Impact of FY-4A Satellite-Based Surface Solar Irradiance on the Classification of Meteorology for Ozone Pollution

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Abstract

Meteorological conditions are important for ozone formation, among which solar radiation is a key factor affecting ozone concentrations through its direct influence on photochemical reactions and indirect influence on precursor emissions. Due to the limited number of ground observation stations, a meteorological classification method for ozone pollution levels, including solar radiation, has not been proposed. In this study, the surface solar irradiance (SSI) obtained from the Fengyun-4A (FY-4A) satellite with high temporal and spatial resolutions was used as one of the input physical parameters to train a classifier for meteorology of ozone pollution and compared with that classifier without SSI to analyze the impact of solar radiation on the classification performance of trained classifiers. By comparing the SSI of the FY-4A satellite with ground-based observations, it was verified that there was a significant difference in values between the two data sources, but their distribution trends were consistent. By analyzing the relationship between hourly ozone concentrations and SSI of the FY-4A satellite, it was found that there was a positive linear correlation between them, and the correlation was the highest when the lead time of SSI was 3 hr. After including SSI, among the 21 cities in the study area, the number of cities with a classification accuracy exceeding 80% increased from 7 to 14, with 20 cities having a positive accuracy growth rate and 8 cities having an accuracy growth rate exceeding 4%. In addition, the SSI of the FY-4A satellite induced a significant improvement in the classification accuracy of level 1 and level 2 samples. In general, the FY-4A SSI data are helpful for improving the classification performance of the trained classifier for the meteorology of ozone pollution in the study area.

Keywords: Fengyun-4A; Surface solar irradiance; Ozone pollution; Meteorological conditions
1 INTRODUCTION

Surface ozone is the product of the photochemical oxidation reactions between carbon monoxide (CO) and volatile organic compounds (VOCs) in the presence of nitrogen oxides (NOx) and sunlight, and it is considered a secondary air pollutant (Monks et al., 2015; Lu et al., 2018, 2020). High ozone concentrations near the ground can exert consequential impacts on human health (Saari et al., 2017; Nuvolone et al., 2018; Fleming et al., 2018; Si and Tian, 2020), crop productivity (Tai et al., 2014; Sharma et al., 2019), vegetation growth (Mills et al., 2011; Juran et al., 2021), and the ecological environment (Cailleret et al., 2018). Since the 1980s, ozone pollution in the United States and Europe has significantly alleviated (Fiore et al., 1998; Lin et al., 2001; Krzyscin et al., 2005, 2007), and Japan has gradually slowed down around 2010 (Wang et al., 2016; Kawano et al., 2022). However, serious ozone pollution events near the ground have occurred frequently during the warm season in China in recent years because of the rapid growth of traffic volume and accelerated industrialization and urbanization (Chen et al., 2019, 2020, 2021; Li et al., 2019, 2021). Especially in such regions as the Beijing-Tianjing-Hebei region, Fenhe and Weihe river plains, Pearl River delta, Yangtze River delta and Chengdu-Chongqing area (Lu et al., 2019a; Yang et al., 2020a; Zhao et al., 2020; Li et al., 2023).

Surface ozone concentrations are closely related to meteorology and precursor emissions (Lu et al., 2019a, 2019b; Li et al., 2019; Chen et al., 2021). The precursors required for ozone formation originate from both anthropogenic and biogenic emissions (Ni et al., 2018; Li et al., 2019; Gao et al., 2022). There are three ways in which meteorological conditions affect the formation of ozone (Li et al., 2016; Wang et al., 2017; Hu et al., 2018; Han et al., 2018, 2019, 2020). (1) They affect
the transportation and diffusion processes of ozone and its precursors. (2) Changes in meteorological factors (e.g., radiation and temperature) lead to changes in atmospheric oxidation, which in turn affect the photochemical process of ozone formation. (3) Changes in VOCs emissions from vegetation indirectly affect the formation of ozone. Many studies have found that high temperature and solar radiation, low humidity, weak wind and clear weather conditions are conducive to the stagnation and production of ozone (Zhao et al., 2016; Gunthe et al., 2016; Su et al., 2019; Yang et al., 2020a). Among meteorological parameters, solar radiation is often considered a key factor affecting ozone formation due to its direct influence on photochemical reactions and indirect influence on circulation transport (Jacob et al., 2009; Kerr et al., 2020; Wang et al., 2020; Kou et al., 2023). In addition, changes in solar radiation can cause temperature changes, which can stimulate biogenic emissions, especially biogenic VOCs (Ma et al., 2022).

