

Article

A Multiscale Normalization Method of a Mixed-Effects Model for Monitoring Forest Fires Using Multi-Sensor Data

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Abstract: This paper points out the shortcomings of existing normalization methods, and proposes a brightness temperature inversion normalization method for multi-source remote sensing monitoring of forest fires. This method can satisfy both radiation normalization and observation angle normalization, and reduce the discrepancies in forest fire monitoring between multi-source sensors. The study was based on Himawari-8 data; the longitude, latitude, solar zenith angle, solar azimuth angle, emissivity, slope, aspect, elevation, and brightness temperature values were collected as modeling parameters. The mixed-effects brightness temperature inversion normalization (MEMN) model based on FY-4A and Himawari-8 satellite sensors is fitted by multiple stepwise regression and mixed-effects modeling methods. The results show that, when the model is tested by Himawari-8 data, the coefficient of determination (R^2) reaches 0.8418, and when it is tested by FY-4A data, R^2 reaches 0.8045. At the same time, through comparison and analysis, the accuracy of the MEMN method is higher than that of the random forest normalization method (RF) ($R^2 = 0.7318$), the pseudo-invariant feature method (PIF) ($R^2 = 0.7264$), and the automatic control scatter regression method (ASCR) ($R^2 = 0.6841$). The MEMN model can not only reduce the discrepancies in forest fire monitoring owing to different satellite sensors between FY-4A and Himawari-8, but also improve the accuracy and timeliness of forest fire monitoring.

Keywords: Himawari-8; FY-4A; forest fires monitoring; brightness temperature inversion; normalization; mixed-effects model



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1. Introduction

Forest fires have the characteristics of strong suddenness, strongly destructive, high risk, and frequent occurrence. Factors such as human activities, the terrain conditions, changes in land use, and climate will all have a certain impact on the probability of fire [1]. They are one of the most difficult and devastating natural disasters with which to deal. Fire influences both forest structure and function [2].

Current remote sensing approaches to forest fire monitoring and detection in China can be grouped as follows: (a) air-monitoring systems, (b) ground-monitoring systems, and (c) space-monitoring systems. Among them, air-monitoring refers to the use of manned aircraft or unmanned aerial vehicles (UAVs) to monitor forest fires. Its advantages are that it can obtain high-quality internal information data of the fire site when the fire occurs, effectively provide the trend of fire spread after a fire, and guide firefighting operations. However, manned aerial vehicles are operated by human pilot(s) and are typically large and expensive. Using a manned aerial vehicle puts the life of the pilot in harm's way, threatened by a hazardous environment and operator fatigue. Aircraft systems may sustain with higher payloads and speed, but hovering in one place and maintaining high and low speeds are the challenges [3]. At the same time, UAVs cannot monitor a wide range of

areas in real time in all-weather conditions. Its main application is to guide firefighting after a fire occurs [4]. Ground-monitoring refers to the manual monitoring of forest fires by establishing ground observation towers or using ground measuring instruments [5]. Its advantages are low cost, accurate positioning, and real-time detection, but ground-based measurement instruments may suffer from limited surveillance ranges and are not suitable for very large areas such as forests [6]. Space-monitoring refers to remote sensing monitoring of forest fires using satellites. It has the shortcomings of low spatial resolution and it is unable to capture detailed fire data to guide firefighting. However, its advantages are particularly obvious, and one of these advantages is that its monitoring range is particularly wide. With the rapid development of remote sensing technology, the high temporal resolution of static satellites makes the timeliness of satellite monitoring particularly high, and satellite monitoring can quickly locate the approximate fire point. Effective monitoring of fire points can quickly guide the subsequent forest fire fighting. Satellite remote sensing monitoring can greatly reduce the environmental damage and resource loss caused by forest fires. Therefore, satellite remote sensing monitoring is an important part of the integrated monitoring system for forest fires in the space, air, and ground of China. The brightness temperature is a key parameter to monitor forest fires by satellite. The monitoring of abnormally high brightness temperature points is an important basis for determining the occurrence of fires.

At present, there are a large number of satellites monitoring forest fires and there are abundant sources of remote sensing data. The conversion from the digital number (DN) of a satellite image to radiance is affected by many factors, including illumination geometry, sensor calibration, and atmospheric condition, among others. As multi-temporal images are often acquired at different times under different atmospheric conditions, solar illumination, sensor calibration, and view angles, radiometric correction is required to remove radiometric distortions [7–10]. The main methods to effectively correct the radiation deviation at this stage are as follows: the random forest normalization method, pseudo-invariant feature method, multiple change detection relative radiation normalization method, and automatic scattergram-controlled regression method, among others. Zhao W [11] proposes a practical normalization method based on random forest. The results show that the spatial pattern of normalized LST data can be significantly improved. Unlike the previous normalization method, the proposed method is only based on satellite observations without other auxiliary data. Therefore, this method shows good potential for normalizing the time effects of wide-angle polar-orbiting satellite observations. The PIF relative radiation normalization method is used to study the radiation normalization of inter-phase remote sensing data. De Carvalho O et al. [12] proposed a new technique for accurately selecting PIF. New sequential methods enable one to select, by different attributes, a number of invariant targets over the brightness range of the images, and to improve the accuracy of PIF radiation normalization. Elvidge et al. [13] proposed the automatic scatter control and regression (ASCR) method. The relevant literature shows that the ASCR method is simple to operate, efficient in execution, and can reduce clouds and shadows; its radiation normalization effect is also significantly better for various commonly used statistical methods. However, owing to ASCR requirements, the area contains a large area of water and land features, so this method should be used in areas with less water bodies or in multi-temporal images. When the water body has undergone major changes, the accuracy of the calculation results will be difficult to guarantee, and cannot reflect the advantages of ASCR. Aiming at the shortcomings of the existing method, Himawari-8 and FY-4A are unified to the same or similar radiative benchmarks, then the mixed-effects brightness temperature inversion normalization model is established by considering the fixed and random effects of the model.

The MEMN method not only meets the requirements of radiation normalization, but also eliminates the influence of solar azimuth angle and solar zenith angle, meeting the requirements of observation angle normalization. At the same time, the MEMN method can reduce the influence of the studied satellites owing to the difference in sensor sensitivity,

the difference in solar zenith angle and solar azimuth angle, and the satellite in-orbit state characteristics, among others, and improves the accuracy of forest fire monitoring. The normalized model based on geostationary satellite parameters with high temporal resolution can greatly improve the timeliness of forest fire monitoring. It can be used for the normalized analysis of remote sensing data from a variety of satellites, which greatly increases the application range of remote sensing data. The MEMN method will become a key technology for accurate monitoring of forest fires by satellite.

