & Stringham, 2008), meteorology (Ertekin & Evrendilek, 2007), materials (Wang et al., 2007), medicine (Ng, 2003) and other research fields.

Stepwise regression procedures work in an alternating order. Begin with no variables; add variables one at a time according to which one will result in the largest increase in $R^2$; stop when $R^2$ will not be significantly increased. The last is Combines Forward/Backward (Stepwise Regression). Select two thresholds $F_{SLS}$ and $F_{SLE}$. Starting like Forward Selection, add new variable, if it has $F>F_{SLS}$. Re-test all “old variables” that have already been added, and retain the old variable only if $F<F_{SLE}$. Continue until no new variables can be entered and no old variables need to be removed. Complicated as it is, the Stepwise Regression is an ideal method to overcome multicollinearity. Thus, it is widely used in geology (Tian et al., 2005; Fu et al., 2009), ecology (Petersen & Stringham, 2008), meteorology (Ertekin & Evrendilek, 2007), materials (Wang et al., 2007), medicine (Ng, 2003) and other research fields.

Stepwise regression procedures work in an alternating order. Begin with no variables; add variables one at a time according to which one will result in the largest increase in $R^2$. At each step remove any variable that does not explain a significant portion of variance. Stop when $R^2$ will not be significantly increased. No matter what variable of regression equation is added or dropped, it needs to check after each step if the significance of other variables has changed. Process repeated (Fig. 1) enter the variable with the highest correlation with $y$ variable first; remove variables that become insignificant due to other variables being added. And the formula of $F$ statistics is shown as follows.

$$ F = \frac{U/k}{Q_{e}(n-k-1)} \sim F(k, n-k-1) \quad (1) $$
3 RESULTS AND DISCUSSION

3.1 Correlation analysis of influencing factors

Scatter Diagram, one of many statistical techniques usually used to measure the strength of the relationship between two variables is visual but not precise enough. The coefficient of correlation, $r$ is a measure of the strength of the linear relationship between two variables. Method of estimating $r$ can portray the correlation between the two variables of interest precisely.

Considering the procurability and integrity of data about influencing factors of solar radiation ($0.01MJ \cdot m^{-2} \cdot a^{-1}$), we select six variables, which are $x_1$ annual mean sunshine hours (0.1 h), $x_2$ annual mean sunshine percentage (%), $x_3$ annual mean total cloud cover (0.01), $x_4$ annual mean vapor pressure (hPa), $x_5$ altitude (0.1 m) and $x_6$ latitude (°). To acquire Pearson correlation coefficient, which measure and interpret the association between variables or solar radiation ($Q$) and variable, we select 96 stations (from 122 stations solar radiation observed) which have integrated records about six variables aforementioned. The correlation terms involved in the correlation coefficient matrix (Table 1), therefore, indicate that the association between solar radiation ($Q$) and each variable is significant. The term of $x_1$ and $x_2$ is 0.9963 close to one, namely, collinearity exists between $x_1$ and $x_2$. Thus, one of them needs to be removed. Here dropping $x_2$ annual mean sunshine percentage, other five variables will be use to establish the regression equation.

<table>
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<th>$x_2$</th>
<th>$x_3$</th>
<th>$x_4$</th>
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<th>$x_6$</th>
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<td>0.4276</td>
<td>0.2347</td>
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</table>

3.2 Solar radiation modeling

3.2.1 Variables of solar radiation modeling

In order to ensure predictors reliable and to promote the model in interpreting the estimation results more precisely, a significance level selected in stepwise regression is 0.01. Moreover, root mean square error (RMSE, $MJ \cdot m^{-2} \cdot a^{-1}$), multiple coefficient of determination ($R^2$), adjusted $R^2$ (Adj-$R^2$) and F statistics are used as evaluation indexes in the regression diagnostics. The root mean square error (RMSE) is an index of discrepancy between the exact and approximate and is a frequently-used measure of the differences between values predicted by a model and the values actually observed from the thing being estimated. The coefficient of determination ($R^2$, goodness of fit) is the proportion of explained sum of squares to total sum of squares. It provides a measure of how well future outcomes are likely to be predicted by the model.
that $R^2$ may overestimate the true amount of variance explained; thus, adjusted $R^2$ compensates by reducing the $R^2$ according to the ratio of subjects per predictor variable.