Although considerable studies have been conducted, it remains challenging for a comprehensive understanding of meteorological influences on ozone pollution. Previous studies mainly investigated the causal influence of major individual meteorological factors on ozone concentrations based on qualitative analysis methods (e.g., correlation analysis) (Gunthe et al., 2016; Tong et al., 2017; Yang et al., 2020; Han et al., 2020) or quantitative analysis methods (e.g., convergent cross mapping) (Pearce et al., 2011; Chen et al., 2019; Chen et al., 2020). Advanced methods should be employed to comprehensively reflect the influence of meteorological conditions on the occurrence of ozone pollution. A meteorological classification method for ozone pollution based on machine learning (e.g., back propagation (BP) neural network) was proposed by Cao et al. (2023). However, solar radiation, as a key factor affecting ozone concentrations, has not been
applied to this method because of the limitation of the number of ground-based observation stations. Surface solar irradiance (SSI) data from satellite remote sensing with high temporal and spatial resolutions are of great significance where ground-measured solar radiation data are not available and are better than numerical modeling in terms of quality (Zhang et al., 2011; Huang et al., 2019; Ma et al., 2019). Fengyun-4A (FY-4A) is the second generation of geostationary orbit quantitative remote sensing meteorological satellite in China, and it was launched at the Xichang Satellite Launch Center on December 11, 2016. The advanced geosynchronous radiation imager (AGRI) sensor mounted on the FY-4A satellite provides high temporal and spatial resolution images of the Chinese region and its surrounding areas (Yang et al., 2019, 2020b; Huang et al., 2022). The SSI data obtained from the FY-4A satellite consider the influence of atmospheric components (e.g., aerosols, clouds, and water vapor content), surface albedo, and altitude. The verification of SSI data obtained from the FY-4A satellite has been conducted in multiple regions in China (Liang et al., 2020; Jia et al., 2021; Wang et al., 2021; Xu et al., 2022).

In this work, in order to better understand the impact of solar radiation on ozone pollution and obtain quantitative description results, the SSI data obtained from the FY-4A satellite with high temporal and spatial resolutions were used as one of the input physical parameters of BP model to train a classifier for meteorology of ozone pollution. The results were compared with the classifier without SSI to quantitatively analyze the impact of solar radiation on the classification performance of trained BP classifiers. Section 2 provides an overview of the data and methodology, including the study area, observational data and associated preprocessing methods, and analysis methods. The analysis methods include the verification of FY-4A SSI data by comparing them with ground-
based observations in the study area, the qualitative analysis of the relationship between FY-4A SSI
data and surface ozone concentrations, and the quantitative analysis of the impact of FY-4A SSI
data on the classification of meteorology for ozone pollution. Section 3 illustrates the results and
analysis. Conclusions and discussions are summarized in Section 4.

2 DATA AND METHODOLOGY

2.1 Study Area

The study area is Sichuan Province, located in southwestern China (97°–109°E and 26°–35°N),
with a total area of 486,000 km² and covering 21 prefecture-level administrative regions. The
terrain of Sichuan Province is complex, mainly characterized by mountains, with four types of
terrain: mountains, hills, plains, and plateaus. Sichuan Province spans several major geomorphic
units, such as the Qinghai-Tibet Plateau, Hengduan Mountains, Yunnan-Guizhou Plateau, Qinling-
Bashan Mountains, and Sichuan Basin. The terrain is high in the west and low in the east, tilting
from the northwest to southeast.

2.2 Data

In addition to the hourly air quality monitoring data and China Meteorological Administration
Land Surface Data Assimilation System (CLDAS) data for a 5-year (2018–2022) period described
by Cao et al. (2023), the SSI data obtained from the FY-4A satellite and ground observation stations
were acquired for the study area.

