



# AI-driven volcanic SO<sub>2</sub> estimates using MSG-SEVIRI and Sentinel-5P TROPOMI

Maddalena Dozzo<sup>1,2</sup> · Alessandro Aiuppa<sup>1</sup> · Giovanni Lo Bue Trisciuzzi<sup>1</sup> · Gaetana Ganci<sup>2</sup>

Received: 24 April 2026 / Accepted: 22 August 2026  
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## Abstract

Sulfur dioxide (SO<sub>2</sub>) is, after H<sub>2</sub>O and CO<sub>2</sub>, the most abundant volcanic gas released during shallow magma degassing and is readily detectable and quantifiable by remote sensing. Monitoring SO<sub>2</sub> provides key information on magma ascent rates, conduit dynamics, and eruption style and intensity, thereby supporting volcano monitoring and hazard assessment. The TROPOMI instrument onboard the low Earth Orbit Sentinel-5 Precursor delivers highly accurate and sensitive SO<sub>2</sub> retrievals but with limited temporal coverage (typically one overpass per day). In contrast, SEVIRI, onboard the geostationary MSG satellite, offers continuous high-frequency observations every 5–15 min, enabling real-time tracking of plume evolution. To further improve SO<sub>2</sub> detection capabilities, this study combines TROPOMI products with data from the MSG-SEVIRI radiometer, by transferring TROPOMI's retrieval accuracy to SEVIRI's high-temporal-resolution observations. To this purpose, a data-driven AI model was implemented to estimate SO<sub>2</sub> vertical column densities (VCDs) at SEVIRI spatial and temporal resolution, using TROPOMI observations as reference. In this study, SO<sub>2</sub> VCDs were retrieved from Sentinel-5P TROPOMI Level 2 Offline DOAS measurements using slant column densities, averaging kernels, and plume height-adapted air mass factors. A multilayer perceptron was designed with an input layer receiving all available spectral bands from SEVIRI and a single linear output neuron, corresponding to the SO<sub>2</sub> VCD measured by TROPOMI. This approach enables SEVIRI data to inherit the sensitivity of TROPOMI while preserving SEVIRI's native high-temporal-resolution and dense spatial sampling. Mount Etna (Italy), a persistently degassing open-conduit volcano, was selected as a test case. The trained network also allowed SO<sub>2</sub> retrieval from SEVIRI imagery acquired before Sentinel-5P's launch, enabling the reconstruction of long-term degassing trends. SO<sub>2</sub> fluxes were computed and quantitatively validated against ground-based monitoring data. This integrated technique provides an effective tool for rapid and reliable volcanic hazard assessment, improving current retrieval methods and enhancing early-warning capability for aviation safety and climate studies.

**Keywords** Machine learning · Mount Etna volcano · Neural networks · Sentinel-5P TROPOMI · SEVIRI · Sulfur dioxide

## Introduction

Sulfur dioxide (SO<sub>2</sub>) is constantly emitted into the atmosphere, with volcanoes representing a major source. Sulfur species play a central role in the processes through which

volcanic activity affects the environment, human and animal health, and atmospheric chemistry (Graf et al. 1997; Hansell and Oppenheimer 2004; Longo et al. 2005). This highlights the importance of monitoring volcanic activity, thus contributing to the detection of early signs of eruptions (Shinohara 2008; Oppenheimer et al. 2011, 2014; Carn et al. 2016; Kern 2025), in the perspective of mitigating the relative hazards which can involve population, but also aviation (Oppenheimer et al. 2011; Carn et al. 2017). SO<sub>2</sub> is emitted from magma at relatively shallow depths (Oppenheimer et al. 2011; Wallace and Edmonds 2011), making it one of the most effective gases for tracking volcanic activity using remote sensing methods.

Measuring volcanic SO<sub>2</sub> flux is important not only for tracking the progression of an ongoing eruption

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Editorial responsibility: F. Galetto

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✉ Gaetana Ganci  
gaetana.ganci@ingv.it

<sup>1</sup> Dipartimento di Scienze della Terra e del Mare, Università Degli Studi Di Palermo, Via Archirafi 22, 90123 Palermo, Italy

<sup>2</sup> Istituto Nazionale di Geofisica e Vulcanologia, Osservatorio Etneo, Piazza Roma 2, 95125 Catania, Italy

(Delgado-Granados et al., 2001), but also because volcanic SO<sub>2</sub> emissions can influence global climate through the formation of sulfate aerosols, which modify the Earth's radiative balance and may produce atmospheric cooling following major eruptive events (Robock, 2000; Longo et al. 2005; Hansell and Oppenheimer 2010; Fischer et al. 2019). More broadly, volcanic gas observations can also be interpreted together with petrological and geochemical information to constrain magma storage, ascent, and degassing processes and can be integrated with complementary observational datasets and atmospheric dispersion models to improve plume tracking and hazard assessment (e.g., Aiuppa et al. 2007; Burton et al. 2013; Fischer et al. 2019).

Remote sensing techniques for tracking SO<sub>2</sub> emissions can be ground-based, for example using networks of UV-DOAS instruments installed close to volcanic vents (McGonigle 2007; Salerno et al. 2009; Kern 2025); or UV camera (Mori and Burton 2006; Bluth et al. 2007), or satellite-based (Carn et al. 2017). The latter play a crucial role, as many volcanoes worldwide are not equipped with permanent ground-based monitoring networks (Loughlin et al. 2015). Furthermore, during intense volcanic activity, ground sensors may become unreliable or fail completely, especially near the vent, where high ash and aerosol concentrations can hinder plume detection (e.g., Kern et al. 2012; Boichu et al. 2015).

Satellite SO<sub>2</sub> measurements with sufficient spatial resolution to detect hundreds of SO<sub>2</sub> emission sources became possible in 2004 with the launch of the Ozone Monitoring Instrument (OMI) spectrometer aboard NASA's Aura satellite, within the Earth Observing System (EOS), which provides imagery with a spatial resolution of 13 km × 24 km at nadir (e.g., Krotkov et al. 2006; Schoeberl et al. 2006; Theys et al. 2015; Carn et al. 2016, 2017; Li et al. 2020).

The latest generation of satellite SO<sub>2</sub> sensors includes the TROPospheric Monitoring Instrument (TROPOMI) hyperspectral imaging spectrometer, operating aboard the Sentinel-5 Precursor (S5P) satellite launched in 2017 (Veefkind et al. 2012). TROPOMI currently provides the highest spatial resolution among similar instruments (5.5 km × 3.5 km at nadir) and delivers daily, near-global measurements of atmospheric SO<sub>2</sub> (e.g., Theys et al. 2019; Fioletov et al., 2020). Other infrared satellite sensors, such as IASI (e.g., Clarisse et al. 2008, 2014; Bauduin et al. 2016) and AIRS (Prata and Bernardo 2007), also provide valuable global SO<sub>2</sub> observations with typically two measurements per day (daytime and nighttime overpasses), although at coarser spatial resolution compared to TROPOMI.

Although low Earth orbit (LEO) sensors are among the most valuable instruments for volcanic SO<sub>2</sub> monitoring, their revisit time remains limited. Moreover, the restriction to daylight measurements impacts their capability to capture rapid variations in SO<sub>2</sub> emissions, as discussed previously (Corradini et al. 2021). In some cases the large swath width of sensors such as

TROPOMI allows a substantial portion of a volcanic plume to be captured within a single overpass, thus preserving indirect information on plume evolution, but the long revisit times could limit effective risk mitigation, which instead requires near-real-time monitoring (e.g., Grandin et al. 2024; Dozzo et al. 2025). Such high-frequency monitoring depends strongly on the high temporal resolution uniquely offered by geostationary (GEO) platforms, enabling timely detection and near-continuous tracking of rapidly evolving situations (Mota et al. 2024).

A range of geostationary multispectral satellite instruments is currently used for the detection, near-real-time observation and quantification of volcanic SO<sub>2</sub>, with SEVIRI onboard the European Meteosat Second-Generation (MSG) representing one example (Gauthier et al. 2016; Corradini et al. 2020). Its effectiveness is largely attributed to the 8.7-μm channel, which is particularly sensitive to volcanic SO<sub>2</sub> due to its strong and characteristic absorption feature (Prata et al., 2007; Prata and Bernardo 2007; Corradini et al. 2009, 2021).

The synergy of GEO and LEO instruments to improve the temporal characterization of volcanic SO<sub>2</sub> plumes has been recently explored by Liu et al. 2026 during the 2024 Kanlaon eruption. The authors demonstrate the strong potential of multisatellite fusion for plume tracking, nighttime monitoring, and mass-loading reconstruction.

In this study, we combine S5P-TROPOMI and MSG-SEVIRI data to obtain accurate SO<sub>2</sub> values, leveraging the high measurement accuracy of the first sensor together with the higher spatial resolution (approximately 3 km × 3 km) and revisit times (15 min, or 5 min in rapid scan mode) of SEVIRI.