2. Materials and Methods

2.1. Data Introduction

Forest fire monitoring requires particularly high timeliness of remote sensing images, Himawari-8 satellite carries the world's advanced AHI (advanced Himawari imager). The temporal resolution of the entire observation is 10 min once, so Himawari-8 was selected as the normalized reference image. FY-4A is a Chinese-made geostationary satellite, but its spatial resolution and time resolution are relatively low compared with Himawari-8, so it makes sense to choose FY-4A as the satellite to be calibrated. Topographic factors such as slope, aspect, and elevation are collected from the digital elevation model (DEM) of SRTM with 90 m resolution; in the JAXA Himawari Monitor, the official website of Himawari-8, clear sky images with low cloud content are selected, and all data used in the experiment are remotely sensed images of the same moment. The Himawari-8 data were downloaded from the Japan Meteorological Agency (JMA, Tokyo, Japan) in the Himawari standard format (HSD), and the FY-4A AGRI 4 km data were downloaded from the National Satellite Meteorological Satellite (NSM) website, which were interpolated to obtain the same standard 2 km spatial data as Himawari-8. The purpose of interpolation of FY-4A from 4 km to 2 km is to make the pixels contained in each grid complete pixels in statistical data, so as to eliminate the deviation caused by statistical data. This is because the principle of grid statistics in this paper is to count the maximum, minimum, and mean values of all the complete pixels contained in the grid. In the subsequent analysis, the grid size is set to 7×7 , that is, the size of each grid is $14 \text{ km} \times 14 \text{ km}$. If the FY-4A data of 4 km spatial resolution are used for statistics, each grid will contain the number of incomplete FY-4A pixels, and the statistical results of the data will cause certain errors. Thus, we interpolate FY-4A from 4 km to 2 km. The solar zenith angle and solar azimuth angle parameters were collected from the FY-4A L1_GEO data.

The theoretical basis for satellite remote sensing fire point detection is that infrared radiation is significantly enhanced when the material is in a high temperature combustion state, and the fire point image element temperature is usually about 800 K. The temperature radiation peak is located near $4 \mu\text{m}$ [14–17]. Therefore, the band near the central wavelength of $4 \mu\text{m}$ (seventh channel of Himawari-8 and eighth channel of FY-4A) was selected for bright temperature inversion. In this study, Hunan Province in China was selected as the study area (Figure 1).

2.2. Data Pre-Processing

Taking into account the differences in the coordinate systems and spatial resolutions of the above-mentioned different types of data sources, the source data are transformed and processed first: (1) Convert the FY-4A AGRI 4 km data to the WGS84 coordinate system, and interpolate its spatial resolution at the same time to 2 km, thus matching the Himawari-8 data. (2) Considering that the Himawari-8 HSD data are an uncalibrated full-disk observations, it needs to be radiometrically calibrated [18,19], involving band clipping to obtain the brightness temperature inversion and the band required to collect the solar zenith angle and solar azimuth angle.

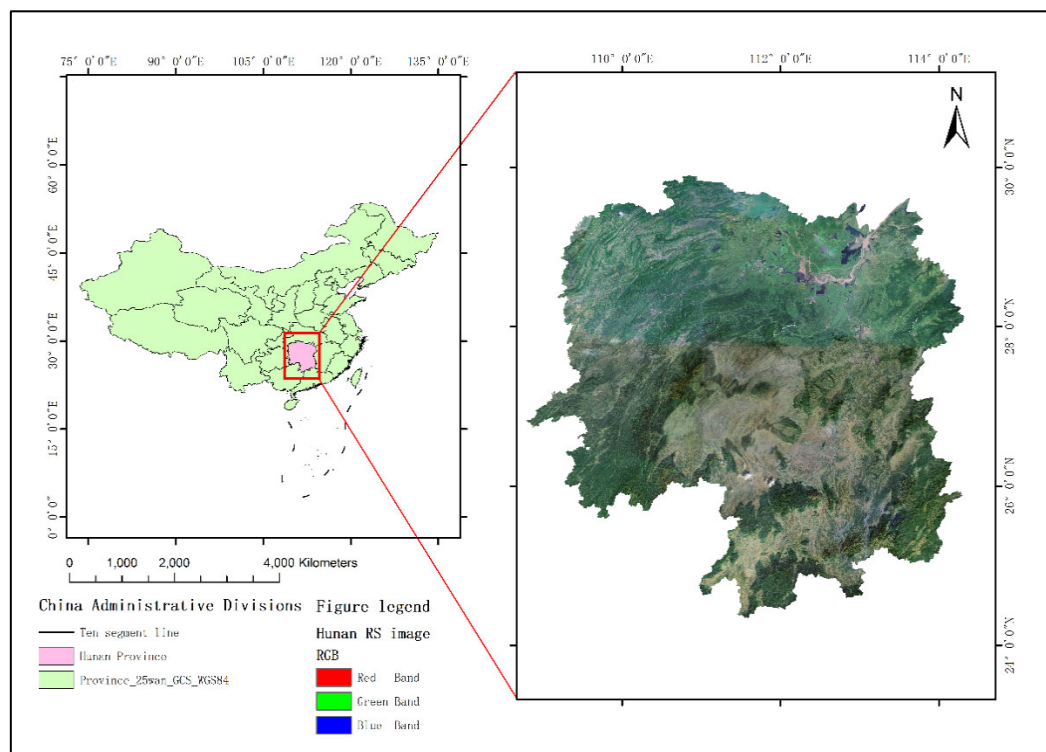


Figure 1. The map of the study area.

On the basis of the above-mentioned data preprocessing, in order to eliminate data collection errors caused by irregular sample selection and inconsistent spatial resolution, a collection data grid is established. The values of slope, aspect, and elevation parameters were obtained by calculating the SRTM DEM by ArcGIS. At the same time, the cloud cover data [20,21], emissivity parameters [22–25], and land cover types [26–28] are obtained by raster calculation.