FY-4A satellite was launched on December 11, 2016, and its current fixed point is over the
equator at a longitude of 104.7°E. The AGRI aboard FY-4A has 14 spectral bands from 0.47 to 13.5
μm, including 6 visible/near infrared, 2 midwave infrared, and 4 longwave infrared bands. The SSI
data used in this work were obtained from the AGRI sensor as one of the level-2 quantitative
inversion products, with units of W m\(^{-2}\). In this work, the SSI data of the FY-4A satellite for a 5-
year (2018–2022) period were obtained from the National Satellite Meteorological Center of the
China Meteorological Administration (http://satellite.nsmc.org.cn/). The original dataset displayed
as the geostationary projection is re-sampled onto an equal latitude-longitude grids based on nearest
neighbor method, with temporal and spatial resolutions of 1 hr and 4 km, respectively.

The SSI of ground-based observations in 2021 were provided by the Wenjiang National Basic
Meteorological Station in Chengdu (103.86°E and 30.75°N) of the China Meteorological
Administration (CMA) radiation observation network, with units of W m\(^{-2}\) and a temporal
resolution of 1 min. The SSI data of the FY-4A satellite and ground-based observations were
matched at temporal and spatial scales. The spatial matching method was used to extract the SSI
of 9 pixels (3 pixels × 3 pixels) around the ground observation stations to calculate the average
value. Fig. 1 shows the spatial distribution of SSI obtained from the FY-4A satellite in Sichuan
Province and the location of the Wenjiang national basic meteorological station (marked as a green
spot) at 14:00 Beijing Time (BJT) on June 29, 2022. The spatial distribution of SSI obtained from
the FY-4A satellite was characterized by high values in the east and low values in the west.

2.3 Analysis Methods

The application of SSI obtained from the FY-4A satellite in the classification of meteorology
for ozone pollution includes four components: (1) verification of SSI obtained from the FY-4A
satellite in the study area by comparing them with ground observations; (2) analysis of the
relationship between SSI obtained from the FY-4A satellite and ground ozone concentrations; and
(3) analysis of the impact of the FY-4A SSI data on the classification of meteorology for ozone
pollution.
2.3.1 Verification of FY-4A SSI

Due to the limited spatial resolution of SSI obtained from ground observation stations, the FY-4A satellite data may be used as a supplement. The quality assessment and applicability evaluation of hourly SSI obtained from the FY-4A satellite in the study area was completed by comparing the data with ground observations at the Chengdu weather station in 2021. The analysis was conducted at the time when both ground-based observations and the FY-4A satellite had valid data (value greater than 0 W m\(^{-2}\)). Five statistical metrics were calculated, including the correlation coefficient (R), mean bias error (MBE), relative mean bias error (rMBE), mean absolute error (MAE), root mean square error (RMSE), as follows:

\[
R = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \cdot \sum_{i=1}^{n} (y_i - \bar{y})^2}}
\]

(1)

\[
MBE = \frac{\sum_{i=1}^{n} (x_i - y_i)}{n}
\]

(2)

\[
rMBE = \frac{\sum_{i=1}^{n} (x_i - y_i)}{\sum_{i=1}^{n} y_i}
\]

(3)

\[
MAE = \frac{\sum_{i=1}^{n} |y_i - y_i|}{n}
\]

(4)

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2}
\]

(5)

where \(n\) is the sample size, \(x\) is the hourly SSI obtained from the FY-4A satellite, \(y\) is the 1-min SSI.
at the hour obtained from the ground observation station, and $\bar{x}$ and $\bar{y}$ are the averages of $x$ and $y$.

2.3.2 Relationship between FY-4A SSI and ozone concentrations

By analyzing the monthly and daily distribution characteristics of the hourly FY-4A SSI data and ground ozone concentrations from 2019 to 2021 in the study area, the relationship between them was determined. Based on the analysis of Cao et al. (2023), the main period of ozone pollution in Sichuan Province is from April to September each year, so the data from this period were used to generate the daily distribution in this work. In addition, according to the daily variations in SSI and ozone concentrations, the relationship between hourly ozone concentrations and SSI at different lead times was analyzed.

2.3.3 Impact of FY-4A SSI on the classification of meteorology for ozone pollution

The classification method of meteorology for ozone pollution proposed by Cao et al. (2023) had 5 input physical parameters, including temperature ($T_m$), relative humidity ($RH$), precipitation ($Pre$), mixing layer height ($MLH$), and nitrogen dioxide concentrations ($\rho_{NO2}$). According to China's national air quality standards, ozone pollution is defined as hourly ozone concentrations exceeding 200 $\mu$g m$^{-3}$ or 8-hourly maximum ozone concentrations exceeding 160 $\mu$g m$^{-3}$ (Han et al., 2020).