In this regard, a multilayer perceptron neural network was trained using the first 11 SEVIRI spectral bands, spanning the visible, near-infrared, and thermal infrared regions (approximately 0.6–13.4 μm), including the 8.7-μm channel that is particularly sensitive to volcanic SO<sub>2</sub> absorption. The use of this multispectral set allows the model to exploit complementary information related to plume thermal contrast, atmospheric water vapor and ash/cloud interference. This approach also enables the quantification of sulfur dioxide for periods preceding the launch of TROPOMI, thereby providing measurements for those years with unprecedented accuracy and spatial and temporal resolution (Theys et al. 2019).

Neural Networks (NN) have been successfully applied in several applications targeting the estimation of atmospheric constituents (e.g., Del Frate et al. 2002; Di Noia et al. 2013) and in the field of volcanic emissions, NN-based algorithms have been developed and applied for instance for the detection and retrieval of volcanic ash from MODIS observations (Picchiani et al. 2011). However, quantitative SO<sub>2</sub> retrievals from MODIS are challenging when ash and SO<sub>2</sub> are co-emitted, because both species affect similar thermal infrared wavelengths, making their spectral signatures difficult to separate and increasing retrieval uncertainties in optically thick plumes (Corradini et al. 2009).

After the launch of TROPOMI, numerous studies have also exploited Artificial Intelligence for the automatic identification of sulfur dioxide emissions (e.g., De Santis et al. 2021; Dozzo et al. 2025, 2026) and quantification of total column sulfur dioxide (Hedelt et al. 2019), besides the identification of the volcanic source from plume shape in regions where multiple volcanoes are present (Markus et al. 2023).

In this work, machine learning techniques have been applied, creating products with unprecedented spatial and high-temporal-resolution that enable the identification and quantification of sulfur dioxide. The accuracy of the SO<sub>2</sub> flux estimates is evaluated through comparison with ground-based data and with values reported in the literature, with the advantage of identifying the volcanic plume even in the years preceding the launch of TROPOMI.

## Materials and methods

### Data

#### TROPOMI

Sentinel-5P, launched in 2017, is a low Earth orbit satellite that follows a quasi-polar, sun-synchronous path at an altitude of 824 km, allowing it to provide daily near-global observations of the Earth's atmosphere. Its sensor covers a swath width of 2600 km, with an orbital cycle of 16 days composed of about 227 individual orbits, averaging 14 orbits per day. Onboard, the TROPOspheric Monitoring Instrument (TROPOMI) sensor records measurements in four spectral ranges (ultraviolet, visible, near-infrared, and short-wave infrared), allowing the detection of sulfur dioxide (Theys et al. 2017), as well as multiple other gases such as ozone (O<sub>3</sub>) (Veefkind et al. 2012), nitrogen dioxide (NO<sub>2</sub>) (van Geffen et al. 2020), carbon monoxide (CO) (Borsdorff et al. 2018), methane (CH<sub>4</sub>) (Hu et al. 2018), and formaldehyde (HCHO) (De Smedt et al. 2018), along with aerosol characterization (Veefkind et al. 2012). Spatial resolution at nadir was initially 3.5 km (across-track) by 7 km (along-track) until August 2019, after which along-track resolution improved to 5.5 km. The satellite uses passive remote sensing, capturing sunlight that is reflected by, or emitted from, the Earth's surface and atmosphere at the top of atmosphere to derive these measurements.

In this work, we used the standard Level 2 (L2) DOAS Offline SO<sub>2</sub> TROPOMI data in netCDF-4 format, made available via the European Space Agency Copernicus Open Access Hub in the Sentinel-5P Pre-Operations Hub (<https://dataspace.copernicus.eu/explore-data/data-collections/sentinel-data/sentinel-5p>; accessed on 10 April 2026). L2 products are derived from raw Level 0 data, which are first calibrated and georeferenced to produce Level 1 data, consisting of radiance and irradiance measurements. Then, SO<sub>2</sub> concentrations in the

L2 products are retrieved from the ultraviolet (UV) spectrum using algorithms based on DOAS, applying a combination of three spectral fitting windows: 312 to 326, 325–335, or 360–390 nm (Theys et al. 2017). More recently, the Covariance-Based retrieval algorithm (COBRA) (Theys et al., 2021) has been developed as an alternative to standard DOAS.

#### SEVIRI

The Meteosat Second Generation (MSG) series represents Europe's main operational weather satellites. The first spacecraft, MSG-1 (Meteosat-8), was launched on 28 August 2002 and entered full service on 21 January 2004. Operating in geostationary orbit at an altitude of about 35,786 km (orbital radius ~42,164 km), MSG completes one revolution around the Earth every 24 h, with its nadir located near 3° W over the Equator.

The SEVIRI (Spinning Enhanced Visible and Infrared Imager) instrument aboard the Meteosat Second Generation (MSG) satellites has 12 spectral channels spanning the visible, near-infrared and thermal-infrared regions. In volcanic monitoring, SEVIRI is primarily exploited through its infrared and thermal-infrared channels to characterize plume properties such as water vapour content, ash loading and plume-top temperature. The channels in the 6.2–7.3 µm range are commonly used for water-vapour analysis, while those centred around 8.7, 10.8 and 12.0 µm are widely used for volcanic ash and plume detection. The 8.7 µm channel is additionally sensitive to SO<sub>2</sub> absorption; however, since SEVIRI lacks an ultraviolet channel around 310 nm, it does not allow for direct SO<sub>2</sub> retrieval. In this study, the NN was trained using the first 11 channels centered at 0.6, 0.8, 1.6, 3.9, 6.2, 7.3, 8.7, 9.7, 10.8, 12.0, and 13.4 µm. These channels provide a spatial resolution of 3 km at the subsatellite point, determined by the SEVIRI detector architecture, whereas the high-resolution visible (HRV) channel achieves 1-km<sup>2</sup> resolution. VIS/NIR channels (0.6, 0.8, and 1.6 µm) contribute only in daylight, whereas the thermal-IR channels are effective also at night. SEVIRI acquires Full Disk imagery every 15 min in the standard 'Prime' service (currently performed by Meteosat-10), covering Europe, the Atlantic, Africa, and all regions with a satellite elevation greater than 10°. In addition, Meteosat-11 operates in Rapid Scanning Service (RSS) mode, imaging the northern third of the disk every 5 min, while Meteosat-9 provides Indian Ocean Data Coverage from its position at 45° E.

Where available, RSS data were considered, downloading files from the EUMETSAT User Portal (<https://data.eumetsat.int/data/map/EO:EUM:DAT:MSG:MSG15-RSS>; accessed on 10 April 2026), subsequently integrating the dataset with those acquired every 15 min (<https://data.eumetsat.int/data/map/EO:EUM:DAT:MSG:HRSEVIRI>; accessed on 10 April 2026).

SO<sub>2</sub> retrievals from SEVIRI can be affected by limited sensitivity to low concentrations, plume height dependency and reduced quantitative accuracy compared to hyperspectral

LEO sensors, together with the fact that in situations with optically thick volcanic plumes, SEVIRI is generally less accurate than TROPOMI.