2.3. Determination of Model Parameters

The factors that may influence the results of brightness temperature values during the brightness temperature inversion were analyzed. The correction coefficients of the data were obtained from the header file of Himawari-8 data: the parameters solar zenith angle (SOZ) and solar azimuth angle (SOA) were obtained by geometric correction and radiometric correction; the parameters black body temperature (TBB) and surface specific emissivity (emissivity) were obtained by brightness temperature inversion; and DEM data were preprocessed to obtain the parameters of slope, aspect, and elevation, as well as the longitude and latitude of each sample pixel.

The following were selected: longitude, latitude, solar zenith angle, solar azimuth angle, slope, aspect, elevation, and emissivity as the independent variables for modeling, and TBB was selected as the dependent variable to build the MEMN model. The correlation analysis of each variable was performed, and the results are shown in Figure 2.

2.4. Data Collection

When collecting parameters such as latitude, longitude, slope, aspect, elevation, solar zenith angle, solar azimuth angle, emissivity, brightness temperature, and so on, the remote sensing data for collecting parameter values are derived from different sensors, and their spatial resolutions are also different. In order to reduce the error, a grid data acquisition method is proposed. Based on the principle of grid analysis, the grid is established by ArcGIS software. Each grid contains the same number of pixels, the legal pixel is the pixel at the centroid point of each grid, and the maximum pixel value in each grid is collected as

the result value of the legal pixel. The maximum pixel value refers to the pixel in which the maximum brightness temperature value is located in each grid area. The parameters used for statistics are as follows: brightness temperature value, emissivity value, solar altitude angle, solar azimuth angle, slope, slope direction, and elevation. The legal pixel value is the pixel at the centroid point of each 7×7 grid, which is used for statistics such as longitude and latitude. Therefore, the grid size setting determines the data collection results. According to the analysis of the multiple linear regression result and scatter plot analysis based on the study data, it is found that the relationship between emissivity and brightness temperature is linear, and that emissivity is the best factor for fitting the linear basic model of brightness temperature. Therefore, we start to set different sizes of grids to count the brightness temperature and emissivity, and choose the most linearly related grid as the grid to count all the modeling factor parameters. When selecting the grid size, we set the grid to different sizes, analyze the linear correlation between emissivity and brightness temperature under each size condition, and set the grid size under the highest linear correlation condition as the final collection grid size used in the data. It can be seen from Figure 3 that, when the grid is set to 7×7 (each grid contains 7×7 pixels), the linear correlation between surface emissivity and brightness temperature is the highest. Therefore, the 7×7 grid is selected as the grid for data collection.

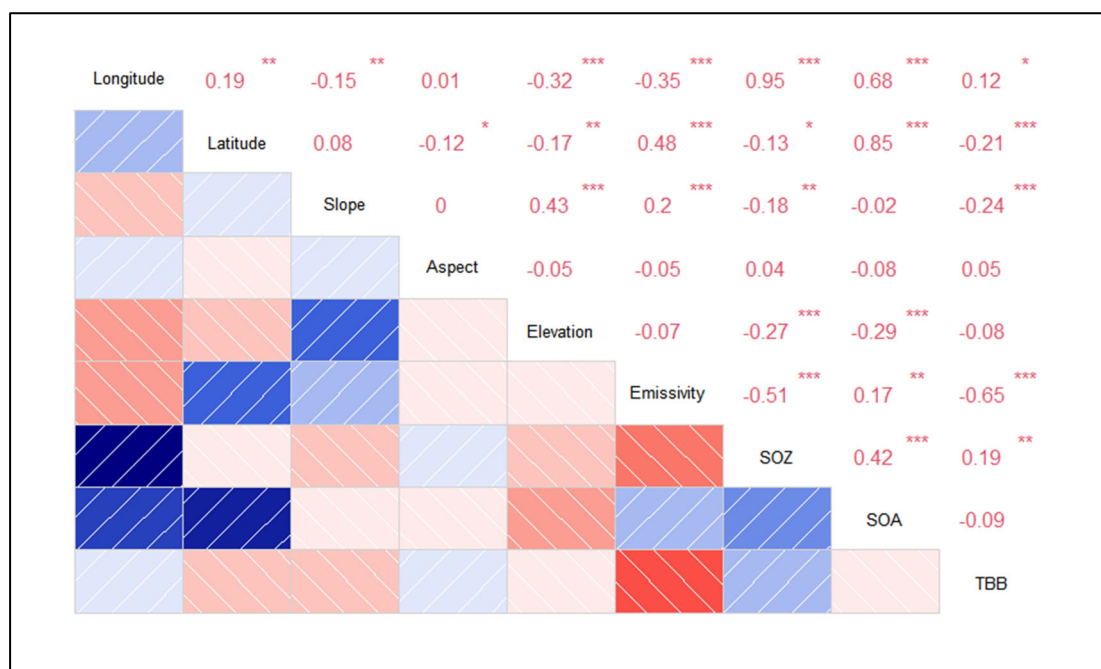


Figure 2. The values in the graph indicate the degree of autocorrelation among the factors; the higher absolute value indicates higher correlation, where * represents the significance of the significant factors, each * is a 5% significance level, and more * means more significance. The diagonal line of the grid in the figure indicates the trend of correlation; the diagonal line to the left indicates negative correlation and the diagonal line to the right indicates positive correlation.

2.5. Classification of Model Parameters

The site of factors such as elevation, slope, and aspect is mainly based on the classification standard of site factors of “Technical Regulations for Forest Resources Planning and Design Investigation (GB/T26426-2010)”. On this basis, the elevation is graded per hundred meters. All parameters are graded as in Table 1.

