A Simple Method for Surface Radiation Estimating Using FY-4A Data

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(Manuscript received 15 September 2020, in final form 26 March 2021)

ABSTRACT: Fengyun-4A (FY-4A) is a geostationary meteorological satellite with four advanced payloads, which can be used to quantitatively detect Earth’s atmospheric system with multispectral and high spatial and temporal resolution. However, the applicable model limits the application of the FY-4A satellite data. In this paper, the empirical statistical model developed for the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor is extended for FY-4A Advanced Geosynchronous Radiation Imager (AGRI), and it is applied to observed data to evaluate the applicability of the model for AGRI measurements. To improve the accuracy of radiation estimation, the artificially intelligent particle swarm optimization (PSO) algorithm was used for model optimizing. Results show that the estimated radiation has diurnal variation that is in accord with the characteristics of radiation variation. The estimated net surface shortwave radiation (Sn) and observed values show good correlation. However, large deviations from observations are found in the estimated values when the empirical model based on MODIS is directly used to process AGRI data. Thus, the empirical statistical model based on MODIS can be applied to AGRI data, but the empirical parameters need to be revised. Optimization of the empirical statistical model by the PSO algorithm can effectively improve the accuracy of the radiation estimate. The mean absolute percentage error (MAPE) of Sn estimated by optimized models is reduced to 15%. The MAPE of the net surface longwave radiation (Ln) estimated by optimized models is reduced to 31%, and the MAPE of the net radiation (Rn) estimated by optimized models is reduced to 27%. However, for the uncertainty caused by error accumulation effect, the influence of PSO optimization on Rn is not as obvious as that of Ln. However, the analysis of error distribution shows that PSO optimization does improve the estimation results of Rn. Based on AGRI data, the surface radiation can be estimated simply, and the regional or larger-scale surface radiation retrieval can quickly be realized by this method, which has large application potential and popularization value.

KEYWORDS: Radiances; Shortwave radiation; Longwave radiation; Remote sensing; Algorithms

1. Introduction

Net radiation (Rn) is an important component of the energy balance between the land and the atmosphere, controlling energy and water exchanges in the land–atmosphere interaction. Rn is also a vital factor in climate and hydrology studies. Therefore, accurate determination of regional-scale net radiation from remote sensing retrievals has become a hot research topic, especially over nonuniform underlying surfaces. This research topic has attracted considerable attention in recent years (Zhang et al. 2004; Zhou et al. 2007; Wang and Liang 2008).