Data observed in 116 stations which have integrated records about aforementioned five variables, $x_1$ annual mean sunshine hours, $x_3$ annual mean total cloud cover, $x_4$ annual mean vapor pressure, $x_5$ altitude, $x_6$ latitude and $Q$ solar radiation, will be used to establish the solar radiation model by the stepwise regression method. According to the coefficients of correlation between solar radiation and each variable (Table 1), the variable is added or removed, and to be checked after each step if the significance of other variables has changed. Based on Tian et al. (2005), it is assumed that three variables ($x_1$, $x_5$, $x_6$) have been added to the regression equation. Then the variables ($x_4$, $x_3$) are added and variable $x_5$ is removed, meanwhile, evaluation indexes in the regression diagnostics have been recorded in Table 2. The data presented in Table 2 indicates that $R^2$, Adj-$R^2$ increase and RMSE decrease, while variables $x_4$, $x_3$ have been added to the regression equation. While variable $x_5$ has been removed, $R^2$, Adj-$R^2$ and RMSE have not been changed remarkably but $F$ statistics increase obviously. Therefore, four variables $x_1$, $x_3$, $x_4$, and $x_6$ are retained for the final solar radiation modeling.

Table 2  Summary statistics updated with each step for the solar radiation model based on MSRA

<table>
<thead>
<tr>
<th>Variables</th>
<th>RMSE</th>
<th>$R^2$</th>
<th>Adj-$R^2$</th>
<th>$F$</th>
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<td>$x_1$, $x_3$, $x_6$</td>
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<td>$x_1$, $x_4$, $x_5$, $x_6$</td>
<td>264.591</td>
<td>0.917682</td>
<td>0.914715</td>
<td>309.356</td>
</tr>
<tr>
<td>$x_1$, $x_3$, $x_4$, $x_5$, $x_6$</td>
<td>257.307</td>
<td>0.922853</td>
<td>0.919346</td>
<td>263.169</td>
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<tr>
<td>$x_1$, $x_3$, $x_4$, $x_6$</td>
<td>257.770</td>
<td>0.921871</td>
<td>0.919056</td>
<td>327.432</td>
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</table>

3.2.2  Coefficient of solar radiation modeling

After four predictor variables selected, the parameters need to be determined. The estimation of parameters for the solar radiation model is carried out here using mean square error (MSE), relative mean square error (R-MSE) and computational efficiency (CE) as evaluation indexes in the error analysis. If the sample sizes are large enough, its mean square error is the same as its standard deviation, and its relative mean square error is the proportion of the absolute value of mean square error to the corresponding observed value.

$$Q_{Ref} = 170292 + 20.73189x_1 - 0.19171x_1x_6 + 0.07212x_1x_6 \quad (2)$$

$$Q_{Line} = 299608.16779+18.20611x_1+1976.62392x_3-609.31017x_4-7310.72926x_6 \quad (3)$$

$$Q_{Int} = 355453.51165+17.67786x_1-2057.18878x_3-355.29898x_4+767.34475x_6+0.1136x_1x_3-0.01519x_1x_4-0.235735x_1x_6+8.54718x_3x_4-10.11656x_3x_6-19.90513x_4x_6 \quad (4)$$

Here we use variables $x_1$, $x_3$, $x_4$, and $Q$ to build multiple linear regression Eq. (3) and binomial regression Eq. (4); and quote Eq. (2) from the reference (Tian et al., 2005) to compare with them. The scatter plots of observed and simulated annual global solar radiations is shown in Fig.2, in which (a) comes from the Eq. (2) model; (b) comes from the Eq. (3) model; (c) comes from the Eq. (4) model. Comparison of errors and efficiency among different models of solar radiation are shown in Table 3.

Fig. 2  Scatter plots of observed and simulated annual global solar radiations

(a) Estimated by Eq.(2); (b) Estimated by Eq.(3); (c) Estimated by Eq.(4)
Table 3  Comparison of errors and efficiency among different models of solar radiation

<table>
<thead>
<tr>
<th></th>
<th>model 2</th>
<th>model 3</th>
<th>model 4</th>
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<tr>
<td>MSE</td>
<td>297.68</td>
<td>252.15</td>
<td>234.54</td>
</tr>
<tr>
<td>R-MSE</td>
<td>0.0580</td>
<td>0.0491</td>
<td>0.0457</td>
</tr>
<tr>
<td>CE</td>
<td>0.800403</td>
<td>1</td>
<td>0.294891</td>
</tr>
</tbody>
</table>

MSE, mean square error (MJ·m⁻²·a⁻¹); R-MSE, relative mean square error and CE is computational efficiency, mean value of the 18 samples with different sizes.