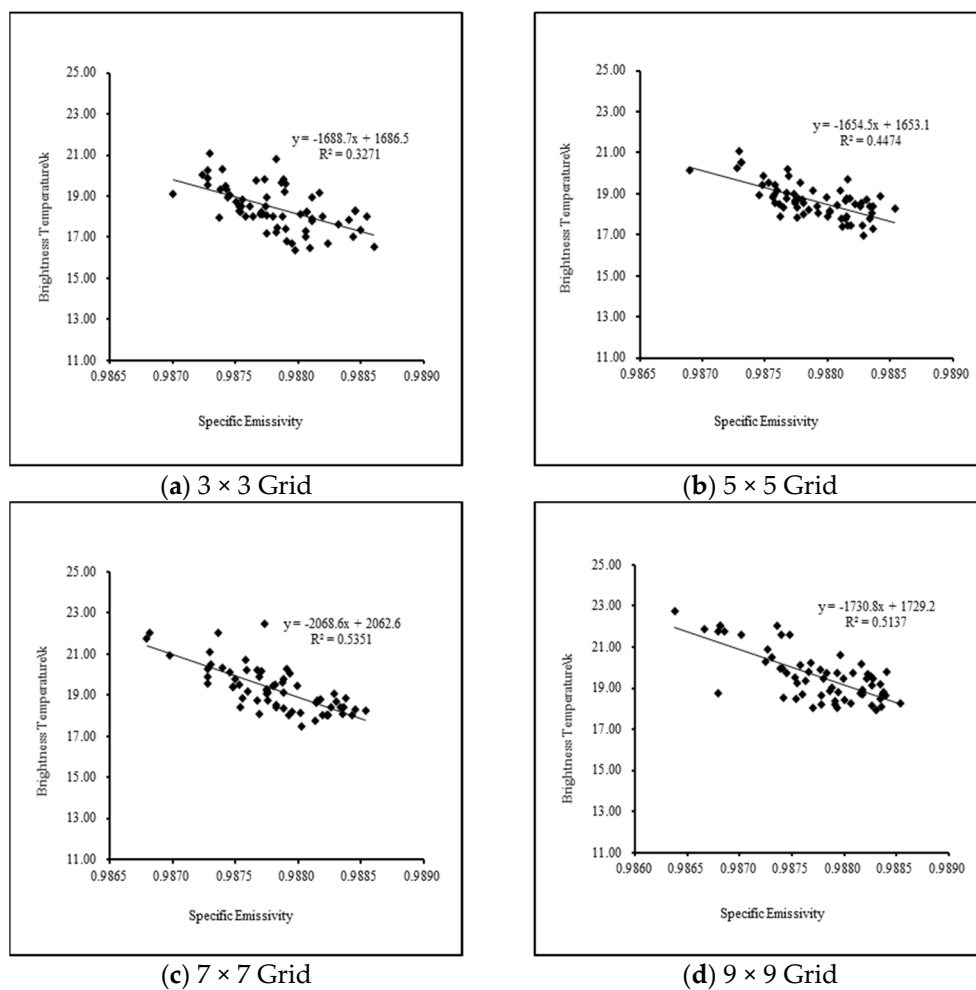


Figure 3. The linear relationship between the statistical values of the brightness temperature and the calculated values of the surface specific emissivity, which is the main correlation of the underlying model, can be seen by analyzing the statistical values for different grid size conditions. The two possess the most relevant linear relationship when the grid of the statistics is set to Figure 2c.

Table 1. Parameter grading of the hybrid model.

Site Factors		Grade Division						
Elevation		Level 1 per 100 m						
Slope gradient	[0,5] I	[6,15] II	[16,25] III	[26,35] IV	[36,45] V	≥46 VI		
Slope aspect	(337.5, 22.5] North slope	(22.5, 67.5] Northeast slope	(67.5, 112.5] East slope	(112.5, 157.5] Southeast slope	(157.5, 202.5] South slope	(202.5, 247.5] Southwest slope	(247.5, 292.5] West slope	(292.5, 337.5] Northwest slope

2.6. Normalized Modeling

(1) Multiple linear regression. Multiple linear regression analysis can avoid the multicollinearity of variables or the random influence of independent variables on dependent variables, so as to extract the independent variables of the main influencing factors to explain the change of dependent variables [29,30].

(2) Linear mixed-effects model (LME) expression. According to the number of random effect factors, the linear mixed-effects model (LME) is divided into two basic forms: single-level and multi-level. This study is a relational model constructed based on a multi-level linear model that contains two random effect factors. The general expression of the mixed effect model is as follows [31,32]:

$$y = X\beta + Z\alpha + \varepsilon \quad (1)$$

In Formula (1), y is the vector of observations; β is the fixed-effects parameter vector; α is the random effects parameter vector; the matrices X and Z are design matrices corresponding to fixed and random effects, respectively (through analysis, this research identifies emissivity as a fixed effect and identifies slope, aspect, elevation, and solar azimuth angle as random effects); and ε is the error vector.

2.7. Model Accuracy Evaluation

The evaluation of the regression prediction model is an indispensable step in the model building process. The evaluation of model accuracy is carried out using the Akaike information criterion (AIC), Bayesian information criterion (BIC), mean absolute error (MAE), coefficient of determination (R^2), and root mean square error (RMSE). These formulas are shown respectively as follows:

$$AIC = -2 \ln(L) + 2K \quad (2)$$

$$BIC = -2 \ln(L) + \ln(n)k \quad (3)$$

$$MAE = \sum_{i=1}^n |y_i - \hat{y}_i| / n \quad (4)$$

$$R^2 = 1 - \sum_{i=1}^n (y_i - \hat{y}_i)^2 / \sum_{i=1}^n (y_i - \bar{y})^2 \quad (5)$$

$$RMSE = \sqrt{\sum_{i=1}^n (y_i - \bar{y}_i)^2 / (n - 1)} \quad (6)$$

In Formulas (2)–(6), y_i is the measured value of the i -th sample, $\hat{y}_i$ is the estimated value of the i -th sample, $\bar{y}$ is the average measured value, n is the number of samples, K is the number of model parameters, and L is the maximum likelihood function value of the model. Among them, the smaller the value of AIC and BIC , the better the fitting effect of the model. The closer the values of MAE and $RMSE$ are to 0, and the closer the value of R^2 is to 1, and the higher the accuracy of the model [33].

3. Results

3.1. Multiple Linear Regression

According to the correlation analysis, it is known that longitude, latitude, emissivity, slope, aspect, elevation, solar azimuth angle, and solar zenith angle can be used as modeling factors. Among them, latitude, longitude, emissivity, and TBB are highly correlated. After analysis, the factors with a good fitting effect are selected as the independent variables of the basic model. After classification, K-means clustering, and factors' combination, the remaining factors with a good fitting effect can be selected as random effects to join the basic model. In order to determine the independent variables of the basic model, multiple linear stepwise regression analysis of multiple independent variable factors of the basic model is used, and the results are shown in Tables 2 and 3.

Table 2. Multiple regression model analysis of variance.

Factor Group	Sum of Squares	Freedom	Mean Square	F Value	Pr > F
Longitude	7.1550	1	7.1550	7.5492	0.006372 **
Latitude	29.8800	1	29.8800	31.5249	4.534×10^{-8} **
Emissivity	220.2950	1	220.2950	232.4239	$<2.2 \times 10^{-16}$ ***
Residuals	280.5530	296	0.9480		

Note: * represents the level of significance of the significant factor, and a higher number of * indicates a more significant factor.