The Rn can be retrieved from satellite remote sensing in two ways. The first method is using radiative transfer model, that is, the transfer of radiation with different wavelengths should be considered in detail to determine the Rn reaching the surface (Ellingson and Gille 1978; Gautier 1998; Strow et al. 2003; Letu et al. 2020). However, it requires accurate and high-resolution atmospheric temperature and humidity profiles and gas composition as input. The calculation itself is also very complicated. The second method is using an empirical and semiempirical statistical model based on solar radiation, atmospheric temperature and humidity, etc., and surface parameters observed by satellite to estimate the Rn. In this type of empirical statistical model, components of net surface longwave radiation (Ln) and net surface shortwave radiation (Sn), that is, downward and upward solar radiation and longwave radiation, are estimated to obtain the Rn. Downward longwave radiation (DLR) can be estimated using surface meteorological observations (Cheng et al. 2017; Guo et al. 2019; Jin et al. 2006; Malek 1997), vertical profiles of temperature and water vapor from satellite observations (Ellingson 1995; Zhou et al. 2007; Tang et al. 2006). Upward longwave radiation (ULR) can be directly estimated using surface temperature and emissivity measured by satellites (Cheng and Liang 2016). Downward shortwave radiation (DSR) is estimated based on ground-based observations of shortwave radiation or measurements of satellite shortwave channels. Upward shortwave radiation (USR) is estimated based on broadband albedo products and DSR (Letu et al. 2020; Ma et al. 2020; Wang and Liang 2017; Tang et al. 2006). Because the model is simple, and the input data are easy to obtain, this model can be used easily. However, for the differences of underlying surface, climate type, and satellite model, the empirical model exhibits poor universality. Modifying or optimization is necessary for the application of the empirical statistical model and to improve the accuracy of model results. For example, Zhang et al. (2018) developed a method based on a radiative transfer model for surface incident shortwave radiation (ISR) estimating from Moderate Resolution Imaging Spectroradiometer (MODIS) data using...
surface bidirectional reflectance distribution function parameters, aerosol optical depth (AOD), and cloud optical depth (COD). This study shows that the AOD and COD as constraints would improve the ISR accuracy. Wang and Liang (2009) established a simple empirical statistical model to estimate net radiation based on ground measurements of temperature, humidity, and vegetation index. However, Wang et al. (2016) found that the algorithm used in this model has substantial errors in estimating surface fluxes in the arid region of Northwest China. The applicability of this model in the arid region can be improved by revising those empirical parameters based on measured data. Similar applicability studies can improve the accuracy of estimates in certain areas. A new problem emerging along with applicability studies is how to determine empirical parameters efficiently and accurately. In traditional methods, parameters are determined by means of least squares fitting method based on observed data in specific region. However, given the shortcomings of the method itself, only one local optimal parameter can be obtained. One way to obtain the parameter is iteration, which requires numerous steps, and the process is time-consuming to determine a large number of parameters. The artificial intelligence algorithms developed in recent years provides a possible way to solve this problem (Lu et al. 2018; Granata et al. 2020; Ma et al. 2020; Letu et al. 2020). Note that these algorithms have been successfully applied in other research fields. For example, the land surface model was optimized by artificial intelligent particle swarm optimization (PSO) and the performance of soil moisture simulation was improved (Yang et al. 2016). Ines and Mohanty (2009) optimized hydrological parameters by the genetic algorithm (GA) and improved the accuracy of soil moisture assimilation results. Gill et al. (2006) optimized a large-scale hydrological model by particle swarm algorithm and improved the accuracy of model simulation. Letu et al. (2020) combines the advantages of a deep neural network with high speed and radiative transfer model to develop a hybrid method to estimate surface shortwave radiation for the Himawari-8 geostationary satellite. However, relevant studies of statistical models for remote sensing retrievals are still far less than enough. Whether the intelligence algorithm can be used to optimize the input parameters and improve the accuracy of net radiation estimate by statistical models is an issue that needs further study.

In addition to the improvement of retrieval accuracy, another important issue in Rn retrievals from satellite remote sensing is to determine the diurnal variation characteristics of the net radiation. Numerous observations have shown that many parameters such as the Rn and sensible heat flux in the land-atmosphere interaction exhibit significant diurnal variation characteristics. Whether the parameters retrieved from remote sensing can reflect their specific diurnal variation features is an important issue in the test of the retrieval algorithm (Wang et al. 2007). The representation of diurnal variation characteristics of various variables is related not only to retrieval algorithm but also to satellite observation way. Given the high spatial and low temporal resolutions of polar-orbiting

FIG. 1. Geographical location of the observational sites. Black triangles denote the verifying sites, and red triangles denote the PSO optimization sites.
satellite observations, obtaining diurnal variation characteristics of various parameters is restricted by the satellite revisit period. Combined satellite observations are required to obtain diurnal variations of various parameters based on data collected by polar-orbiting satellites. However, the inherent deviations between different detectors and deviations caused by different observation angles of the combined satellites will lead to large uncertainties in the results, which will subsequently affect studies of diurnal variation characteristics. Geostationary satellite observations provide continuous, high-resolution observational data on regional scale, and these information can be used to study diurnal variations. At the end of 2016, China successfully launched the second-generation geostationary meteorological satellite, the Fengyun-4A (FY-4A) satellite (Zhang et al. 2017), which is China’s first three-axis, quantitative remote sensing satellite in geosynchronous orbit. FY-4A carries an advanced payload that can perform multispectral and high spatial–temporal resolution quantitative detection of many parameters of Earth’s atmosphere system. The Advanced Geosynchronous Radiation Imager (AGRI) on board the satellite contains 14 imaging channels featuring a highest spatial resolution of 500 m for visible and near-infrared bands and a spatial resolution of 4 km for thermal infrared channels. The highest temporal resolution is 5 min for China. The FY-4A provides great remote sensing data for retrieving various parameters in the atmosphere and on the surface, especially for studies on diurnal variation characteristics of these parameters. For this reason, the development of remote sensing retrieval algorithm for the FY-4A satellite is of great significance in climate and hydrology studies.