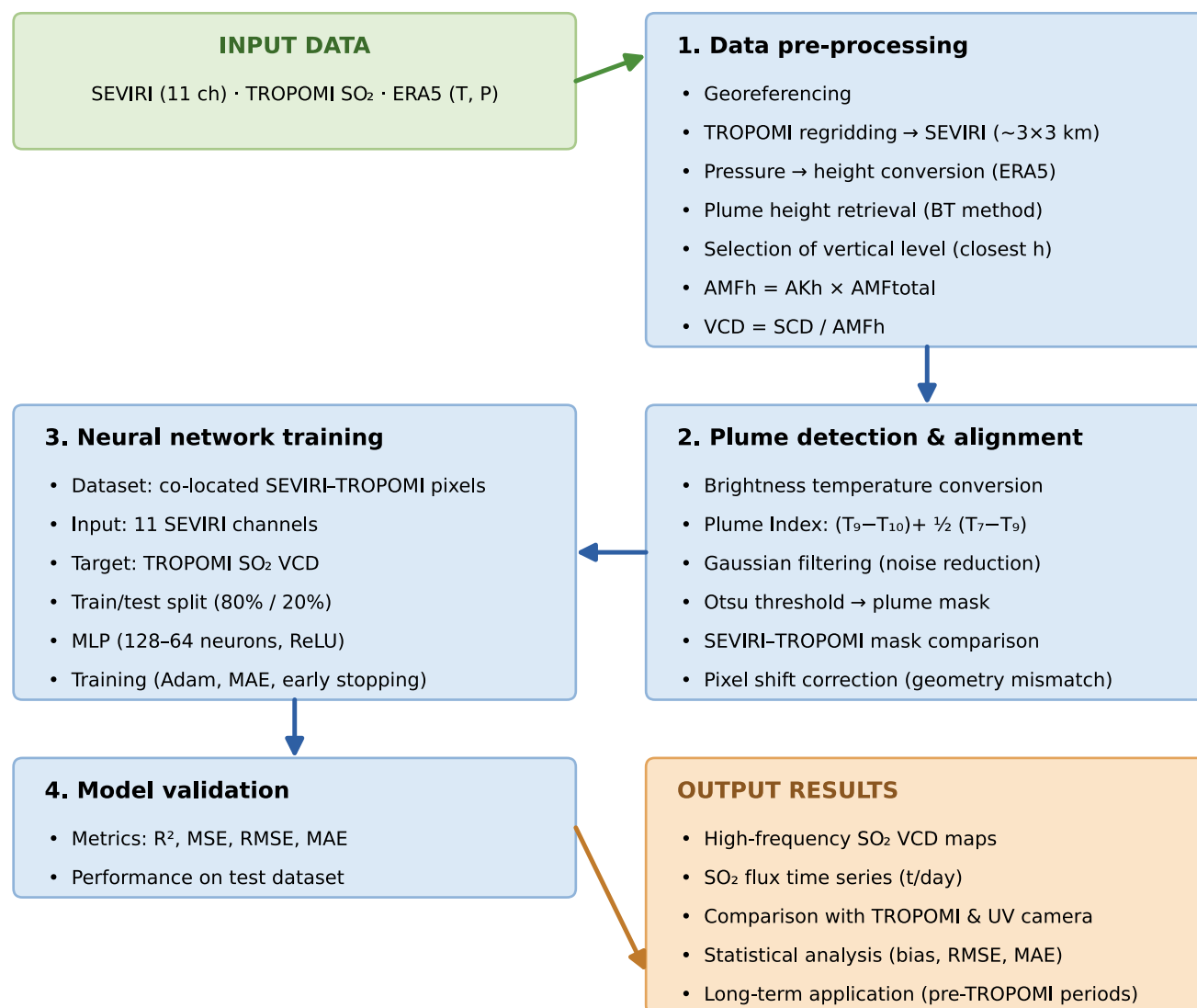
### Algorithm workflow

In Fig. 1, the flowchart used in this study is shown, illustrating the input data, the steps performed, and the results obtained.

### Data preprocessing

The first step in data preprocessing involved regridding the TROPOMI data onto the SEVIRI grid. This was achieved by first georeferencing the images to the geographic coordinates of the study area, resulting in an effective spatial resolution of approximately  $3 \times 3 \text{ km}^2$ .

Once the two datasets were placed on the same spatial grid, an essential initial step in the calculation of  $\text{SO}_2$  flux



**Fig. 1** Flowchart with the steps followed in this work. 1) Input data (green parallelograms): MSG-SEVIRI (11 channels), Sentinel-5P TROPOMI SO<sub>2</sub> Level 2 Offline DOAS product and ERA5 temperature/pressure profiles; 2) main processing steps (light blue rectangles): during the preprocessing, TROPOMI is regridded to the SEVIRI grid (although the native TROPOMI geometry remains available in the source files), while a pixel-shift correction, described below, is applied in SEVIRI pixel space after regridding. Plume height is retrieved from SEVIRI (exploiting the brightness temperature method (BT)) and used to select the closest vertical level h in the averaging kernel (AK), a height-adapted air mass factor

is computed as  $\text{AMFh} = \text{AKh} \times \text{AMFtotal}$ , and the vertical column density (in  $\text{mol/m}^2$ ) as  $\text{VCD} = \text{SCD} / \text{AMFh}$  (where VCD is the vertical column density and SCD is the slant column density, both in  $\text{mol/m}^2$ ). A SEVIRI plume index is computed from brightness temperatures, to improve the discrimination of the plume from background, while limiting contamination from water clouds. The height-adapted VCDs are used as training targets for the multilayer perceptron (MLP) that maps SEVIRI radiances to SO<sub>2</sub> VCD; 3) output data (orange parallelogram): here are included high-frequency SO<sub>2</sub> VCD maps and SO<sub>2</sub> flux time series (t/d) and the comparison with TROPOMI and UV camera data

was the estimation of plume height, which is required to retrieve the Vertical Column Density (VCD) at the correct altitude. Plume height was estimated from SEVIRI, using the consolidated brightness temperature method (Prata and Grant 2001; Corradini et al. 2018). For each product, the atmospheric temperature profile was acquired from ECMWF Reanalysis v5 (ERA5) long-term reference data (<https://cds.climate.copernicus.eu/>; accessed on 10 April 2026), which have a spatial resolution of about  $27 \times 27 \text{ km}^2$ , at the time closest to that of the SEVIRI image under analysis, considering 6-hourly profiles (00, 06, 12, 18 UTC) (Molina et al. 2021; Ji et al. 2025). ERA5 pressure levels were converted to geometric height using the hypsometric relation through layer-wise hydrostatic integration, enabling the association between SEVIRI brightness temperature and plume altitude.

We started with the slant column density (SCD) values provided in the product, and then converted them to VCDs, using the averaging kernel (AK) information provided in the dataset. This parameter is defined as the derivative of the retrieved vertical column with respect to the partial column profile (Jacobian), and it describes how measurement sensitivity varies with altitude (Eskes and Boersma 2003). Atmospheric pressure profiles from the dataset were first converted to height above ground using the barometric formula with a scale height of 8 km. This provided the vertical coordinate in meters for each retrieval layer, allowing the identification of the level closest to the previously retrieved plume altitude.

The air mass factor (AMF), which accounts for variations in measurement sensitivity caused by clouds, aerosols, surface reflectivity, and the assumed  $\text{SO}_2$  vertical distribution profiles (Theys et al. 2017), was recalculated following Eq. (15) in Eskes and Boersma (2003). Specifically, the AMF corresponding to the plume height (AMF<sub>h</sub>) was obtained by multiplying the averaging kernel (AK) value at the vertical level closest to the previously retrieved altitude by the total AMF provided in the product, following Eq. (1):

$$AMF_h = AK_h \times AMF_{total} \quad (1)$$

where  $AK_h$  is the averaging kernel at the retrieved height  $h$  and  $AMF_{total}$  is the total air mass factor computed using the a priori profile. The AMF<sub>h</sub> was then used to compute the vertical column density for each pixel, following Eq. (2):

$$VCD = \frac{SCD}{AMF_h} \quad (2)$$

Through the recalculation of the VCD from SCD using the AK information and an AMF adapted to the plume height retrieved from SEVIRI at each instant, end-to-end physical consistency is insured: the  $\text{SO}_2$  column is referenced to the same altitude used to select winds for flux calculation. This approach reduces biases linked to a mismatched vertical sensitivity in the AMF and stabilizes the learning target for the neural network across instants with different plume heights.

Pixels with AMF<sub>h</sub> values less than 0.5 were filtered out. Indeed, very low AMF values are typically associated with large cloud radiance fractions and could for example indicate an unfavorable viewing geometry, a low plume altitude, or cloud/aerosol shielding, resulting in low measurement sensitivity and unreliable column estimates.

The neural network was trained by first selecting scenes where SEVIRI and TROPOMI overpasses occurred at approximately the same time, to maximize training accuracy. For these scenes, the plume pixels were identified and isolated in both products using a simple threshold, which was selected manually and differed for the various dates. Where the volcanic cloud was not clearly distinguishable in the SEVIRI images due to similar radiance values produced, for example, by meteorological clouds and atmospheric water vapor (Corradini et al., 2008a), plume identification was carried out using an object detection approach applied to the thermal infrared channels, starting by drawing a rectangular bounding box around the plume. In detail, the radiances from SEVIRI channels 7 (IR 8.7  $\mu\text{m}$ ), 9 (IR 10.8  $\mu\text{m}$ ), and 10 (IR 12.0  $\mu\text{m}$ ) were first converted into brightness temperatures, then a plume index was computed for each pixel as follows:

$$Plume\ index(x, y) = (T_9(x, y) - T_{10}(x, y)) + \frac{1}{2} (T_7(x, y) - T_9(x, y)) \quad (3)$$

where the first difference represents the brightness temperature difference between channels 9 and 10, sensitive to volcanic ash absorption (Prata, 1989a, b; Prata and Kerkmann, 2007), and the second difference, made between channels 7 and 9, is sensitive to  $\text{SO}_2$  plume and water clouds, in order to reduce the influence of the background. The 1/2 factor was chosen empirically, combining the two brightness-temperature differences as  $(T_9 - T_{10}) + \alpha (T_7 - T_9)$  and testing  $\alpha$  from 0 to 1 in steps of 0.1. For each  $\alpha$ , the resulting plume mask was compared with manual plume outlines and the value that best separated the plume from the background was selected.

To reduce noise and improve spatial coherence, the resulting index was smoothed by an isotropic Gaussian filter with standard deviation  $\sigma = 1$  pixel (3 km at nadir), implemented by convolution centered on each pixel. Subsequently, Otsu's automatic thresholding method (Otsu, 1979) was applied to determine an optimal data-driven threshold, resulting in a binary mask that separates plume pixels from the background. Although the Otsu-based segmentation performance may be affected under low plume-to-background contrast or in the presence of clouds and ash, any resulting inaccuracies are limited to the sample selection stage and do not directly affect the final  $\text{SO}_2$  VCD retrieval.

An example of this procedure is illustrated in Fig. 2, where the left image is an example of a SEVIRI acquisition where the volcanic cloud was not clearly distinguishable from the background, while the image to the right shows the retrieved plume after its detection using the methodology outlined above.