Table 3. Multiple regression model fitting results.

Parameters	Values	Standard Value	Value T	Pr > F	R ²
(Intercept)	2.300×10^3	1.509×10^2	15.238	$<2 \times 10^{-16}$ ***	0.4731
Longitude	-2.594×10^{-1}	5.606×10^{-2}	-4.627	5.55×10^{-6} ***	
Latitude	3.305×10^{-2}	7.204×10^{-3}	4.588	6.61×10^{-6} ***	
Emissivity	-2.280×10^3	1.496×10^2	-15.245	$<2 \times 10^{-16}$ ***	

Note: * represents the level of significance of the significant factor, and a higher number of * indicates a more significant factor.

Latitude, longitude, and emissivity are factors that have significant effects on TBB, which can be used as independent variables to fit the basic model. In stepwise regression analysis, when longitude and latitude are used as the fixed factors of the basic model, the accuracy of the basic model is low. At the same time, when longitude and latitude are used as fixed factors to fit the mixed-effects model, the accuracy of the model is only slightly improved, and it is not convenient for the practical application of the model. In order to simplify the model form, it can be seen from Tables 2 and 3 that the value of F and value of T of emissivity are obviously optimal. Therefore, without considering the longitude and latitude as the fixed factor of the basic model and the random effect of the mixed-effects model, the emissivity is determined to be the independent variable of the basic model for fitting.

3.2. Determination of the Basic Model

Fitting the basic model, the results are shown in Table 4.

Table 4. Results of the basic model fit.

Parameters	Values	Down Limit	Up Limit	Fitting Data		
				R ²	MAE	RMSE
a	-1747.4422	-1978.5302	1516.3542	0.4244	0.7907	1.0142
b	1745.5010	1517.2530	1973.7489			

The specific form of the basic model is determined by Table 4 as follows:

$$TBB = -1747.44 \times EMS + 1745.50 \quad (7)$$

In Formula (7), TBB is the value of brightness temperature and EMS is the emissivity value of the main correlation factor.

3.3. Fitting the Mixed-Effects Model

Taking into account the slope, aspect, elevation, solar zenith angle, and solar azimuth angle will affect the true brightness temperature value. Based on the fixed linear model, slope, aspect, elevation, solar zenith angle, and solar azimuth angle are taken as random effects to introduce different combination positions of model parameters a and b. The mixed-effects model is fitted after introduction, and the results are summarized in Table 5.

According to the evaluation indexes in Table 5, it can be known that, when fitting the site type (LDLX) combined with slope, aspect, and elevation, and SOA and SOZ as random effects into the fixed model, the accuracy of the model is improved. The amount of AIC and BIC decreased. Among them, M2, M6, and M10 are the model results and evaluation when the random effects LDLX, SOZ, and SOA are added to parameter b of the fixed model, respectively. Obviously, when LDLX and SOA are used as random effects, the accuracy of the model is improved greatly, and when SOZ is used as a random effect, the accuracy of the model is improved slightly. Among them, M4, M8, and M12 are the model results and evaluation when the random effects ldlx, soz, and soa (LDLX, SOZ, and SOA

are clustered by the K-means method) are added as random effects to parameter b of the fixed model. It can be seen that, when *ldlx* and *soa* are used as random effects, the accuracy of the model is greatly improved, and *soz* is the result of singular fitting. After the analysis, *soz* is not considered as a random effect, and *ldlx* and *soz* are determined as random effects of the MEMN model.

Table 5. Linear mixed effects model parameter estimates.

Random Factor	Model	Parameter Combination	R^2	AIC	BIC	RMSE	MAE
LDLX	M1	a	0.5181	865.8	880.6	0.9314	0.7206
	M2	b	0.5181	865.8	880.6	0.9314	0.7205
ldlx	M3	a	0.6640	754.4	769.2	0.7752	0.5794
	M4	b	0.6640	754.4	769.2	0.7752	0.5794
SOZ	M5	a	0.4452	867.8	882.6	0.9959	0.7751
	M6	b	0.4454	867.8	882.6	0.9957	0.7749
soz	M7	a	Singular fit				
	M8	b	Singular fit				
SOA	M9	a	0.5194	867.0	881.8	0.9306	0.7289
	M10	b	0.5196	867.0	881.8	0.9305	0.7288
soa	M11	a	0.7942	632.7	647.6	0.6067	0.4381
	M12	b	0.7942	632.7	647.6	0.6067	0.4381
Ldlx + soa	M13	a + a	0.8418	590.4	609.0	0.5321	0.3977
	M14	b + b	0.8418	590.4	609.0	0.5321	0.3977
	M15	b + a	0.8418	590.4	609.0	0.5321	0.3977
	M16	a + b	0.8418	590.4	609.0	0.5321	0.3977

Note: The parameter combinations a and b refer to the mixed-effects model construction by adding random effects to each parameter separately.

According to Table 5, we selected M14 as the optimal model. Analysis of the evaluation indicators of the M14 model shows that the coefficient of determination R^2 increased from 0.4244 to 0.8418, an increase of 98.35%; the MAE decreased from 0.7907 to 0.3977, a decrease of 49.37%; and the RMSE decreased from 1.0142 to 0.5321, a decrease of 47.52%. The R^2 displays a significant improvement, and MAE and RMSE are significantly reduced. Therefore, the determined model form is as follows:

$$TBB_{ij} = a \times EMS_{ij} + (b + b_i + b_j) + \varepsilon_{ij} \quad (8)$$

In the formula, TBB_{ij} is the brightness temperature value of the i -th grade site type and j -th grade solar azimuth angle. EMS_{ij} is the emissivity value for the i -th grade site type and the j -th grade solar azimuth angle. b_i is the random effect parameter of the site effect, and b_j is the random effect parameter of the solar azimuth angle effect. $b_i \sim N(0, \psi_1)$, ψ_1 is the design matrix of the random effect parameter of the site; and $b_j \sim N(0, \psi_2)$, ψ_2 is the design matrix of the random effect parameters of the solar azimuth angle. ε_{ij} is the error term of the i -th grade site type and j -th grade solar azimuth angle.