Two critical values (160 $\mu$g m$^{-3}$ and 200 $\mu$g m$^{-3}$) of surface hourly ozone concentrations were used to divide ozone pollution into three levels and thus into three meteorological groups (level 1: meteorology is very unfavorable to the occurrence of ozone pollution; level 2: meteorology is unfavorable to the occurrence of ozone pollution; level 3: meteorology is conducive to the occurrence of ozone pollution). The classification performance of the trained single model was better than that of the trained multiple individual models in major ozone pollution-prone regions in
the study area. However, solar radiation closely related to ozone generation was not included in the model because there were only 7 solar radiation observation stations in the study area, and the observation data were insufficient to train the model. In this work, SSI data obtained from the FY-4A satellite were verified using ground-based measurements and used as one of the input physical parameters to train a single BP classifier in the study area. The influence of solar radiation on the classification performance of the trained BP classifiers was quantitatively analyzed by comparing their classification accuracy.

Fig. 2 presents an overview of the impact of the FY-4A SSI on the classification of meteorology for ozone pollution based on the method proposed by Cao et al. (2023). The hourly data of the main ozone pollution period from 2018 to 2020 were divided into training data and test data, and the data of the period from 2021 to 2022 were used as verification data to quantitatively examine the performance of the trained BP classifiers by comparison with observations. The main ozone pollution period was defined as April to September each year and from 09:00 to 21:00 BJT every day according to the study by Cao et al. (2023).

3 RESULTS AND ANALYSIS

3.1 Verification of FY-4A SSI

The comparative analysis of hourly SSI obtained from the FY-4A satellite and ground-based observations was conducted throughout the whole year and in each season in 2021. The number of valid samples for the whole year was 3211, with 874 in spring (March to May), 967 in summer (June to August), 728 in autumn (September to November), and 642 in winter (January, February, and December). Due to the threshold setting of 70° for the solar zenith angle in the surface solar
irradiance inversion algorithm of the FY-4A satellite, there is no surface solar irradiance value when
the solar zenith angle exceeds this threshold, resulting in relatively fewer effective samples in
winter (Liang et al., 2020; Xu et al., 2022). Fig. 3 shows the scatter plots and probability
distributions of hourly SSI obtained from the FY-4A satellite and ground-based observations
throughout the whole year and in each season in 2021. The hourly SSI of the FY-4A satellite were
mainly distributed between 224 and 1052 W m$^{-2}$, with an average value of 540.46 W m$^{-2}$ and a
standard deviation of 166.09 W m$^{-2}$. However, the ground-based observations were mainly
distributed between 1 and 1286 W m$^{-2}$, with an average value of 311.45 W m$^{-2}$ and a standard
deviation of 263.28 W m$^{-2}$. The SSI in autumn and winter was lower than that in spring and summer.
The hourly SSI observed by the FY-4A satellite and ground-based observations showed a linear
relationship throughout the whole year and in each season, and the correlation coefficients were
calculated, with values of 0.74, 0.74, 0.75, 0.73, and 0.71 for the whole year and for spring, summer,
autumn, and winter, respectively. The linear relationship between the FY-4A satellite and ground-
based observations passed the significance test at the 0.01 level ($p$ value < 0.001). Table 1 presents
the MAE, MBE, rMBE, and RMSE values, which were calculated from the FY-4A SSI with respect
to the ground-based observations. The MBE, MAE, and RMSE values were greater than 200 W m$^{-2}$
throughout the whole year and in each season, indicating that the SSI obtained from the FY-4A
satellite was overestimated compared with ground-based observations, which was consistent with
previous studies and might be related to the view angle of satellite and the ubiquitous cloud
inhomogeneity (Du et al., 2022; Xu et al., 2022; Shi et al., 2023). The larger difference of the FY-
4A and ground-based observations can be explained as the spatial and temporal scale mismatch.
More particularly, the spatial scale mismatch is that since ground-based measurement represents the value of station location and satellite-derived value represents the pixel average, if the ground station is shadowed by broken clouds or surrounding structures, the instantaneous SSI of ground-measured would be lower than the pixel average. The temporal scale mismatch is that the hourly SSI of the FY-4A is the instantaneous value at a certain time within 15 min after that hour, while the ground-based measurement is the average value within 1 min before that hour (Liang et al., 2020).