The SEVIRI and TROPOMI retrieved plumes were then compared spatially. When necessary, a fully automated translation was applied in SEVIRI image coordinates to maximize the overlap between the two plume masks. This adjustment accounts for the fact that TROPOMI measurements are acquired from a low Earth orbit platform with an oblique viewing geometry, depending on the satellite's position along its orbit. As a result, the observed plume can appear displaced relative to SEVIRI's geostationary view. Applying this shift hence enables a more accurate pixel-by-pixel comparison between the two datasets. Operationally, after regridding the TROPOMI VCD field to the SEVIRI grid, binary plume masks for both sensors were built. Then, a pure translation of the regridded TROPOMI field in SEVIRI pixel space was estimated by maximizing the normalized cross-correlation between the two binary masks. The correlation peak yields an integer-pixel offset, which we applied to the TROPOMI field. Finally, the centroids of the shifted TROPOMI and SEVIRI masks were computed in map coordinates to quantify any residual offset and a final nearest-pixel correction was applied, updating the TROPOMI raster georeferencing accordingly.

## Neural network

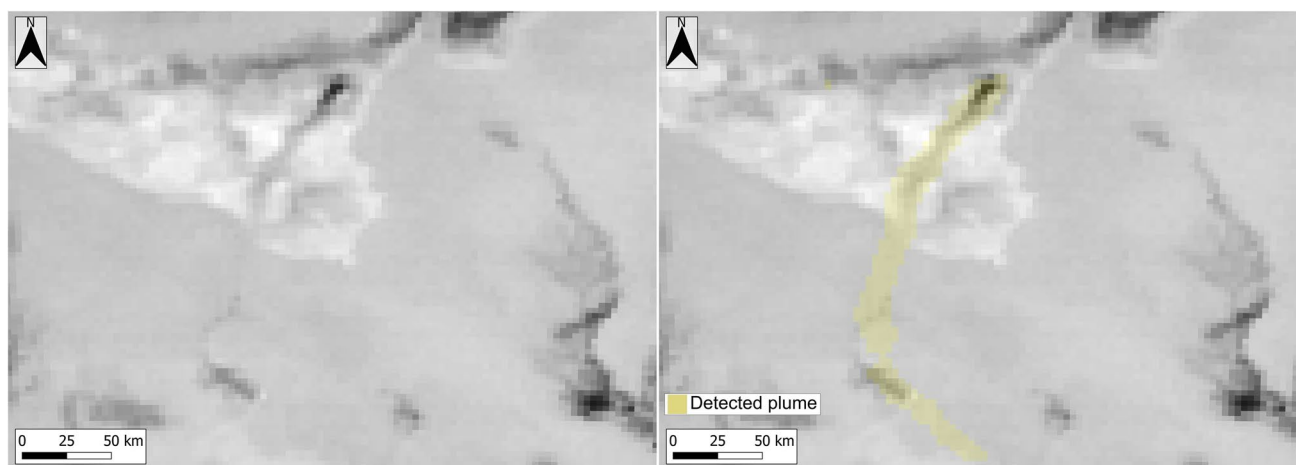
A multilayer perceptron (MLP) neural network was trained using georeferenced SEVIRI data and TROPOMI products, co-aligned and resampled onto the same spatial reference and grid.

The eleven SEVIRI channels were used as predictor variables, while the single-band TROPOMI height-adapted SO<sub>2</sub> VCD product was exploited as the target for network training.

Before the training, all pixels with missing or invalid (nonfinite) values in both datasets were excluded to ensure numerical stability. Since hidden fill values may also occur, we explicitly masked them to prevent propagation into the training. The final dataset was compiled from 12 distinct acquisition dates: 24 December 2018, 27 December 2018, 28 December 2018, 19 February 2021, 28 February 2021, 4 March 2021, 12 March 2021, July 14, 2021, August 9, 2021, September 21, 2021, October 23, 2021, and June 2, 2025. The dataset was then split into a training set (80% of the total pixels) and a test set (20% of the total pixels). This train–test split was chosen a priori to maximize training samples while keeping a holdout portion for testing.

The MLP is a type of artificial neural network characterized by a layered architecture that includes an input layer, an output layer, and one or more intermediate hidden layers each composed of neurons or nodes (Roosta et al. 2023). The network's primary goal is to reduce prediction error by iteratively adjusting the weights of the connections between nodes, guided by the difference between the predicted outputs and the true values. Residuals were computed in linear physical units (mol/m<sup>2</sup>) as  $r = y_{\text{true}} - y_{\text{pred}}$ . No logarithmic transformation was applied to either the target values or the residuals, thereby preserving the physical magnitude of the retrieval errors. Model optimization was performed using a robust L1 loss (MAE), while both MAE and RMSE were used to evaluate model performance.

The network was implemented in Keras, a high-level deep-learning library built on top of TensorFlow, which allows users to easily create neural networks by combining different layers. The usual workflow consists of defining the



**Fig. 2** Left: SEVIRI acquisition of 27 December 2018 on Mt. Etna (Italy); right: the same acquisition with the detected SO<sub>2</sub> plume represented in yellow. For display purposes, the maps are shown as zoomed subsets of the full analysis domain

model, configuring it with a training method and loss function, training it on data, and then evaluating its performance or using it for predictions.

The architecture of the NN is shown in Fig. 3. It consists of an input layer corresponding to the number of SEVIRI channels considered, with each SEVIRI pixel represented by an 11-element feature vector. This is followed by two fully connected hidden layers with 128 and 64 units, respectively, using the rectified linear unit (ReLU) activation function. The final output layer consists of a single neuron that provides the predicted  $\text{SO}_2$  VCD ( $\text{mol/m}^2$ ) value for each pixel. The 128–64 configuration was selected after testing a small grid of candidate architectures (i.e.,  $\{64, 128, 256\} \times \{32, 64, 128\}$ ), as it provided the lowest validation MAE (approximately 2% lower than the other configurations) under early stopping while showing no evidence of overfitting. Moreover, the model performance was not significantly affected by nearby configurations.

This architecture allows the MLP to learn a non-linear relationship between the SEVIRI radiances and the  $\text{SO}_2$  column amount. The retrieval can therefore be written as:

$$\text{VCD}_{\text{SO}_2}(x, y) = f[R_i(x, y)] \quad (4)$$

where  $R_i(x, y)$  represents the radiance measured in the SEVIRI channel  $i$ , with  $i = 1, \dots, 11$ .

Model training was conducted with a maximum of 200 epochs, where an epoch corresponds to one complete pass through the entire training dataset. The value of 200 was selected as an upper limit to ensure sufficient iterations for convergence when required. In practice, training was controlled by an early-stopping criterion, so the optimization terminated automatically once the validation error no longer improved, preventing unnecessary iterations and reducing the risk of overfitting.

A batch size of 32 was adopted, meaning that the model processed 32 training samples (i.e., individual pixel-based input–target pairs) at a time before updating its internal parameters. This value represents a compromise between computational efficiency and stable optimization during training.

Model performance was evaluated on the held-out test set using different statistical indicators, including the coefficient of determination ( $R^2$ ), the mean squared error (MSE), the root mean squared error (RMSE), and the mean absolute error (MAE), which are formulated as follows:

$$R^2 = 1 - \frac{\left[ \sum (y_i - \hat{y}_i)^2 \right]}{\left[ \sum (y_i - \bar{y})^2 \right]} \quad (5)$$

$$\text{MSE} = \left( \frac{1}{n} \right) \times \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

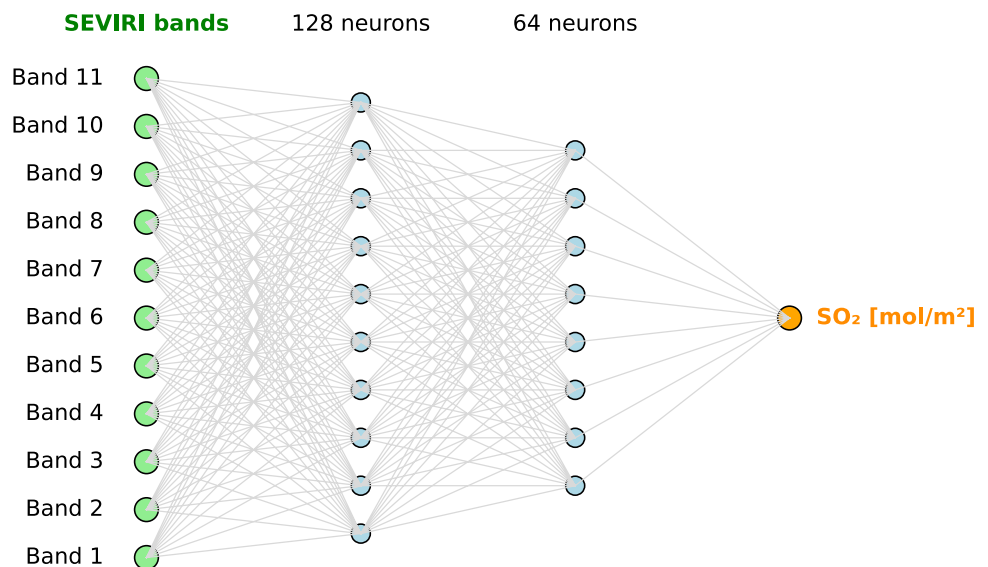
$$\text{RMSE} = \sqrt{\left( \frac{1}{n} \right) \times \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (7)$$

$$\text{MAE} = \left( \frac{1}{n} \right) \times \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

where  $y_i$  = observed value;  $\hat{y}_i$  = predicted value;  $\bar{y}$  = mean of the observed values;  $\Sigma$  = summation for  $i = 1, \dots, n$ ; and  $n$  = number of samples in the test set.