It can be seen from Figure 4 that, compared with the basic model, the prediction value of the mixed-effects model is less discrete, and the residuals of the mixed-effects model are more concentrated on both sides of the X axis. To sum up, the model based on the random effects of *ldlx* and *soa* groups can display greatly improved accuracy.

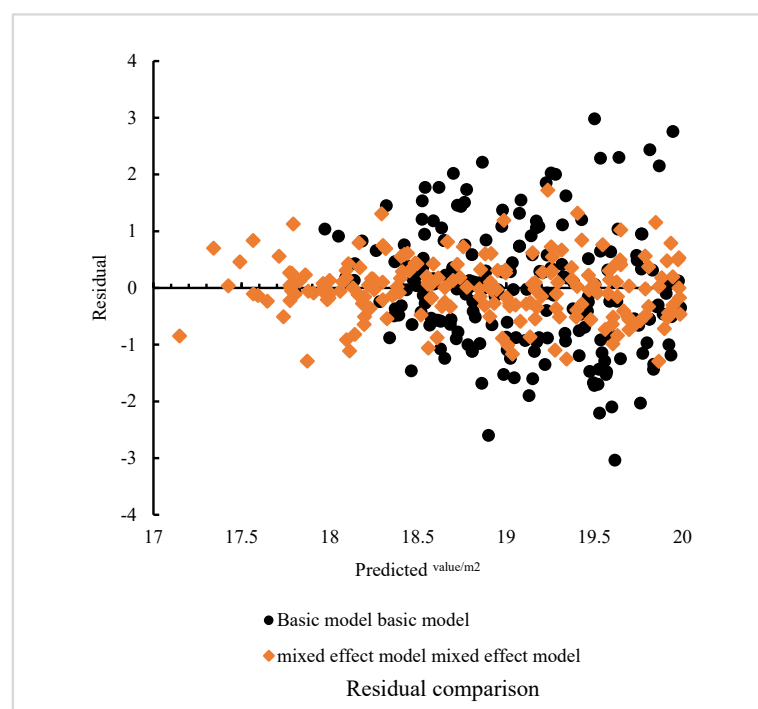


Figure 4. The orange diamond indicates the dispersion of the mixed-effects model predictions, and the black circle indicates the dispersion of the basic model predictions.

3.4. Comparison of the Accuracy of Normalization Methods

The data used in the model evaluation are the Himawari-8 and FY-4A image data at 06:30 (UTC) on 10 December 2019 in Hunan Province in China. The measured values of factors such as emissivity, solar zenith angle, slope, aspect, elevation, and brightness temperature are collected. The predictive values of brightness temperature are calculated by the MEMN model and the RF model in the literature [6]. The accuracy between the two models was compared and evaluated based on three indicators: coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE).

The radiance of the reference image Himawari-8 (Figure 5a) is quite different from the image FY-4A (Figure 5b), which is the image to be corrected. The normalized image (Figure 5c) is obtained after normalization by the RF method. At the same time, the normalized image (Figure 5d) is obtained by the MEMN method.

The pixel values of normalized images were statistically analyzed. Figure 6 is the linear correlation comparison chart between the MEMN method and RF method. Table 6 shows the comparison of the model accuracy evaluation index of two methods. It can be seen that the accuracy of the MEMN method is better than that of the RF method.

Table 6. Comparison of evaluation indicators for different normalization methods.

Brightness Temperature Inversion Normalization Method	R^2	MAE	RMSE
MEMN Method	0.8045	0.4657	0.5648
RF Method	0.7318	0.5583	0.6817
PIF Method	0.7264	0.5603	0.7155
ASCR Method	0.6841	0.6193	0.7882