Most existing algorithms for satellite remote sensing retrieval of radiation flux are based on polar-orbiting satellites. The numbers of empirical statistical algorithms for the MODIS detector are large and they are more mature (Tang et al. 2006; Tang and Li 2008; Wang and Liang 2009). Some channels of AGRI are similar to those for the MODIS detector. A natural idea is to modify the existing MODIS remote sensing retrieval algorithm so that it can be applied to AGRI and facilitate the application of FY-4A satellite data in various fields. However, considering the differences between AGRI and MODIS, such as spectral response functions, detection angle, and spectral ranges of channel, the original surface information obtained from AGRI may differ from that detected by MODIS. So, for AGRI data, the estimation accuracy of the existing algorithms must be verified first.

In this study, based on the ground in situ data, the applicability of empirical statistical models for radiation retrieval is verified. Then, to improve the accuracy of radiation retrieval from AGRI remote sensing data in different underlying surfaces, the empirical statistical models are optimized by PSO algorithm. Error distribution characteristics of retrieved radiation are then discussed. The present study aims to promote the application of AGRI data and improve the accuracy of regional-scale radiation retrievals.

2. Data

a. Ground in situ data

To test the accuracy of remote sensing retrieval model, observational data collected at the ground site, that is, the Dingxi
Drought Meteorological and Ecological Environment Test Base (DX), are used in this study. Other data came from the following stations: Zhongwei (ZW) and Gannan (GN) boundary layer observation stations; Yanting (YT) purple soil agricultural ecological experimental station of Chinese Academy of Sciences, Chinese Science and Technology; Changwu (CW) Loess Plateau agroecological experimental station of the Chinese Academy of Sciences; Ansai (AS) farmland ecosystem station of the Chinese Academy of Sciences (AS); and Linze (LZ) Qilian Mountain Forest Ecosystem Observation Station. Figure 1 shows the geographical location of these sites and general condition of the underlying surface. The data length and use of these stations are shown in Table 1.

The DX station is located at Dingxi City, Gansu Province. It is a comprehensive experimental site. It belongs to semiarid climate, with an altitude of 1897 m, an annual average temperature of 6.7°C, and an annual mean precipitation of 386 mm (Wang et al. 2019). In situ observations have been widely used in climate, hydrology, environment, and other scientific research in semiarid area of China (Zhao et al. 2013). The ZW station is located at Zhongwei City, Ningxia Province. It is a boundary layer observation site set up by the College of Atmospheric Science, Lanzhou University. It belongs to temperate continental monsoon climate, with an altitude of 1225 m, annual average temperature of 8.4°C, and annual average precipitation of ~200 mm. The terrain of the observation site is flat, mainly desert underlying surface. The GN station is located in Hezuo City, Gansu Province. It is a boundary layer observation site set up by the College of atmospheric science, Lanzhou University. It belongs to the alpine humid climate, with an altitude of 2959 m, an average annual temperature of 1.7°C, and an average annual precipitation of ~300 mm. It belongs to an alpine and semiarid mountain forest steppe climate. The research aims to reveal the driving mechanism of forest ecosystem change, clarify the action mechanism and scale effect of forest ecology and hydrological process, and predict the response of forest vegetation to climate change (Niu et al. 2014).

b. Remote sensing data

The satellite remote sensing data used in this paper, including level-1 products of AGRI and cloud detection products, are provided by the National Satellite Meteorological

![Figure 2: Spectral response function of AGRI and MODIS channels used in this study.](image)

<table>
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<th>TABLE 3. Coefficients of the Sn models used in this study. Then numbers 1–4 indicate the subscripts on the a, b, or x coefficients.</th>
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<td>Original model</td>
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The time period is from 1 January 2018 to 25 May 2019. Before verifying the remote sensing retrieval model, geographic calibration and cloud detection are performed first for the radiation data. Observations on those days when precipitation occurred are excluded, and observations during cloudy periods are also excluded. Eventually, samples on a sunny day are selected for this study (shown in Table 1).