Network weights were optimized using the Adam algorithm (Kingma and Ba 2014; Xu et al. 2015; Goodfellow et al. 2016; Isola et al. 2017) to minimize the MAE between predicted and observed values. Early stopping was applied by monitoring the validation loss, stopping the training when no improvement

**Fig. 3** Multilayer perceptron neural network architecture used in this study. The network is composed of an input layer in green, represented by all the SEVIRI spectral bands, two hidden layers (composed of 128 and 64 neurons) and an output (in orange), providing the  $\text{SO}_2$  VCD values in  $\text{mol/m}^2$



was observed for a predefined number of epochs and restoring the model weights corresponding to the best validation performance. During training, no significant divergence between training and validation errors was observed, indicating that the selected architecture did not lead to substantial overfitting.

After training, the saved MLP neural network was applied to all SEVIRI images available for each of the 12 analyzed dates. For each pixel, the 11 SEVIRI spectral measurements were provided as input to the network, which predicted one SO<sub>2</sub> vertical column density value. Repeating this operation for all pixels in each image produced SO<sub>2</sub> VCD maps at SEVIRI temporal resolution, i.e., every 5 min when RSS data were available, or every 15 min otherwise.

Sulfur dioxide emission fluxes were computed from the predicted volcanic clouds using the widely used traverse method (Urai, 2004; Pugnaghi et al., 2006; Campion et al., 2010; Merucci et al., 2011; Theys et al., 2019). Before the computation of the flux, the background SO<sub>2</sub> level was estimated as the median (e.g., Rousseeuw and Leroy 1987) of all finite pixels with positive VCD values for each image, under the assumption that most of the scene represents a plume-free atmosphere. The background-corrected VCD field was obtained by subtracting this value from the original VCD, and negative residuals were set to zero.

Plume pixels were then identified using an adaptive threshold based on scene statistics, defined as the median SO<sub>2</sub> VCD of the finite positive pixels in the image plus two standard deviations computed from the same pixel set. This choice was adopted as a compromise between excluding weak plume margins and including isolated noisy pixels.

The cross-plume transect was automatically defined based on the detected plume orientation. Plume heights retrieved from SEVIRI were used to select the corresponding wind speed, computed from zonal and meridional wind components and then used in the flux calculation.

To assess the practical benefit of the height-adaptive retrieval, the MLP NN was retrained using the TROPOMI COBRA SO<sub>2</sub> total column products (Theys et al. 2021) (<https://dataspace.copernicus.eu/>, accessed 10 April 2026). The resulting SO<sub>2</sub> fluxes were then compared with those obtained using the proposed retrieval approach, thereby quantifying the influence of the customized VCD on the final flux estimates.

### Case study: Mt. Etna 2015–2025

Etna volcano was selected as a case study in view of its persistent degassing, sustained by passive gas release from shallow convecting magma (Allard 1997). This degassing is commonly accompanied by mild intracrater Strombolian activity. Periodically, such activity is interrupted by effusive eruptions (Branca and Del Carlo 2004, 2005; Andronico and Lodato 2005; Branca et al. 2011) and, more rarely, by intense

paroxysmal explosive events (Andronico et al. 2021). Etna is extensively monitored using a well-developed ground-based network run by INGV-OE (Salerno et al. 2009; Scollo et al. 2009).

While applying the above-described algorithm to Etna, we selected a geographical mask to restrict the analysis to a specific bounding box (approximately 12–24°E, 31–41°N), ensuring complete coverage of the volcanic plume. Images chosen for the training phase correspond to measurement days concentrating in periods of intense degassing or eruptive episodes, which allowed the plume to be clearly identified even in SEVIRI imagery.

As detailed in the Material and Methods section, the 2021 training subset consists of 19 February, 28 February, 4 March, 12 March, 14 July, 9 August, 21 September, and 23 October 2021. These dates were selected because they span a range of eruptive and degassing conditions, including both sustained passive emissions and paroxysmal episodes, and therefore provide SO<sub>2</sub> plumes with different intensities, heights, and dispersal patterns. In particular, the February–October 2021 period at Mt. Etna was characterized by frequent explosive activity at the South-East Crater (Marchese et al. 2021; Calvari and Nunnari 2022; Aiuppa et al. 2023; Ganci et al. 2023), often producing well-developed plumes that were clearly detectable in both TROPOMI and SEVIRI imagery. These conditions made 2021 especially suitable for training and evaluating the MLP, because they allowed us to test the ability of the method to reconstruct high-temporal-resolution SO<sub>2</sub> VCD maps and flux time series over a broad range of plume conditions.

The training dataset also includes observational days encompassing the major eruptive episode of 24–27 December 2018, referred to as the “Christmas eruption” (Cannavò et al., 2019; Borzi et al. 2020; Calvari et al. 2020). After roughly 15 months of quiescence following the February–April 2017 eruption, mild Strombolian activity and small lava flows reappeared at Bocca Nuova (BN) and the North-East Crater (NEC) in July 2018, culminating in a late-August eruption at the New South-East Crater (NSEC). On the morning of 24 December 2018, after weeks of minor Strombolian explosions and intermittent ash emissions, volcanic activity sharply increased.

A seismic swarm of thousands of shallow quakes (0–3 km depth) (Alparone et al., 2020; Giampiccolo et al., 2020) preceded the opening of a ~3 km-long fissure on Etna’s southeastern flank, from ~3000 m down to ~2400 m a.s.l., along a preexisting volcano-tectonic structure (Bonforte et al., 2019). Multiple vents produced intense Strombolian explosions and lava fountains, generating lava flows into the Valle del Bove, while summit craters generated an ash plume rising to 8–9 km a.s.l. and drifting southeastward (Calvari et al., 2020; Corradini et al., 2020). Activity diminished by 25 December and lava effusion ended on 27 December.

The 2nd of June 2025 was also considered, during which the Southeast Crater produced a paroxysmal eruption. Strombolian activity began at 01:52 UTC, preceded by a weak thermal anomaly detected at 23:50 UTC on the 1st of June. Eruption build-up caused activity transitioned into a lava fountain at 08:05 UTC that generated a dense eruptive plume that reached 11 km a.s.l from 08:37 UTC. Lava overflows occurred from the southern (02:40 UTC) and eastern (03:19 UTC) flanks, followed by the opening of an eruptive fissure on the northeastern flank at 08:48 UTC. Lava fountain activity waned after 10:00 UTC, ceasing by 10:45 UTC. The eruptive episode ended at ~03:00 UTC on June 3 ([www.ct.ingv.it](http://www.ct.ingv.it); accessed 10 April 2026).

For these events, eruptive plume height information was also made available from the Volcano Observatory Notices for Aviation (VONA) bulletin (Corradini et al. 2018) issued by Istituto Nazionale di Geofisica e Vulcanologia—Osservatorio Etneo (INGV-OE) ([www.ct.ingv.it/index.php/monitoraggio-e-sorveglianza/prodotti-del-monitoraggio/comunicati-vona](http://www.ct.ingv.it/index.php/monitoraggio-e-sorveglianza/prodotti-del-monitoraggio/comunicati-vona), accessed on 10 April 2026) at different times, as well as in the literature (e.g., Corradini et al. 2020), allowing us to confirm the values obtained from our own plume height calculations performed in the initial part of the study.

As periods preceding the launch of TROPOMI, we considered some eruptive events that occurred in 2015 and 2016.

In 2015, Etna underwent a remarkable eruptive phase that intensified in the second half of the year with the reactivation of the Voragine crater (VOR), inactive for more than a decade (Vulpiani et al. 2016; Corsaro et al. 2017; Pompilio et al. 2017). Following months of intermittent Strombolian eruptions (Corsaro et al. 2017), activity escalated rapidly in late November, culminating between 3 and 5 December in an exceptional paroxysmal sequence, with four powerful, short-lived (~47–97 min) lava fountain episodes occurring within less than 38 h. These events produced eruptive columns rising up to 14–15 km above sea level, widespread tephra fallout, and fountain-fed rheomorphic lava that filled both the VOR and BN craters (Vulpiani et al. 2016; Bonaccorso and Calvari 2017; Corsaro et al. 2017).

Immediately after the last paroxysmal episode at VOR, during the early hours of 6 December, eruptive activity shifted to the NSEC. This phase was characterized by persistent Strombolian and effusive activity that lasted approximately 48 h. Between 6 and 9 December, the vent produced continuous Strombolian explosions and fed multiple lava flows, directed mainly toward the Valle del Bove. The initial lava streams were well-fed and incandescent, occasionally accompanied by modest ash fallout, and remained confined within the depression (Corsaro et al. 2017). During 7 and 8 December, effusive activity persisted without significant variation, maintaining steady lava output from

additional secondary vents on the northeastern and eastern flanks of NSEC, which produced flows toward the Valle del Leone and further into the Valle del Bove (Corsaro et al. 2017). From 10 December onward, ash emissions gradually decreased, and by mid-month all visible volcanic activity had ceased, marking the end of the eruptive sequence (Corsaro et al. 2017).