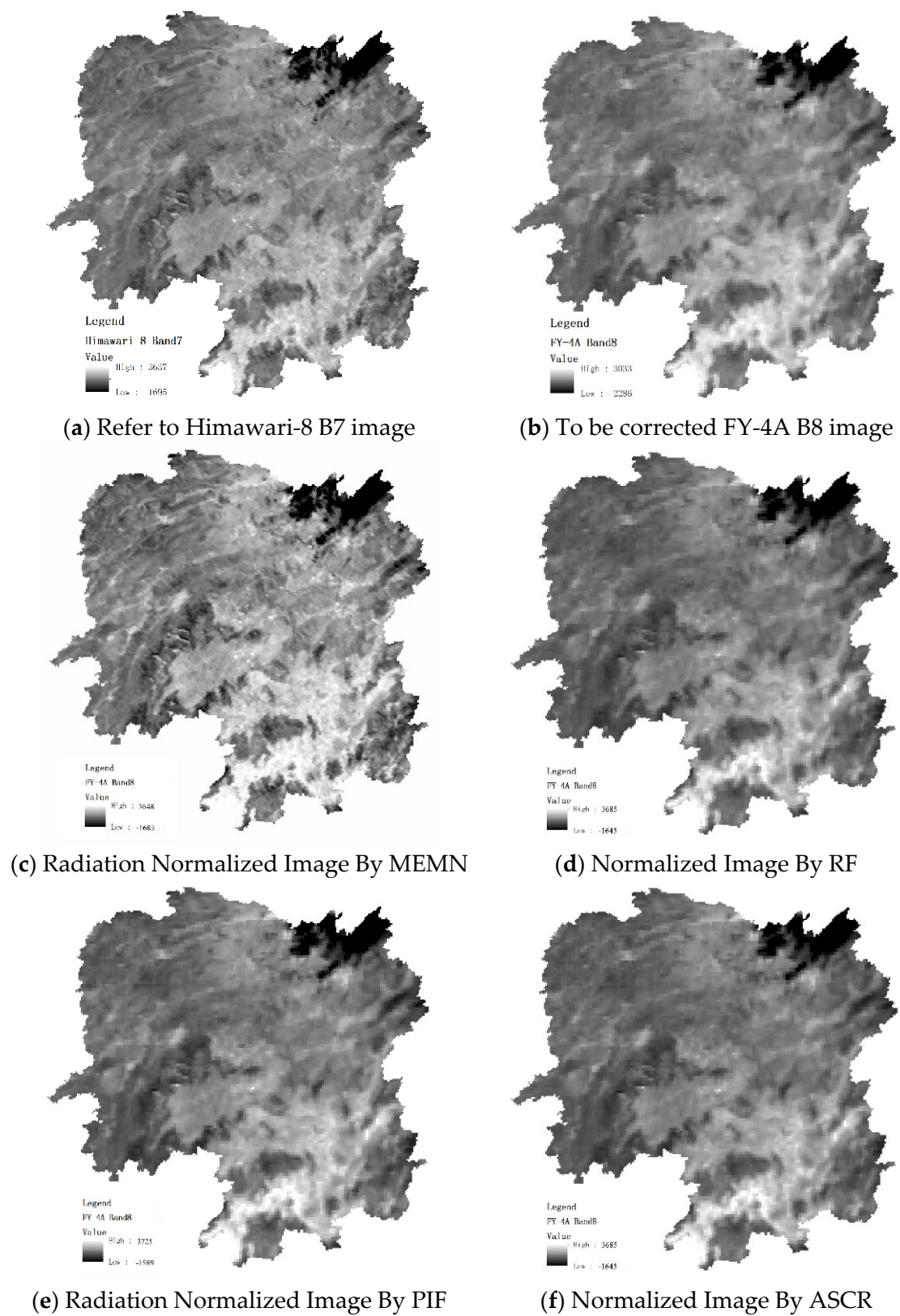


Figure 5. Original image and normalization results of different methods (mid-wave infrared channel).

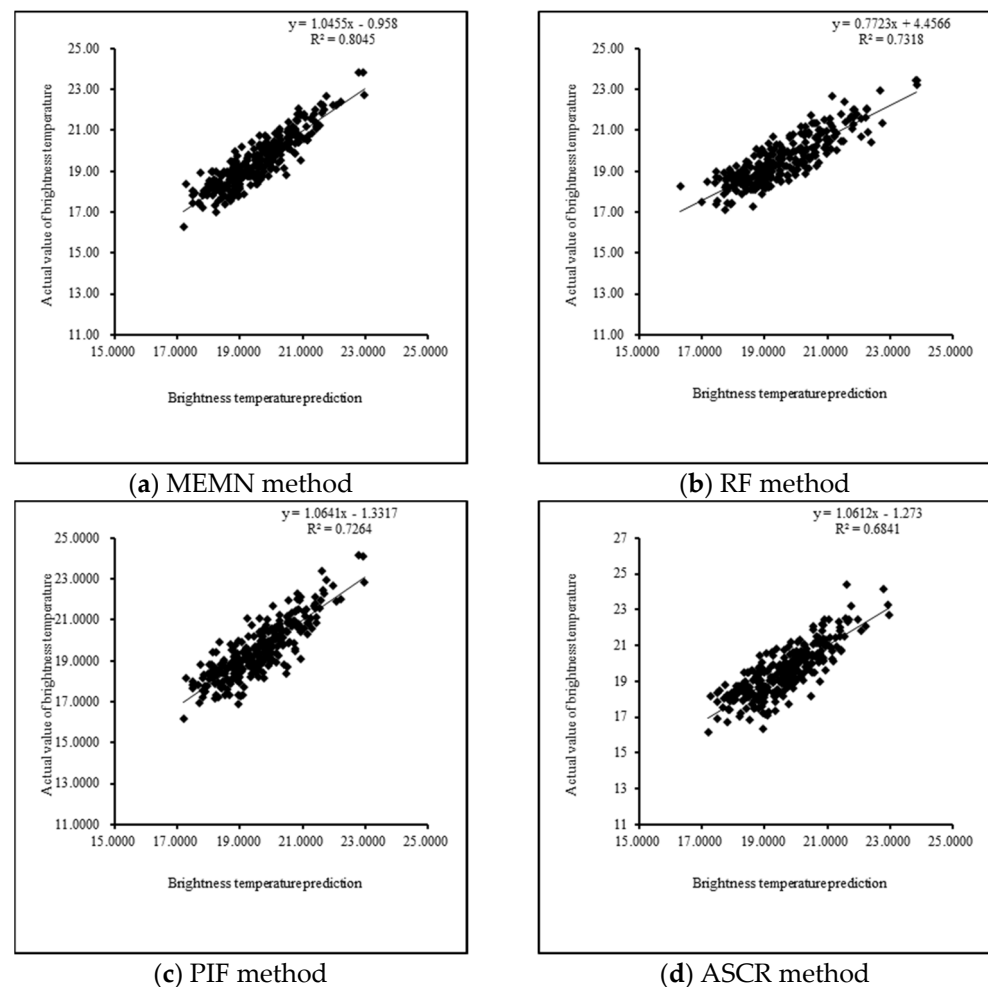


Figure 6. Comparison of the accuracy of the mixed-effects model normalization method with the random forest normalization method.

3.5. The Results of Fire Detection Verification

In order to verify the improvement of the effect of the MEMN method on the fire monitoring of the original image, we selected the FY-4A raw data, the Himawari-8 raw data, and the data processed by the MEMN method to identify the fire in Hunan Province at a certain time using the corresponding fire discrimination algorithm, and compared it with the fire situation published in China at that time to verify the accuracy. The results are analyzed in Figure 7. Figure 7a shows the fire point determined by the forest and grassland fire information sharing platform in China. Figure 7b shows the fire point of FY-4A raw data determined by the decision tree fire point recognition algorithm [34] based on FY-4A B8 and FY-4A B12. Figure 7c shows the fire point of Himawari-8 raw data determined by the LSA SAF Meteosat fire point recognition algorithm [35] based on Himawari-8 B7 and Himawari-8 B14. Figure 7d shows the fire point of FY-4A and Himawari-8, which is normalized by the MEMN method and then determined by the fire point recognition algorithm.

Table 7 shows that, compared with the number of fires in Hunan Province on 10 December 2019 counted by the National Forest Grassland Fire Prevention and Extinguishing Information Sharing Platform, the fire detection rate of forest fires in FY-4A original remote sensing image is 54.5%, and the fire detection rate of forest fires in Himawari-8 original remote sensing image is 72.7%. The fire detection rate of forest fires in remote sensing images normalized by the MEMN method is 90.9%. The MEMN normalization method has greatly improved the accuracy of forest fire monitoring.