3. Method

The radiation estimation model used in this paper is based on MODIS remote sensing data, the comparison of channel parameters between AGRI and MODIS is shown in Table 2, and the spectral response function of each channel is shown in Fig. 2. The models to retrieve surface radiation are described below.

\[ \text{Sn} = \frac{I_0 \cos \theta}{D^2}. \] (1)

where

\[ \alpha = 1 - a_1 \mu^{-1} - a_2 \mu^{-1}; \] (2)

\[ \beta = b_1 + b_2 \ln \mu + b_3 \mu^3; \] (3)

\[ I_0 \] denotes the top-of-atmosphere (TOA) solar radiation received at one astronomical unit; \( D \) refers to the Earth–sun distance (astronomical unit); \( \theta \) is the solar zenith angle (rad); \( \mu \) corresponds to the cosine value of the solar zenith

| TABLE 4. Coefficients of the Ln models used in this study. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                 | \( f_1 \)    | \( f_2 \)    | \( f_3 \)    | \( f_4 \)    | \( f_5 \)    | \( f_6 \)    | \( f_7 \)    | \( f_8 \)    |
| **Original model** |           |           |           |           |           |           |           |           |
| Daytime          | 162.142    | 3.909     | -1.989    | 11.766    | -167.043   | 35.638     | -22.376     | -1.902     |
| Nighttime        | 95.437     | 4.899     | -1.993    | 11.997    | -119.872   | 63.200     | -36.611     | -1.966     |
| **PSO optimized model** |           |           |           |           |           |           |           |           |
| Daytime          | 105.26     | 7.78      | -6.33     | 23.45     | -135.46    | 43.29      | -59.12      | -5.28      |
| Nighttime        | 94.36      | 7.88      | -8.73     | 21.01     | -106.78    | 43.24      | -39.0       | -3.18      |
angle; $a_1-a_4, b_1-b_3,$ and $x_1-x_3$ are empirical parameters; and the values of the specific parameters can be found in the work of Tang et al. (2006). These values are also listed in Table 3. The $r$ specifies broadband albedo of TOA, which is written as (Song and Gao 1999)

$$r = -0.337 \text{ref}_2^2 - 0.2707 \text{ref}_2 + 0.7074 \text{ref}_3 \text{ref}_3 + 0.2915 \text{ref}_3 + 0.5256 \text{ref}_3,$$  \hspace{2cm} (4)

where $\text{ref}_2$ and $\text{ref}_3$ are the reflectance of the second and third channel of AGRI.

The $w$ represents perceptible water. In the radiation retrieval from MODIS data, the value of $w$ is usually specified as the ratio of channel 2 and channel 19. However, AGRI lacks the band corresponding to MODIS channel 19. For this reason, following the existing research (Wang and Liang 2009), the radiation ratio of channels 13 and 14 is used to express $w$:

$$w = \frac{\text{LR}_{14}}{\text{LR}_{13}}, \hspace{2cm} (5)$$

where $\text{LR}_i$ denotes the radiation intensity of channel $i$ ($W \cdot m^{-2} \cdot \mu m^{-1} \cdot sr^{-1}$). The change of LR, with relative humidity (RH) is shown in Fig. 3. With the increase of RH, the values of $\text{LR}_9, \text{LR}_{10},$ and $\text{LR}_{14}$ change slightly, but the values of $\text{LR}_{11}, \text{LR}_{12},$ and $\text{LR}_{13}$ show significant linear attenuation. Therefore, the change of perceptible water in the atmosphere can be indirectly expressed by the ratio of channel radiation intensity. The correlation between $\text{LR}_{14}/\text{LR}_{13}$ and RH is the most significant among the channel ratios. Therefore, $\text{LR}_{14}/\text{LR}_{13}$ ratio is used to express $w$. Since the whole Sn estimation model needs PSO optimization, the specific relationship between $\text{LR}_{14}/\text{LR}_{13}$ and $w$ is not discussed here, but $\text{LR}_{14}/\text{LR}_{13}$ is brought into Sn estimation model for overall coefficient adjustment.