In early 2016, Mount Etna's activity remained mild, with sporadic ash emissions from the NSEC and passive degassing at the NEC.

A major escalation occurred in mid-May. On 16 May, strombolian activity resumed at both NSEC and NEC, intensifying at NEC the following day (Cannata et al. 2018; Edwards et al. 2018; Marchese et al. 2018) and culminating on 18 May in a lava fountain at the VOR crater. This event represents the beginning of a short paroxysmal sequence lasting until 25 May, during which two additional lava fountains (19 and 21 May) and sustained strombolian and effusive activity (24–25 May) took place. Lava flows from summit fissures and crater overflows formed an extensive lava field reaching up to 3 km downslope.

## Results

When evaluated across all date configurations, the multilayer perceptron model trained on 11 SEVIRI spectral bands exhibited stable performance, with  $R^2$  values generally around 0.8, indicating that approximately 80% of the variance in the observed  $\text{SO}_2$  VCD was captured by the predictions. Among the analyzed dates, the highest  $R^2$  value (0.86) was obtained for 28 February 2021, whereas the lowest  $R^2$  value (0.75) was found for 14 July 2021. This date-to-date variability is plausibly related to differences in plume compactness, signal strength, radiometric contrast, and the degree of cloud/ash interference or SEVIRI–TROPOMI mismatch. In this context, the intrinsic limitations of the problem refer to observational and physical factors, including differences in sensor characteristics, spatial and temporal mismatch between SEVIRI and TROPOMI observations, the dependence of TROPOMI sensitivity on plume height and the difficulty of separating weak  $\text{SO}_2$  signals from the effects of meteorological clouds, ash, and atmospheric water vapor in multispectral SEVIRI observations. The MSE remained on the order of  $10^{-6} \text{ mol}^2/\text{m}^4$ , corresponding to RMSE values around  $10^{-3} \text{ mol}/\text{m}^2$  and MAE values on the order of  $10^{-4} \text{ mol}/\text{m}^2$ . These metrics quantify the pixel-wise agreement between the AI-predicted  $\text{SO}_2$  VCD and the TROPOMI-based reference field and are therefore expressed in physical column units. Their effect on the final  $\text{SO}_2$  flux estimates is indirect, thus the uncertainty associated with the

satellite-derived fluxes is discussed separately below and reported in relative (%) terms.

These error magnitudes demonstrate the model's capability to reproduce the observed  $\text{SO}_2$  VCD with high accuracy. The combination of high  $R^2$  and quite low RMSE/MAE indicates strong predictive skill and low bias, although the spread increases at higher concentrations ( $> 0.03 \text{ mol/m}^2$ ). This likely reflects the smaller number of pixels with high VCD values in the training dataset, which makes model predictions less constrained in that range.

These results confirm the robustness and temporal stability of the MLP in reproducing the observed  $\text{SO}_2$  VCD under different atmospheric conditions. Moreover, they show that the relationship learned from TROPOMI–SEVIRI collocated observations at the TROPOMI overpass time remains usable for SEVIRI acquisitions outside the polar-orbiting sampling window. Thus, although the model was trained only with early-afternoon TROPOMI measurements, it can be used to generate  $\text{SO}_2$  VCD estimates from SEVIRI at much higher temporal frequency, extending plume monitoring from

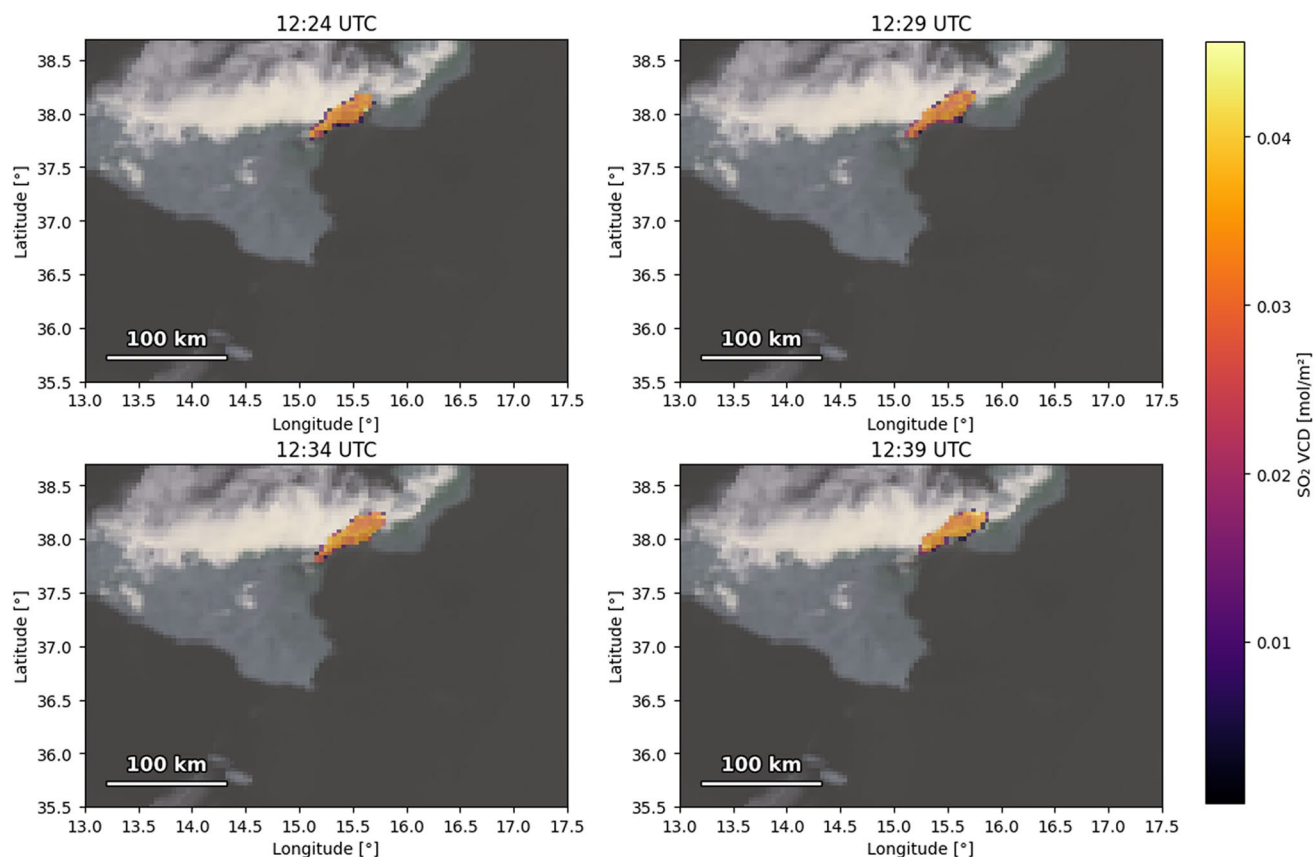
isolated polar overpasses to the quasi-continuous sampling of a geostationary platform.

The detection limit for the AI-derived SEVIRI  $\text{SO}_2$  product was also estimated, directly from the predicted VCDs by analyzing the variability of the predicted background signal, finding a value of around 0.04 DU.

Figure 4 shows an example of four different  $\text{SO}_2$  plumes predicted at different times (every 5 min) on 14 July 2021 on Etna, also reporting the  $\text{SO}_2$  VCD values in  $\text{mol/m}^2$ . Other dates are reported in the Appendix section, showing three different examples of predicted  $\text{SO}_2$  plumes at late afternoon/nighttime (Figs. 9, 10, and 11).

The  $\text{SO}_2$  flux in tons per day (t/d) was calculated for all time instants on the dates selected for testing, and the results were compared with those obtained from processing of images acquired from the permanent UV camera system, run by UniPa and INGV-OE and housed in the “La Montagnola” monitoring hut (located on upper southern Etna's flank at  $\sim 3 \text{ km}$  distance from the vents; for more information on hardware, software and data processing, see D'Aleo

Predicted  $\text{SO}_2$  plume - 14 July 2021



**Fig. 4**  $\text{SO}_2$  plumes predicted at different times (every 5 min from 12:24 to 12:39 UTC) on 14 July 2021 on Etna. The color bar with the  $\text{SO}_2$  VCD values in  $\text{mol/m}^2$  is reported on the right. For display purposes, the maps are shown as zoomed subsets of the full analysis domain

et al., 2016; D'Aleo et al., 2019; Delle Donne et al. 2019; Aiuppa et al. 2023; Lo Bue Trisciuzzi 2025). The UV camera system provides high-temporal-resolution, ground-based measurements of volcanic SO<sub>2</sub> plumes and thus represents a valuable instrument for assessing the temporal evolution of the flux estimates. UV camera flux retrievals are obtained by combining SO<sub>2</sub> column amounts derived from ultraviolet image sequences with plume speed estimates, allowing second-scale monitoring of volcanic degassing. The reported ground-based SO<sub>2</sub> fluxes are affected by several sources of uncertainty. Clouds, ash particles, and other light-scattering effects can reduce the measured signal by weakening or partially masking the UV radiation traveling through the volcanic plume, thereby resulting in artificially low SO<sub>2</sub> column densities and fluxes (see Appendix, Fig. 12). Measurements from UV cameras are therefore commonly filtered using visibility indices to exclude measurements acquired under non-optimal observing conditions when calculating representative daily mean fluxes (Delle Donne et al. 2019; Aiuppa et al. 2023; Lo Bue Trisciuzzi et al., 2025). In this study, no filtering was applied in order to preserve and illustrate the full set of daily measurements. Even in optimal measurement conditions, however, measurements are affected by light dilution, caused by atmospheric scattering of light between the plume and the camera (e.g., Kern et al. 2010a, b; Campion et al. 2015), resulting in a systematic underestimation of fluxes. An estimation of the potential impact of this effect on the adopted UV camera system was previously quantified by Aiuppa et al. 2023 at ~32%, with an average random error associated with each measurement of ~20%. Additional uncertainties also arise from the limited field of view of the UV camera system, which mainly captures gas emissions from the southern portion of the crater area (Aiuppa et al. 2023).