In addition, the distribution of scattering points in Fig. 3 shows that the SSI obtained from the FY-4A satellite was significantly higher than that from ground-based observations at low SSI levels, and the two data sources showed a small difference at high SSI levels. Fig. 4 shows the MBE values at different SSI levels for each season. The SSI was divided into 10 levels based on ground-based observations, including (0, 100), [100, 200), [200, 300), [300, 400), [400, 500), [500, 600), [600, 700), [700, 800), [800, 900), and [900, +\infty)). The MBE values at different SSI levels varied within -92.98~363.98 W m\(^{-2}\) in spring, -106.02~357.03 W m\(^{-2}\) in summer, -112.36~372.19 W m\(^{-2}\) in autumn, and -92.23~347.08 W m\(^{-2}\) in winter, which decreased with increasing SSI. When a negative MBE occurred, the SSI level in autumn was at [600, 700), which was the smallest SSI level among the four seasons, while the other three seasons were all at [700, 800). Overall, the SSI of the FY-4A satellite has the characteristics of obvious overestimation for the low observed surface solar irradiance while underestimation for the relatively large observed values, which is consistent with previous studies (Liang et al., 2020; Xu et al., 2022). The overestimation can also be explained as the aforementioned spatial scale mismatch, where ground-based observations contain more cloud
features that are not resolved in the satellite pixels. The underestimation may be due to the lack of
consideration of cloud and albedo enhancement events (Shi et al., 2023).

Figs. 5 and 6 present the monthly and diurnal variations of SSI obtained from the FY-4A
satellite and ground-based observations, and their corresponding MBE values. The monthly and
diurnal variation trend of the FY-4A was consistent with ground-based measurements. The SSI
from April to September was higher than that in other months, with a peak appearing in July. The
correlation coefficient between the monthly values of the two data sources was 0.96. The diurnal
variations of the two data sources showed a “single peak” type with a peak at approximately noon
and correlation coefficient of 0.82. The monthly and diurnal variations of MBE values also
indicated that the FY-4A had the characteristics of overestimating low SSI and underestimating
relatively large SSI. In general, the SSI obtained from the FY-4A satellite and ground-based
observations showed significant differences in values, but showed systematic bias and consistent
distribution trends. Therefore, it was sufficient to analyze its impact on ozone pollution.

3.2 Relationship between FY-4A SSI and Ozone Concentrations

In the analysis of the relationship between hourly SSI obtained from the FY-4A satellite and
hourly surface ozone concentrations, Chengdu was used since more serious ozone pollution occurs
there and it also represents more developed areas in Sichuan Province. Fig. 7 shows the monthly
and diurnal variations of hourly FY-4A SSI and ozone concentrations for a 3-year (2019–2021)
period in Chengdu. The monthly variations in SSI and ozone concentrations showed similar
distribution trends, with a remarkable positive correlation. The diurnal variations of hourly SSI and
ozone concentrations were analyzed using data from April to September each year, and it was a
“single peak” type, with a peak at 14:00 BJT for SSI and at 16:00 BJT for ozone concentrations.
Accordingly, the SSI of the FY-4A satellite had a good indicative significance for the occurrence of ozone pollution. Fig. 8 shows the scatter plots and probability density of hourly ozone concentrations and FY-4A SSI from April to September each year at different lead times, including 0 hr, 1 hr, 2 hr, 3 hr, and 4 hr. The ozone concentrations showed a positive linear correlation with FY-4A SSI, and the correlation was the highest when the lead time of FY-4A SSI was 3 hr. The above analysis qualitatively indicated the important role of SSI in ozone changes, which was consistent with previous studies (Zhao et al., 2016; Yang et al., 2020a).