The solar radiation intensity received by the satellite detector is not only related to the solar zenith angle but also closely related to the satellite zenith angle. Considering that MODIS is a detector on board a polar-orbiting satellite, the scanning time of each satellite is basically the same for the same observation point on the ground, and the solar zenith angle changes with the seasons, which affects the channel radiation intensity received by the detector. However, for geostationary satellites, the same observation point on the ground, the factors that cause the change of the received solar radiation intensity are mainly reflected in the satellite zenith angle. Due to the characteristics of high time frequency observation of geosynchronous satellites, the change information of solar zenith angle is included in the channel reflectance. Therefore, in order to generalize Eqs. (1)–(3) to AGRI detector, the solar zenith angle $\theta$ in these equations is replaced by the satellite zenith angle $\theta_s$ of the geostationary satellite. So $\mu$ corresponds to the cosine value of the $\theta_s$. On the basis of AGRI remote sensing data, the Sn estimated model is optimized using the measured data of DX, LZ, and YT sites; the optimization results are shown in Table 3.

The method for estimating $\text{Ln}$ on the surface by MODIS empirical statistical model is expressed as (Wang and Liang 2009)

$$\text{Ln} = \text{DLR} - \text{ULR}, \hspace{2cm} (6)$$

where
The model for estimating longwave radiation mainly involves surface temperature (LST) and emissivity $\varepsilon$. The LST and $\varepsilon$ are estimated by an optimized local split-window algorithm, which developed for FY-4A/AGRI data (Wang et al. 2019). The $\sigma$ denotes the Stefan–Boltzmann constant ($5.67 \times 10^{-8}\text{Wm}^{-2}\text{K}^{-4}$). The spectral range of channel 14 of AGRI covers channels 33 and 34 of MODIS (Table 2). Hence, channels 33 and 34 in the MODIS empirical statistical model correspond to channel 14 of AGRI.

c. PSO algorithm

The PSO algorithm is the same as employed in Wang et al. (2019), and the following text is derived from there with minor modifications.

$$
DLR = L\text{air} \left[ f_1 + f_2 LR_9 + f_3 LR_{11} + f_4 LR_{14} + f_5 \left( \frac{LR_{14}}{LR_{12}} \right) \right] \\
+ f_6 \left( \frac{LR_{14}}{LR_{13}} \right) + f_7 \left( \frac{LR_{10}}{LR_{12}} \right) + f_8 H ;
$$

(7)

$$
ULR = (1 - \varepsilon) DLR + \varepsilon \sigma LST^4 ;
$$

(8)

Ln refers to the longwave net radiation (W m$^{-2}$); Lair takes radiation intensity values of channels 13 and 12 in daytime and nighttime, respectively; $H$ denotes the altitude (km); $f_1$-$f_8$ are empirical parameters; and the specific values are given in Table 4.

**Fig. 5.** Temporal variation of $R_n$ on 3 May 2018. The triangles correspond to those in Fig. 1.

**Fig. 6.** The time series of estimated radiation and measured values.
Fig. 7. Comparison of estimated radiation and measured values.
From the above models, 28 empirical parameters in the model need to be redefined based on specific regions and for FY-4A. The PSO is a simple and effective spatial search method first proposed by Kennedy and Eberhart (1995) based on a study of foraging behavior of birds.

This algorithm aims to find the minimum of the objective function in parameter space by updating the position and velocity of a group of random particle swarms. Supposing that \( n \)-dimensional problem is optimized, to select \( m \) particles, the position and velocity functions of \( i \) particles can be respectively shown as follows:

\[
p_i = (p_{i1}, p_{i2}, \ldots, p_{im}) \quad \text{and} \quad v_i = (v_{i1}, v_{i2}, \ldots, v_{im}),
\]

The updated position and velocity of the \( i \) particle are respectively computed as follows:

\[
v_{in}^{t+1} = \omega v_{in}^t + c_1 r_1 (L_m - p_{in}^t) + c_2 r_2 (G_n - p_{in}^t),
\]

\[
p_{in}^{t+1} = p_{in}^t - v_{in}^t,
\]

\[
L_i = (L_{i1}, L_{i2}, \ldots, L_{im}), \quad G_n = (L_{g1}, L_{g2}, \ldots, L_{gn}), \quad \text{and} \quad g = \min[F(L_i)],
\]