The relative total uncertainty associated with each individual SO<sub>2</sub> flux estimate from satellite was computed, considering the main error sources affecting the flux, which are the retrieved SO<sub>2</sub> column density, the uncertainty related to plume geometry and delineation and wind speed.

We found a median value of 50.0% and a mean value of  $52.0 \pm 12.3\%$ . The interquartile range spans from 41.1 to 58.9%, while 95% of the retrieved fluxes show relative uncertainties below 75%. These values indicate that the proposed methodology provides stable uncertainty estimates over a wide range of volcanic conditions while explicitly accounting for the main sources of error affecting satellite-derived SO<sub>2</sub> emission rates.

A statistically significant inverse relationship was found between SO<sub>2</sub> flux magnitude and relative uncertainty. Pearson correlation analysis yielded  $r = -0.45$ , while the non-parametric Spearman correlation is equal to  $-0.30$ . These results indicate that weaker plumes generally exhibit larger relative uncertainties, reflecting the reduced signal-to-noise

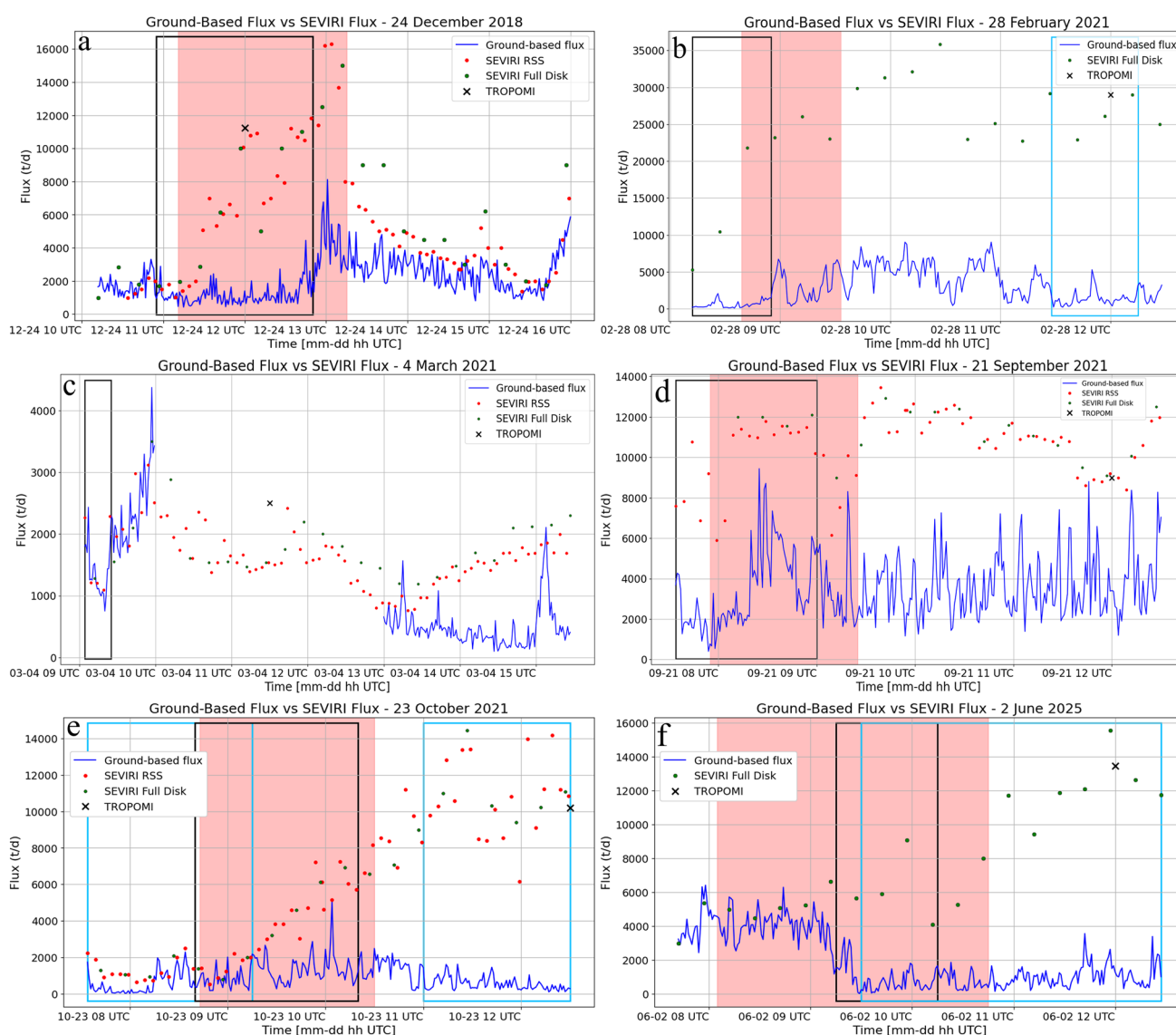
ratio and the increasing relative contribution of fixed uncertainty components for low-emission events.

The uncertainty distribution also depends on observation conditions. Daytime observations generally exhibit lower and more stable uncertainties, whereas nighttime retrievals may reach relative uncertainties of around 80%. This behavior is expected because nighttime conditions reduce the spectral information available to the retrieval. In particular, the visible and near-infrared SEVIRI channels (0.6, 0.8, and 1.6  $\mu\text{m}$ ) provide useful information only during daytime, while the 3.9  $\mu\text{m}$  channel changes from a combined reflected-solar and thermal signal during the day to a purely thermal signal at night. Consequently, nighttime retrievals rely primarily on the thermal infrared channels, especially the SO<sub>2</sub>-sensitive 8.7  $\mu\text{m}$  band, making the retrieval more sensitive to thermal contrast, cloud contamination, background variability, and uncertainties in plume delineation. Furthermore, because the MLP was trained using daytime TROPOMI–SEVIRI collocations, nighttime observations represent radiometric conditions that are only weakly represented in the training dataset, which may contribute to increased retrieval bias and uncertainty.

Figure 5 compares the temporal evolution of SO<sub>2</sub> flux rates, expressed in tons per day (t/d), derived from satellite and ground-based observations during selected daily time windows between 2018 and 2025. The analyzed time windows correspond to the entire intervals during which ground-based measurements were taken, averaged per minute. Where available, SEVIRI measurements at 5-min intervals were used in RSS mode, integrated with SEVIRI Full Disk images. The SO<sub>2</sub> flux derived from TROPOMI was also calculated and reported in the plots, obtained using the traverse method.

The December 24, 2018 example (Fig. 5a) shows an overall good agreement between ground-based and satellite-derived data, except for the paroxysmal (lava fountaining) phase (red-shaded area). During this interval, which also corresponds to the ash-rich plume conditions, the UV camera-based fluxes are systematically lower than those derived from space. This behavior is consistent with previous observations at Etna (D'Aleo et al., 2016; D'Aleo et al., 2019; Delle Donne et al. 2019; Lo Bue Trisciuzzi 2025), and is most likely related to the high ash content of the plume. Under such conditions, increased ultraviolet plume opacity, reduced radiative contrast, and enhanced multiple-scattering effects all contribute to an underestimation of SO<sub>2</sub> fluxes in the UV camera retrievals (Boichu et al. 2015; Kern et al. 2010a, b, 2012, 2013; Kern 2025). A similar during-fountaining underestimation in UV camera-based fluxes is observed in all the examples of Fig. 5.

The SEVIRI-derived fluxes show, instead, a marked SO<sub>2</sub> flux increase at the onset of the lava fountaining episode, that is well captured by our high (5 min) temporal resolution records.