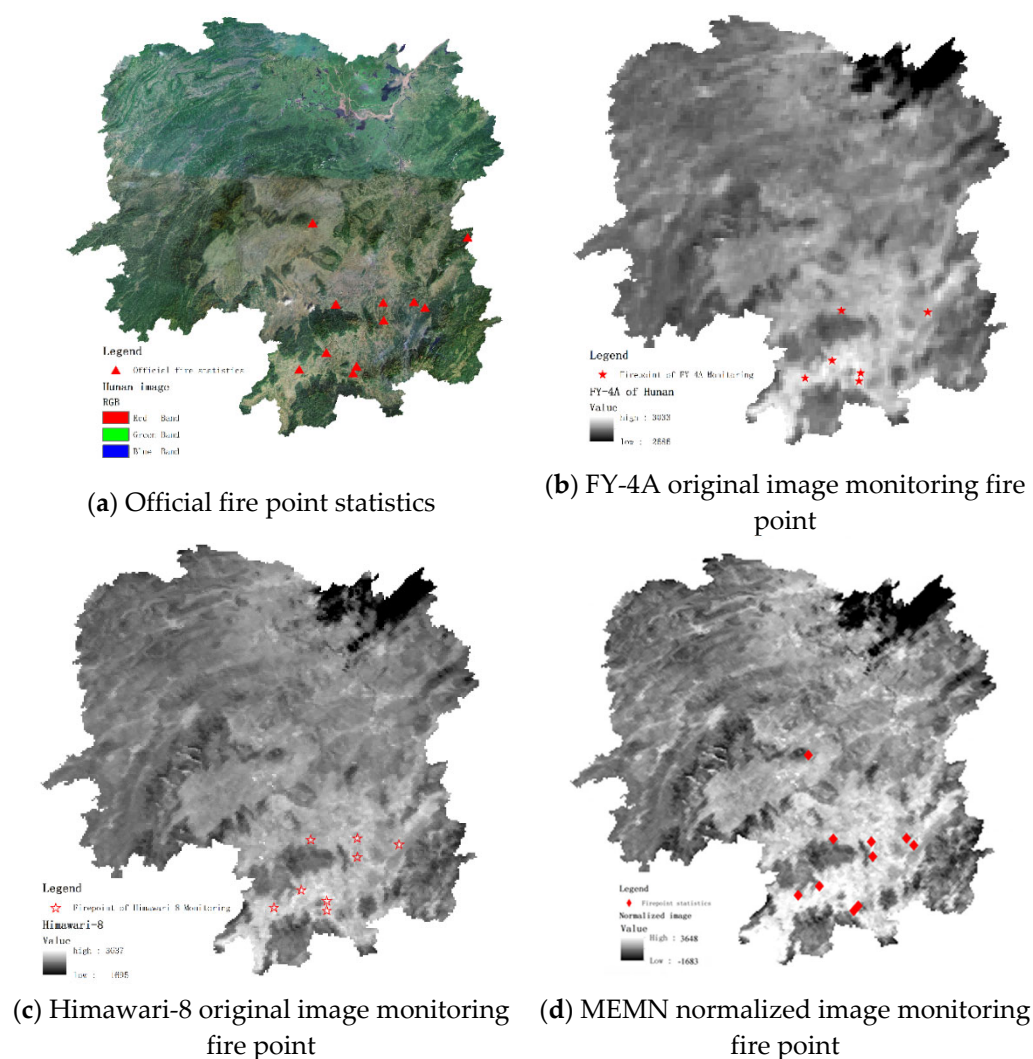


Figure 7. Comparison of the fire point monitoring results of different images.

Table 7. Comparative analysis of the fire detection rate.

	Actual Number of Fire Points	Number Detected	Fire Detection Rate
FY-4A original image	11	6	54.5%
Himawari-8 original image	11	8	72.7%
MEMN normalized image	11	10	90.9%

4. Discussions

Aiming to address the problems that the single normalization scale leads to insufficient accuracy of multi-source sensor forest fire monitoring and the low temporal resolution of polar orbit satellite sensor leads to a lack of timeliness in forest fire monitoring, this article extracts and analyzes the influencing factors of brightness temperature in Hunan Province in China, introduces the regression prediction method of the mixed-effects model, constructs the normalized brightness temperature inversion model based on Himawari-8 and FY-4A, and verifies the model. The main conclusions are as follows.

(1) The MEMN model based on Himawari-8 solves the problems of the single factor and weak adaptability of model parameters in traditional methods such as the RF method, PIF method, and ASCR method. The grid data acquisition method is used to solve the problem of irregular sample selection and determine the modeling parameter values of each sample. Then, the basic model was fitted by multiple stepwise regres-

sion: $TBB = -1747.44 \times EMS + 1745.50$. Finally, the random effects site type (ldlx) and solar azimuth angle (soa) are added to the foundation after classification, clustering, and combination. Then, the MEMN model based on Himawari-8 is established: $TBB_{ij} = a \times EMS_{ij} + (b + b_i + b_j) + \varepsilon_{ij}$. The results of the accuracy evaluation and applicability test show that the MEMN model based on Himawari-8 has higher accuracy, and the determination coefficient is 0.8418 after introducing the random effect group of site type (ldlx) and solar azimuth angle (soa).

(2) Taking the normalized model of Himawari-8 as a reference and using the data collected by FY-4A to evaluate the accuracy of the model, the result showed that R^2 reached 0.7542. Comparing the results calculated by the random forest normalization method of the literature [6] to the data of the same period, the indicators of the MEMN method are better than those of the RF method. This result means that the MEMN method based on Himawari-8 is more applicable to the FY-4A sensor, and the normalized effect is better.

(3) The MEMN method has the following advantages. First, it considers more parameters, more standardized sample selection, and relatively high accuracy. Second, it can meet the requirements of observation angle normalization and radiation normalization at the same time. Finally, the model has good ability to divide the terrain and radiation errors equally, as well as to reduce the infrared radiation difference between different satellite sensors.

The key technology of this study is to combine the mixed-effects model with the normalization method. After analysis, the radiation normalization parameter is regarded as the fixed effect of the mixed-effects model, and the observation angle normalization parameter is regarded as the random effect, so as to realize the image normalization research that meets the two scales at the same time. The results have certain theoretical significance for the improvement of the normalization method, and have practical value for improving the accuracy and timeliness of forest fire monitoring.

5. Conclusions

In this paper, two geostationary satellite normalization models with different spatial resolution and time resolution are constructed, and the effect is ideal. This model is suitable for the normalization between single-phase cross-sensors. The construction of the normalized model of a multi-temporal cross-sensor and multi-temporal single sensor is still to be studied and analyzed. It is possible to combine the multi-temporal cross-sensor and multi-temporal single sensor. The construction of the mixed-effects model of the sensor is the main research direction in the next step.

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