3.3 Impact of FY-4A SSI on the Classification of Meteorology for Ozone Pollution

According to the previous analysis, the FY-4A SSI data from 3 hours in advance were used as one of the input parameters for the BP classifier training model (No. 1) and compared with the BP classifier training model without SSI (No. 2) during the main ozone pollution periods from 2018 to 2020 in Sichuan Province. Table 2 shows the sample numbers and classification accuracy (the percentage of correctly classified samples relative to the total samples) of training data and test data for two trained BP classifiers. For the training data, the classification accuracy of both trained BP classifiers was greater than 70%. For the test data, the classification accuracy of the trained BP classifiers with SSI was greater than 70%, while the accuracy of the trained BP classifiers without SSI was less than 70%.

The classification results of the trained BP classifiers were quantitatively validated by comparison with observations of the main ozone pollution periods from 2021 to 2022 in 21 cities. The 10 cities with a relatively large number of level 3 samples were Chengdu, Zigong, Deyang, Meishan, Yibin, Luzhou, Neijiang, Leshan, Ziyang and Mianyang. Fig. 9 shows the classification accuracy of the trained BP classifiers with (Fig. 9(a)) and without (Fig. 9(b)) SSI obtained from the
FY-4A satellite. The trained BP classifier with SSI had a classification accuracy greater than 60% for all cities, with a classification accuracy greater than 70% for 20 cities and greater than 80% for 14 cities. The trained BP classifier without SSI also had a classification accuracy greater than 60% for all cities, with a classification accuracy greater than 70% for 18 cities and greater than 80% for 7 cities. Furthermore, for the 10 cities with a relatively large number of level 3 samples, the number of cities with classification accuracy exceeding 80% was 9 for the trained BP classifier with SSI and 4 for the trained BP classifier without SSI. The accuracy growth rates of the trained BP classifier with SSI compared to the classifier without SSI were also calculated in 21 cities (shown in Fig. 9(c)). Except for Liangshan, the accuracy growth rates of the other 20 cities in the study area were all positive, with 8 cities having accuracy growth rates exceeding 4%. The 4 cities with higher accuracy growth rates were Ganzi (14.45%), A’ba (13.07%), Chengdu (9.66%), and Deyang (6.51%). According to Zhao et al. (2022), there was no significant linear relationship between ozone and solar radiation when ozone reached pollution levels. Therefore, the addition of SSI could significantly improve the classification accuracy in areas that were not prone to ozone pollution. Overall, FY-4A SSI data were helpful for improving the classification performance of the trained BP classifier in the study area.

Furthermore, Fig. 10 shows the classification accuracy and accuracy growth rates (accuracy with SSI relative to accuracy without SSI ) for three levels in 21 cities. The orange and blue bars show the classification accuracy with and without SSI, respectively. The green bars show the accuracy growth rates. The accuracy growth rates of most cities were positive for level 1 and level 2, while they were 0 or negative for level 3. Specifically, the accuracy growth rates of 20 cities
(except for Liangshan) were positive for level 1, with a maximum growth rate of 14.45% in Ganzi, and the accuracy growth rates of 19 cities (except for Deyang and Panzhihua) were positive for level 2, with a maximum growth rate of 35.35% in Ziyang. Therefore, the SSI data induced a significant improvement in the classification accuracy for the samples of level 1 and level 2, further proving that ozone was closely related to solar radiation before reaching pollution levels, which was consistent with previous study by Zhao et al. (2022).

4 CONCLUSIONS

Meteorological conditions are important for ozone formation. Many studies have investigated the causal influence of major individual meteorological factors on ozone concentrations based on qualitative analysis methods. The solar radiation is a key factor affecting ozone concentrations through its direct influence on photochemical reactions and indirect influence on precursor emissions. The SSI obtained from satellites is a data source with high temporal and spatial resolutions, which is of great significance for where ground-measured solar radiation data are not available and are better than numerical modeling in terms of quality. In this study, the SSI obtained from the FY-4A satellite were verified by comparing them with ground-based observations in Sichuan Province, China. Then, the SSI were used as one of the input physical parameters to train the BP classifier based on the meteorological classification method for ozone pollution proposed by Cao et al. (2023), which can comprehensively reflect the impact of meteorological conditions on ozone pollution, and compared with the BP classifier without SSI to quantitatively analyze the influence of solar radiation on the classification performance of the trained classifiers.