According to Fig.2, it shows that Fig.2 (c) from model 4 having lowest value of mean square error (234.54) and indicating it to be the most precise model Fig.2 (b) is better than Fig.2 (a). The relative mean square errors (R-MSE) presented in Table 3 shows that all the three models are reasonable, and that R-MSE of model 3 and model 4 decrease by 15.3% and 21.2% comparing with model 2. At the same time, the computational efficiency (CE) presented in Table 3 shows that CE of model 2 and model 4 decrease by 20% and 70.5% comparing with model 3. Based on the aforementioned analysis, it indicates model 3 to be the best model among the three models discussed above. So model 3 is finalling used to estimate the annul global solar radiation in China.

3.2.3 Simulation of solar radiation modeling

Two different methods are used to make the required estimates of global solar radiation in China. One is spatial interpolation based on 122 stations’ data (global solar radiation observation record); the other is spatial interpolation based on 731 suppositional stations’ data of global solar radiation, which are simulated by Eq. (3). Fig.3 (a) (1km×1km resolution, 4173×4847 grid) resulting from the first method shows that the spatial distribution of stations is uniform and the spatial distribution of global solar radiation is simulated generally and simply. However, it is difficult to reveal the spatial distribution characteristics of global solar radiation reasonably, based on so few observation data in the whole country. Large errors appear in the result of many regions such as Qilian Mountains, Tarim Basin and southern Tibetan Plateau.

Compared with Fig.3 (a), Fig.3 (b) has a spatial resolution of 1km×1km, and a size of 4173×4847 grid. Its extreme values observed against predicted ones for the same locations are unanimous. Moreover, the values estimated in Fig.3 (b) are closer to the observed (true) solar radiation measurements in the whole study area. It implies abundant information and portrays more details in the spatial distribution of global solar radiation. Classification map of annual global solar radiations in China is shown as Fig. 4. In western China with sparse measured sites, however, these results still leave much to be desired.

4 CONCLUSIONS

(1) There are about 52.4×10¹⁸ kJ solar radiation energy (equivalent to 1790 billion tons of standard coal) to be obtained on the whole land surface of China. The spatial distribution of annual global solar radiation shows the regional characteristics obviously; as is abundant in western and northwestern China, and is scanty in the east and southwest China.

(2) The Tibet Autonomous Region, northeastern Qinghai and western borders of Gansu, whose areas accumulated is about 1.3 million km², are first-class areas. As shown in Fig. 4, annual global solar radiation energy in these areas reaches up to 6680MJ·m⁻²·a⁻¹. The lowest value area of solar radiation (≤4200MJ·m⁻²·a⁻¹) is in the Sichuan Basin and the gorge area of the Yarlung Zangbo Grand Canyon in southern Tibetan Plateau. They are fifth-class areas, whose total area is about 0.75 million km².

(3) The second-class areas of solar radiation (5850—6680MJ·m⁻²·a⁻¹), whose total area is about 2.4 million km², are in the southern Inner Mongolia, northern Shanxi and Ningxia, the middle and northwest of Gansu, eastern Qinghai, the southeast of Tibet and southern Xinjiang. The third-class areas (5000—5850MJ·m⁻²·a⁻¹), mainly distribute in the northeast of Inner
Mongolia, western Jilin and Liaoning, the southeast and north of Hebei, southeastern Shandong, southern Shanxi, northern Henan and Shaanxi, the southeast of Gansu, northern Xinjiang, Yunnan, southern Guangdong, southern Fujian and the southwest of Taiwan, whose area is about 2.8 million km². The fourth-class areas (4200 — 5000MJ·m⁻²·a⁻¹) are mainly in Heilongjiang, the northeast of Jilin and Liaoning, southern Shaanxi, Hunan, Hubei, Jiangsu, Anhui, Jiangxi, Zhejiang, Guangxi, northern Guangdong, northeastern Fujian and the north of Taiwan, whose total area is about 2.35 million km².

(4) A method put forward in this paper provides a new idea to integrate remote sensing information in agroclimatological resources, spatial interpolation or surface fitting. Based on the geographic regression method, using continuous relevant information implicated in satellite images, we are able to estimate the distribution of meteorological elements by the inferential measurement. So, it can improve the simulation results in data sparse regions in China.