where \( p \) and \( v \) refer to position and velocity functions, respectively; \( Y \) denotes iterations; \( \omega \) represents inertia weight; \( c_1 \) and \( c_2 \) correspond to acceleration constants; \( r_1 \) and \( r_2 \) are random numbers between 0 and 1; \( L_i \) and \( G_n \) refer to the local and global optimal locations searched by \( i \) particles, respectively; \( g \) represents the position when the value of the object function is the lowest; and \( F \) is the object function. The object function \( F \) in the PSO algorithm can be a single function or vector function. In this paper, the root-mean-square error (RMSE) is used as the objective function \( F \), and the solution corresponding to minimum RMSE during the iteration is taken as the optimal parameter.

All parameters to be optimized are changed into an interval \([-1.0, 1.0]\) unit by mapping

\[
R_x = \frac{2R_o - (R_{\text{max}} + R_{\text{min}})}{(R_{\text{max}} - R_{\text{min}})},
\]

where \( R_x \) refers to the value after parameter mapping; \( R_o \) denotes the actual parameter value; and \( R_{\text{max}} \) and \( R_{\text{min}} \) represent the actual maximum and minimum parameter values, respectively. The flowchart of the data-processing and calculation method in this paper is shown in Fig. 4.

d. Accuracy evaluation of estimation results

In this paper, three statistics are used to evaluate estimation results (Wang et al. 2019). They are calculated as RMSE:

\[
\text{RMSE} = \left[ \frac{1}{N} \sum_{i=1}^{N} (E_i - O_i)^2 \right]^{1/2}
\]

mean absolute percent error (MAPE):

\[
\text{MAPE} = \frac{1}{N |O|} \sum_{i=1}^{N} \left| \frac{E_i - O_i}{O_i} \right| \times 100\%.
\]

and correlation coefficient \( R \):

\[
R = \frac{\sum_{i=1}^{N} (E_i - \bar{E})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{N} (E_i - \bar{E})^2 \sum_{i=1}^{N} (O_i - \bar{O})^2}}.
\]

where \( E_i \) refers to the estimate sequence, \( E() \) represents the mean value of the estimate sequence, \( O() \) denotes the measured sequence, \( O_i() \) corresponds to the mean value of the measured sequence, and \( N \) denotes the number of samples participating in the calculation.

4. Result analysis

To verify the applicability of the MODIS-based empirical statistical model, the variables in the original empirical parameter estimation are marked with “ori,” whereas the variables optimized by PSO are marked with “pso.” In this study, ground observation data are randomly divided into two groups, namely, “training” and “verifying,” respectively, which are shown in Table 1.
As shown in Fig. 5, the regional differences of Rn estimated by PSO optimization model based on AGRI data are significant and have obvious diurnal variation characteristics. Figure 6 shows the daily variation characteristics of estimated radiation and measured value under typical sunny day conditions of each observation sites. The empirical model can reproduce the daily variation characteristics of radiation, but there is still a certain deviation between the estimated radiation and the measured value. In ZW and GN, with two natural underlying surfaces, the estimated radiation is consistent with the measured values and the deviation is small. In CW and AS, although the daily variation characteristics of the estimated radiation are consistent with the measured values, the deviation between them is more obvious. Next, we will focus on the accuracy of the PSO optimized model and the deviation from the original model.

a. Shortwave radiation

Figures 7a and 7b show the comparison of estimated Sn based on AGRI data and measured values. On the whole, the Sn estimated by the original model is smaller than the measured value. The accuracy of the Sn model can be improved with PSO optimization. The Sn estimated by the optimized model is slightly smaller than the measured value, but the slope of the fitting line between the estimated and measured value is closer to 1, the RMSE of Sn is reduced from 98 to 64 W m\(^{-2}\), and the MAPE is reduced by 10%.