The hourly SSI obtained from the FY-4A satellite showed good correlation with ground-based
observations, with correlation coefficients of 0.74, 0.74, 0.75, 0.73, and 0.71 for the whole year and in spring, summer, autumn, and winter, respectively. For the MBE verification metric, averaged over year and season, the positive values showed that the SSI obtained from the FY-4A satellite was higher than that from ground-based observations. Furthermore, the MBE scores at different SSI levels decreased with increasing SSI, which gradually changed from positive values to negative values. The SSI obtained from the FY-4A satellite had the characteristics of overestimating low SSI and underestimating relatively large SSI. Additionally, the monthly and diurnal variations of the two data sources showed significant differences in values, but systematic bias and consistent distribution trends. Therefore, the FY-4A SSI was sufficient to analyze its impact on ozone pollution.

The monthly and diurnal variations of the FY-4A SSI and surface ozone concentrations showed similar distribution trends. The monthly average values from April to September were higher than those in other months, and the daily distribution was a “single peak” type with a peak at 14:00 BJT for SSI and 16:00 BJT for ozone concentrations. The ozone concentrations had a positive linear correlation with the FY-4A SSI, and the correlation was the highest when the lead time of the FY-4A SSI was 3 hr. The SSI data of the FY-4A satellite had good indicative significance for the occurrence of ozone pollution, and they were used as one of the input parameters of the BP training model. After joining the SSI data, the number of cities with a classification accuracy exceeding 80% among the 21 cities in the study area increased from 7 to 14, with 20 cities having a positive accuracy growth rate and 8 cities having an accuracy growth rate exceeding 4%. Furthermore, the SSI data had a significant improvement in the classification accuracy of level 1
and level 2 samples. In general, the FY-4A SSI data were helpful for improving the classification performance of the trained BP classifier in the study area. This result suggests that the application of solar radiation data can help to better predict the occurrence of ozone pollution events.

Despite the results in this study are expected to provide scientific guidance for a better understanding of the impact of solar radiation on ozone pollution, the current work still has room for improvement. For instance, the relatively large bias of the FY-4A SSI may affect its application. In future work, the correction of the FY-4A SSI may be beneficial for improving its accuracy and enhancing its further application. The machine learning method might be an efficient way (Shi et al., 2023). Besides, since the study area as a whole only consider some physical parameters that are usually considered to have a significant impact on ozone concentrations, the chosen input parameters of the BP model are limited. Furthermore, the wind speed and cloud fraction should also be taken into account, as wind speed represents the diffusion environment and cloud fraction affects the absorption and scattering of incoming radiation, and the major meteorological factors affecting different regions should be identified. The last drawback is that the study area covers just Sichuan Province of China. However, as the method is general, it is possible to expand to other regions.

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Table 1. The error statistical parameters were calculated to compare the hourly SSI obtained from the FY-4A satellite and ground-based observations at the Chengdu weather station throughout the whole year and in each season in 2021.

<table>
<thead>
<tr>
<th>Time</th>
<th>n</th>
<th>R</th>
<th>P-value</th>
<th>Average value (W m⁻²)</th>
<th>Standard deviation (W m⁻²)</th>
<th>MAE (W m⁻²)</th>
<th>MBE (W m⁻²)</th>
<th>RMSE (W m⁻²)</th>
<th>rMBE</th>
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<tbody>
<tr>
<td></td>
<td>FY-4A</td>
<td>Ground observations</td>
<td>FY-4A</td>
<td>Ground observations</td>
<td>MAE (W m⁻²)</td>
<td>MBE (W m⁻²)</td>
<td>RMSE (W m⁻²)</td>
<td>rMBE</td>
<td></td>
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<td>P=0</td>
<td>540.46</td>
<td>311.45</td>
<td>166.09</td>
<td>263.28</td>
<td>257.99</td>
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<td>552.88</td>
<td>322.82</td>
<td>176.25</td>
<td>273.10</td>
<td>259.98</td>
<td>230.06</td>
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<td>Summer</td>
<td>967</td>
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<td>P&lt;0.001</td>
<td>581.54</td>
<td>368.25</td>
<td>198.12</td>
<td>298.14</td>
<td>255.90</td>
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<tr>
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<td>0.73</td>
<td>P&lt;0.001</td>
<td>515.07</td>
<td>261.38</td>
<td>125.29</td>
<td>225.53</td>
<td>275.08</td>
<td>253.70</td>
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<tr>
<td>Winter</td>
<td>642</td>
<td>0.71</td>
<td>P&lt;0.001</td>
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<td>267.21</td>
<td>113.55</td>
<td>209.91</td>
<td>239.04</td>
<td>223.24</td>
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Table 2. The BP classifier training models with and without SSI obtained from the FY-4A satellite were compared during the main ozone pollution periods from 2018 to 2020 in Sichuan Province, China. The main ozone pollution period was defined as from April to September every year and from 09:00 to 21:00 BJT every day according to the study by Cao et al. (2023).