In summary, based on stepwise regression analysis we put forward a new model to estimate solar radiation for data sparse regions in China. Modeling with common meteorological elements, considering the geographical factors influence, herein it has exerted a greater effect in simulating solar radiation continuously. It is not only able to reveal the distribution of the annual solar radiation, but also can provide a satisfactory numerical simulation. Thus, we suggest that the simulation results should be applied widely in agro-ecological regionalization, food provision, vegetation NPP, energy-saving and emission reduction and new energy development study areas and so on. Obviously, in addition to astronomical, geographical and atmospheric elements, solar radiation is also influenced by local topography. In the future, we will improve the effect of simulation taking into account the influence of terrain aspect and unobstructed factor, especially in regions with sparse measured sites.

REFERENCES


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卢毅敏\(^1\), 岳天祥\(^1\), 陈传法\(^1\), 范泽孟\(^1\), 王钦敏\(^2\)

1. 100101; 2. 350002

摘要：

4173×4847

关键词：

中图分类号：TP702 文献标志码：A

1


esa
Matlab, ArcGIS

2

2.1

1 km DEM, 1957—2001, 122 735 1951—2002, 735 12—50a, 735 122 733, 735
1—2a, 735 122, 733, 735

122 10—44a, 735 122, 735

1—2a, 735 122, 733, 735

2002, 2003) 3

3 3 3

3

3
3  
3.1  

假设已有$k$个自变量引入回归方程：$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k$

总变异分解

$$S_{\text{总}} = S_{\text{残}} + Q$$

引入一个变量$x_i$

$$x_i \in \{x_{k+1}, x_{k+2}, \ldots, x_{k+p}\}$$

$$S_{\text{总}} = U(x_1, x_2, \ldots, x_k) + Q(x_1, x_2, \ldots, x_k)$$

$F$检验，$H_0$: $k$个自变量为最优回归方程
$H_1$: $k+1$个自变量为更优回归方程

$$F_u = \frac{Q(x_1, x_2, \ldots, x_k) - Q(x_1, x_2, \ldots, x_k)(k+1)(n-k-2)}{Q(x_1, x_2, \ldots, x_k)}$$

$F$检验临界值：$F_{0.05}$

- $F_u < F_{0.05}$：接受$H_0$，无自变量引入意义
- $F_u > F_{0.05}$：接受$H_1$，求出最大值 max $F_i = F_u$

$k = k+1$; NEXT...

删除一个变量$x_i$

$$x_i \in \{1, 2, \ldots, k\}$$

$$S_{\text{总}} = U(x_1, x_2, \ldots, x_k, x_{k+p}) + Q(x_1, x_2, \ldots, x_k)$$

$F$检验，$H_0$: $k$个自变量为最优回归方程
$H_1$: $k-1$个自变量为更优回归方程

$$F_v = \frac{Q(x_1, x_2, \ldots, x_k) - Q(x_1, x_2, \ldots, x_k)(k-1)(n-k-2)}{Q(x_1, x_2, \ldots, x_k)}$$

$F$检验临界值：$F_{0.05}$

- $F_v > F_{0.05}$：接受$H_1$
- $F_v < F_{0.05}$：接受$H_0$，求出最小值 min $F_i = F_v$

$k = k-1$; NEXT...

$$F = \frac{U/k}{Q_c/(n-k-1)} = F(k, n-k-1) \quad (1)$$

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k$$

$U = \sum (y_i - \bar{y})^2$

$Q = \sum (x_i - \bar{x})^2$
Table 1: Solar Radiation Impact Factors Between Pearson Correlation Coefficient Matrix (N=95)

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Table 2: Solar Radiation Total Amount Multivariate Stepwise Regression Model Variable Introduction and Removal Process Statistical Test Analysis

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<td>F</td>
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Table 3: Solar Radiation Different Models Error Analysis and Efficiency Comparison

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<td>CE</td>
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</table>

3.2.2: Solar radiation different models (mean square error, MSE) (relative mean square error, R-MSE) (comparative efficiency, CE) (computational efficiency, CE)
3.2.3 (a) (2); (b) (3); (c) (4)

1 km×1 km, 4173×4847, 122 731 3

(a) 122 (b) 731 3 40
4

(1) $52.4 \times 10^{18}$ KJ

(2) $6680$ MJ m$^{-2}$ a$^{-1}$

(3) $5850$ MJ m$^{-2}$ a$^{-1}$

(4) $235$ km$^{-2}$

REFERENCES


Robaa S M. 2009. Validation of the existing models for estimating...


附中文参考文献