In comparison with different types of underlying surfaces, as they are shown in Fig. 6, the PSO optimized model has good applicability in natural land surface, and the estimation results of the model are close to the measured values, and the deviation is small. In the farmland underlying surface, although the PSO optimization improves the accuracy of the model, the effect is less obvious than that of the natural underlying surface, which is not only related to the optimization effect of the model but also closely related to the regional representativeness of the observed values. Because of the difference of artificial experimental design, the underlying surface of the CW and AS farmland sites is more complex; especially for the CW station, the difference

![Graphs showing comparison of estimated DLR, ULR, and measured values.](image-url)
of underlying surface is more significant, which brings errors to the model verification results.

b. Longwave radiation

Figures 7c and 7d show the comparison of retrieved Ln and measured values, it is found that when the Ln estimation model developed based on MODIS data is applied to AGRI, the correlation between the estimated result and the measured value is negative, and the MAPE is 94%, the slope of the fitting line is −0.34, and the RMSE is 133 W m\(^{-2}\). Therefore, the Ln estimation model based on MODIS cannot be directly used to AGRI. Considering the similarity between AGRI channels and MODIS channels, PSO optimization is carried out for the original model coefficients on the basis of AGRI data, so as to improve the accuracy of model estimation through coefficients optimization. After PSO optimization, the deviation between the estimated result and the measured value is greatly reduced, and there is a significant positive correlation between the estimated Ln and the measured value, the correlation coefficient is 0.23, the RMSE is reduced to 48 W m\(^{-2}\), and the MAPE is reduced to 31%.

Although the accuracy of estimated Ln is significantly improved after optimization, the MAPE between the estimated Ln and the measured value is still 31%. The estimation of Ln includes two parts: DLR and ULR. From the analysis of Eqs. (7) and (8) it is found that PSO optimization is mainly aimed at DLR, and the estimation result of ULR mainly depends on the accuracy of LST. Due to the limitation of measured data, the discussion on the estimation accuracy of DLR and ULR components is only at ZW and GN sites. As shown in Figs. 8 and 9, PSO optimization significantly improves the estimation accuracy of DLR, and the MAPE between the estimated result and the measured value is reduced from 47% to 14%, and the RMSE is reduced from 122 to 40 W m\(^{-2}\). The ULR estimated by the model is close to the measured value, the RMSE is 31 W m\(^{-2}\) and the MAPE is only 7%. However, there is little difference in the estimated ULR before and after the optimization of the model, which can almost be ignored, indicating that the influence of DLR on ULR is minimal. It also shows that the local split-window algorithm optimized by PSO for AGRI remote sensing data by Wang has good applicability, and the estimation error of Ln mainly comes from DLR.

c. Net radiation

Based on the estimated results of Sn and Ln, the comparison of estimated Rn and measured value in the study area is shown in Figs. 7e and 7f. Although PSO optimization improves the estimation accuracy of Sn and Ln, respectively, due to the uncertainty of error accumulation effect, the improvement effect of PSO optimization is not well reflected in the Rn results. As the GN site, it is shown in Fig. 10, the Sn estimated by the original model almost smaller than the measured value, and the Ln estimated by the original model is much larger than the measured value, but the Rn obtained by the Sn and Ln
estimated by the original model is closer to the measured data than the optimized model. Because of the uncertainty caused by the error accumulation, the Rn estimated by the original model is not as far away from the measured value as the Ln. PSO optimization only reduces the RMSE between estimated and measured value by 20 W m\(^{-2}\) and MAPE by 10%, respectively.

Although the improvement effect of Rn before and after PSO optimization is not significant from the scatter diagram comparison analysis, but from the overall error distribution diagram, as shown in Fig. 11, PSO optimization does improve the estimation accuracy of surface radiation components based on AGRI data in the study area. The peak values of Sn, Ln, and Rn error distribution estimated by the original model are about -60, 150, and 90 W m\(^{-2}\), while the peak values of Sn, Ln, and Rn error estimated by optimized model are about 0, 40, and 50 W m\(^{-2}\).

From the daily variation of the error distribution, the error of Ln and Sn estimated by the original model at noon is much greater than that in other periods, but after PSO optimization, the error of Ln, Sn, and Rn estimated by the model has no obvious diurnal variation characteristics. From the monthly variation of error distribution, the estimation errors before and after the model optimization have no significant seasonal variation characteristics. From the analysis of the time-varying curve of estimation error, the error of PSO optimized model is smaller than that of the original model, especially the optimization effects of Sn and Ln are more significant. Therefore, both the error distribution frequency and the error variation clearly show that PSO optimization can significantly improve the accuracy of AGRI radiation estimation in the study area.