<table>
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<th>Model number</th>
<th>Input parameters</th>
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<th>Number of neuron in each hidden layer</th>
<th>Training data</th>
<th>Test data</th>
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<td>Sample numbers</td>
<td>Classification accuracy (%)</td>
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<td>Classification accuracy (%)</td>
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<td>[7, 9]</td>
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Fig. 1. Spatial distribution of surface solar irradiance (SSI) obtained from the FY-4A satellite and the location of the Wenjiang national basic meteorological station in Chengdu, Sichuan Province, China (marked as a green spot) at 14:00 BJT on June 29, 2022.

Fig. 2. Flowchart of the impact of SSI obtained from the FY-4A satellite on the classification of meteorological conditions for ozone pollution levels based on the method proposed by Cao et al. (2023).
Fig. 3. Scatter plots and frequency distributions were created to compare the hourly SSI obtained from the FY-4A satellite and ground-based observations in 2021. The data were analyzed throughout the whole year and each season. The pink bars represent the frequency distribution of SSI. The blue dashed line represents the axis of symmetry. The green solid line represents the linear regression line of the scatter plot. The black solid lines represent the contour lines of the scattered points. Significance tests at the 0.01 level were carried out for the linear relationship between the FY-4A satellite and ground-based observations. The $p$ values of the significance tests were less than 0.001.
Fig. 4. Bar charts of the mean bias error (MBE) between the hourly SSI obtained from the FY-4A satellite and ground-based observations at different SSI levels for (a) spring, (b) summer, (c) autumn, and (d) winter.
Fig. 5. The monthly variations of SSI obtained from the FY-4A satellite and ground-based observations, and their corresponding MBE values. The correlation coefficient was calculated, and a significance test was carried out for the linear relationship at the 0.01 level. The $p$ value of the significance test was found to be less than 0.001.

Fig. 6. The diurnal variations of SSI obtained from the FY-4A satellite and ground-based observations, and their corresponding MBE values. The correlation coefficient was calculated, and a significance test was carried out for the linear relationship at the 0.01 level. The $p$ value of the significance test was found to be less than 0.01.
Fig. 7. The (a) monthly and (b) diurnal variations of the FY-4A SSI and ozone concentrations for a 3-year period (2019–2021) in Chengdu, China. The data from April to September of each year were used to generate daily distributions.

Fig. 8. Scatter plots of hourly ozone concentrations and the FY-4A SSI at different lead times, including (a) 0 hr, (b) 1 hr, (c) 2 hr, (d) 3 hr, and (e) 4 hr, from April to September for a 3-year period (2019–2021) in Chengdu, China. The colored bar indicates the probability density of the scattered points. The black dotted line indicates the fitted line. The correlation coefficient and $p$ values of the significance tests at the 0.01 level between ozone concentrations and SSI were calculated.
Fig. 9. Classification accuracy of trained BP classifiers (a) with and (b) without SSI of the FY-4A satellite were compared during the main ozone pollution periods from 2021 to 2022 in 21 cities in Sichuan Province, China. The accuracy growth rate of the trained BP classifier with SSI compared to that without SSI was also calculated in 21 cities.
Fig. 10. The classification accuracy of trained BP classifiers with and without SSI of the FY-4A satellite and the accuracy growth rates (accuracy with SSI relative to accuracy without SSI) were calculated for three levels, including (a) level 1, (b) level 2, and (c) level 3, during the main ozone pollution periods from 2021 to 2022 in 21 cities in Sichuan Province, China. The orange and blue bars show the classification accuracy of trained BP classifiers with and without SSI, respectively. The green bars show the accuracy growth rates.