The Sn at night is approximately zero, and the estimated Rn is consistent with the Ln. Figure 12 shows the comparison between the estimated Ln and the measured value before and after PSO optimization for the nighttime. The results show that PSO optimization significantly improves the ability of the model to estimate nighttime Ln, especially for the underlying surface of CW and AS farmland, and the RMSE of nighttime Ln is reduced from 23 to 16 W m\(^{-2}\), the MAPE is reduced from 45% to 33%. From the distribution frequency of estimation error, the estimation error of the original model is mainly concentrated in 50 W m\(^{-2}\), and the estimation error of the optimized model is mainly around 0 W m\(^{-2}\), which indicates that the estimation model of Ln optimized by PSO is suitable for the study area.

5. Conclusions and discussion

Net radiation is a driving factor for the energy balance. Accurate estimation of net radiation components is critical...
Remote sensing is the most convenient and effective means to obtain regional-scale net radiation. Several studies have shown that using the empirical model, radiation intensity and reflectivity of each satellite channel can be used to obtain high-accuracy radiation estimation results. In previous studies, a large number of empirical statistical models have been developed for estimating net radiation for polar-orbiting satellites, especially MODIS sensors. However, limited research has been conducted to develop models for on geostationary satellites. In 2016, China launched the FY-4A geostationary meteorological satellite, which can obtain high-resolution observational data. However, given the difference between the AGRI and the polar-orbiting satellite MODIS detector, the MODIS empirical statistic model cannot be directly used for FY-4A. For this reason, based on the measured net radiation data, the MODIS empirical model were optimized using the artificial intelligence PSO algorithm for AGRI remote sensing data. This method could improve the accuracy of radiation estimation. Our major conclusions are as follows:

1) The diurnal variation characteristic of radiation can be reproduced by the original models, but there are large deviations between estimated radiation and measured values. The differences may be due to the detectors themselves. On the whole, the Sn estimated by the original model is lower than the measured value. The PSO optimization improves the estimation accuracy of the model in varying levels. The MAPE of Sn is reduced to 15%.
2) For Ln, the estimation result of the original model is much larger than the measured value, which is mainly reflected in the DLR. PSO optimization significantly improves the estimation accuracy of Ln. The MAPE of Ln in the study area is reduced to 31%, the MAPE of DLR is reduced to 14%, and the MAPE of ULR is maintained at 7%.
3) Although the estimation accuracy of Sn and Ln, for the uncertainty of error accumulation effect, the improvement effect of Rn is not significantly as Ln. However, PSO optimization also reduces the RMSE of Rn to 67 W·m⁻² and the MAPE to 27%. From the error distribution before and after the model optimization, PSO optimization does improve the estimation accuracy of Rn for daytime and nighttime.

The purpose of this paper is to explore a model suitable for the radiation estimation using AGRI data. In view of the similarity between AGRI and MODIS, the original model is considered to be extended directly. But for the differences between AGRI and MODIS, such as the sensor response function and satellite positioning, the direct application of the original model will bring a large deviation to the estimation results. On the other hand, the accuracy of ULR estimated by the model is high, it is proved that the optimized local
split-window algorithm for AGRI is applicable in the study area (Wang et al. 2019). The Sn model is sensitive to satellite zenith angle, but the ground observation points used in this work cannot cover all satellite observation angles, so the applicability of the model needs to be further tested in the areas where the satellite observation angle is less than 36° and greater than 46°. In addition, there is no special cloud detection research for satellite products in this study. Cloud detection of satellite products is an important and difficult work in remote sensing. The research on cloud detection will be the key part of our future work, which lays the foundation for all-weather radiation estimation.

Acknowledgments. We thank the National Satellite Meteorological Center for providing remote sensing data and technical support for data processing. This study is sponsored by the Gansu Science Foundation for Young Scientists (20R10RA449), National Natural Science Foundations (41805086, 41975016), the innovation team of Lanzhou Institute of Arid Meteorology, CMA (GHSCTXD-2020-4), Open project of Key Laboratory of Desert and Desertification, Chinese Academy of Sciences (KLDD-2020-001), the special scientific funding of public welfare profession of China (meteorology) (major project) (GYHY201506001-5), and the ground application system project for the FY-4 satellite.

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