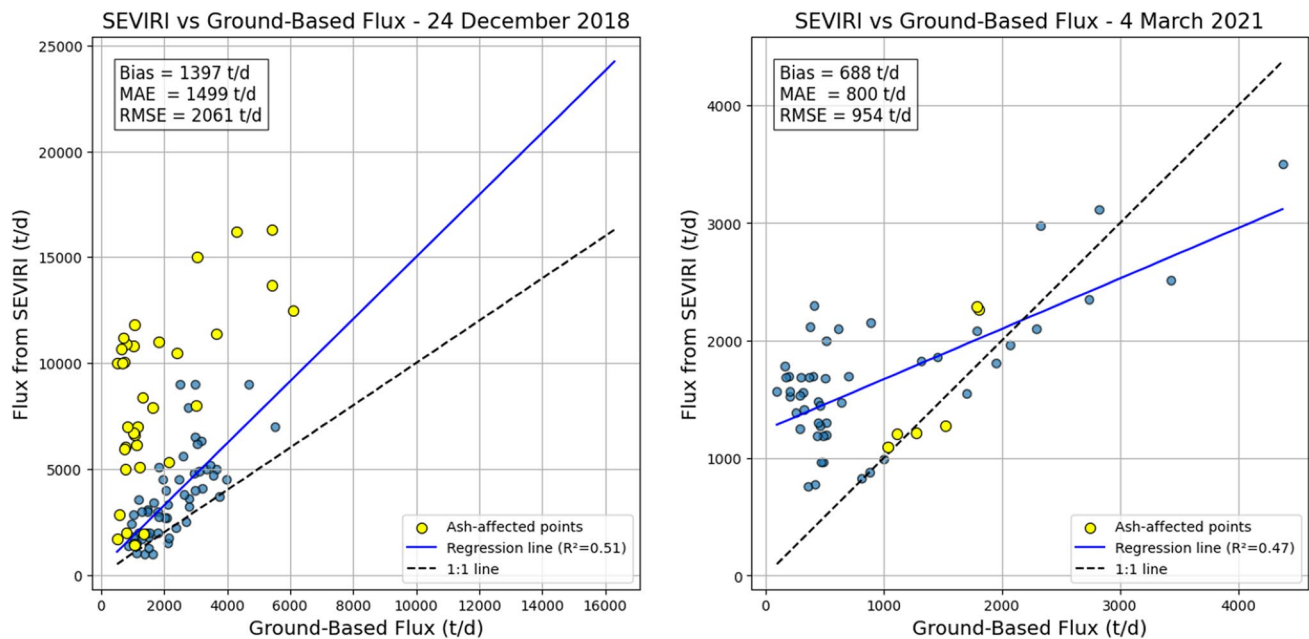
**Fig. 5** Comparison made on Etna during **a** 24 December 2018 (10:00–16:00 UTC), **b** 28 February 2021 (8:12–12:30 UTC), **c** 4 March 2021 (9:00–15:27 UTC), **d** 21 September 2021 (07:34–12:29 UTC), **e** 23 October 2021 (07:34–12:29 UTC), and **f** 2 June 2025 (07:42–12:27 UTC) between  $\text{SO}_2$  flux rates retrieved by the neural network from SEVIRI Rapid Scan Service (RSS) (red dots) and standard full disk (green dots) acquisitions and  $\text{SO}_2$  fluxes from the

ground-based UV camera system (in blue). The black cross represents the flux computed using TROPOMI, while the red-shaded intervals indicate periods when a lava fountain occurred, corresponding to highly explosive eruptive phases. Light blue outlined windows denote time intervals affected by cloud cover, and black outlined windows indicate ash-rich plume conditions, which can both complicate plume detection and affect the accuracy of flux estimates

On 28 February 2021, a violent paroxysmal episode occurred, producing an eruptive column up to 11 km high. Also, in this case, the ash-laden plume caused a severe underestimation of the ground-based flux, while satellite results document a prominent  $\text{SO}_2$  flux escalation, with values exceeding 30,000 t/d.

Ground- and satellite-based fluxes match well on March 4, 2021, consistent with the absence of lava fountaining episodes occurring during the analyzed time window (the

lava fountaining occurred early on that day at around 03:00 UTC). On this date, a gap is present in the ground dataset between 10:00 and 13:00 UTC due to a technical issue. However, the more continuous satellite-derived fluxes define a consistent decreasing trend, typical of post lava fountaining periods (Delle Donne et al. 2019; Lo Bue Trisciuzzi 2025). After 13:00 UTC, the higher  $\text{SO}_2$  values are explained by the satellite continuing to track the plume trajectory.



**Fig. 6** Comparison between SEVIRI-derived and ground-based SO<sub>2</sub> fluxes for 24 December 2018 (on the left) and 4 March 2021 (on the right). Yellow dots indicate measurements acquired during the ash-affected interval. Blue lines show the linear regression fits, with  $R^2$

values given in the legend. The line 1:1 is also reported to verify if there is a systematic overestimation or underestimation in one of the two techniques. Statistical parameters (Bias, MAE, RMSE in t/d) are shown in the upper-left box of each panel

On September 21, 2021, a paroxysmal episode occurred that is consistently associated with elevated satellite-derived flux values, averaging around 11,000 t/d. The continuous tracking of the plume trajectory by SEVIRI indicates sustained dispersion of the volcanic cloud, which likely contributes to the higher observed flux values.

On October 23, 2021, a good agreement between the flux values from the two datasets before the onset of the lava fountaining episode can be observed, with values of about 1000 t/d. A gradual increase in SO<sub>2</sub> flux was observed during the event in both datasets. Afterward, SEVIRI continues to detect the dispersed volcanic cloud over a larger spatial domain, while the ground-based UV camera remains better suited to tracking the temporal evolution of emissions in the near-source region. The two systems therefore provide complementary information, with the satellite emphasizing plume transport and spatial extent, and the UV camera resolving short-timescale source dynamics. In general, the flux values recorded by the UV camera during this date are lower, most likely due to the fact that there was coverage by ash or meteorological clouds throughout almost the entire period analyzed.

The last example date tested was the 2nd of June 2025, which corresponds to the paroxysmal event already described in the Case Study Section. Also, in this case, there is a good initial agreement between the datasets (with values around 5000 t/d). As the paroxysmal episode intensifies, ground-based and satellite-based flux time-series diverge

substantially, with the SEVIRI-derived values reaching a peak at above 16,000 t/d. This behavior likely reflects the complementary sensitivities of the two observing systems together with the presence of ash and clouds in that interval.

For all dates analyzed, the SO<sub>2</sub> flux value calculated from TROPOMI (represented by a black cross) matches well with SEVIRI-derived results. An excellent agreement is also observed between SEVIRI RSS and full disk acquisitions.

Overall, the comparison across all investigated dates shows a consistent pattern: agreement between satellite and ground-based fluxes is highest during moderate degassing phases, while the largest discrepancies occur during ash-rich lava fountaining episodes, during which ground-based UV measurements fail to record the phase of syn-eruptive heightened degassing. We quantitatively estimate the level of agreement/disagreement between the two datasets in Fig. 6, where the scatter plots illustrate the comparison between SEVIRI and ground-based SO<sub>2</sub> fluxes on 24 December 2018 and 4 March 2021. Each point represents a simultaneous observation pair, and the blue regression line highlights the overall relationship between the measurements. In addition to  $R^2$ , we computed the MAE and RMSE, as previously defined in Eqs. (6) and (7).

In both cases, the positive slopes of the regression lines indicate a general agreement between the two measurement series, although the  $R^2$  values (0.51 and 0.47, respectively) suggest moderate correlation.

For December 24, 2018, all matched ground-based and SEVIRI points are shown in the scatter plot, including those acquired during the lava-fountaining/ash-rich interval (highlighted in yellow). However, this time window was excluded from the calculation of the statistical metrics and regression line because it produced substantially larger discrepancies owing to ash-related effects on the ground-based UV camera retrievals discussed above. After removal, the calculated bias is 1397 t/d, with MAE and RMSE values of 1499 t/d and 2061 t/d, respectively. These errors are substantially lower than those obtained when the fountaining period was included (bias: 3377 t/d; MAE: 3440 t/d; RMSE: 4842 t/d), confirming that intense ash-rich eruptive activity can strongly affect the ground-based measurements. On this date, the comparison between SEVIRI-derived and ground-based fluxes indicates a systematic overestimation from SEVIRI with respect to the ground measurements. This behavior is clearly visible in the scatter plot, where the regression line lies above the 1:1 line and shows a slope larger than unity, meaning that SEVIRI fluxes increase more rapidly than those retrieved from the ground camera.

In contrast, for 4 March 2021 the main lava-fountaining phase occurred earlier than the analyzed time window, so the statistics shown in Fig. 6 were computed using the full set of matched points. On this date, the bias is 688 t/d and MAE and RMSE values are equal to 800 t/d and 954 t/d, respectively, indicating a better match between ground-based and SEVIRI-derived fluxes. This improved agreement is consistent with the absence of major lava fountaining during the analyzed window, which reduced observational interference and enhanced the reliability of the comparison. The regression line lies below the 1:1 line and exhibits a slope smaller than unity, revealing a slight systematic underestimation by SEVIRI compared to ground-based fluxes, especially at higher emission values. This bias likely reflects the combined effects of the intrinsic sensitivity limits of the SEVIRI observations, uncertainties in the TROPOMI reference retrievals used for training, and the limited ability of the model to represent all observation conditions.

Overall, the analysis confirms that SEVIRI-derived fluxes generally follow the trend of ground-based data, while the remaining discrepancies reflect specific sources of bias, including light dilution and ash-related optical effects in UV camera-based retrievals, as well as plume height and wind-related uncertainties in the satellite-based flux estimates.

Some tests were also carried out on imagery acquired before 2018, when TROPOMI was not yet operational, using the previously trained neural network. We specifically focus on the eruptive episodes of December 2015 and May 2016.

Fluxes obtained for these periods after the application of the MLP neural network were compared with ground-based

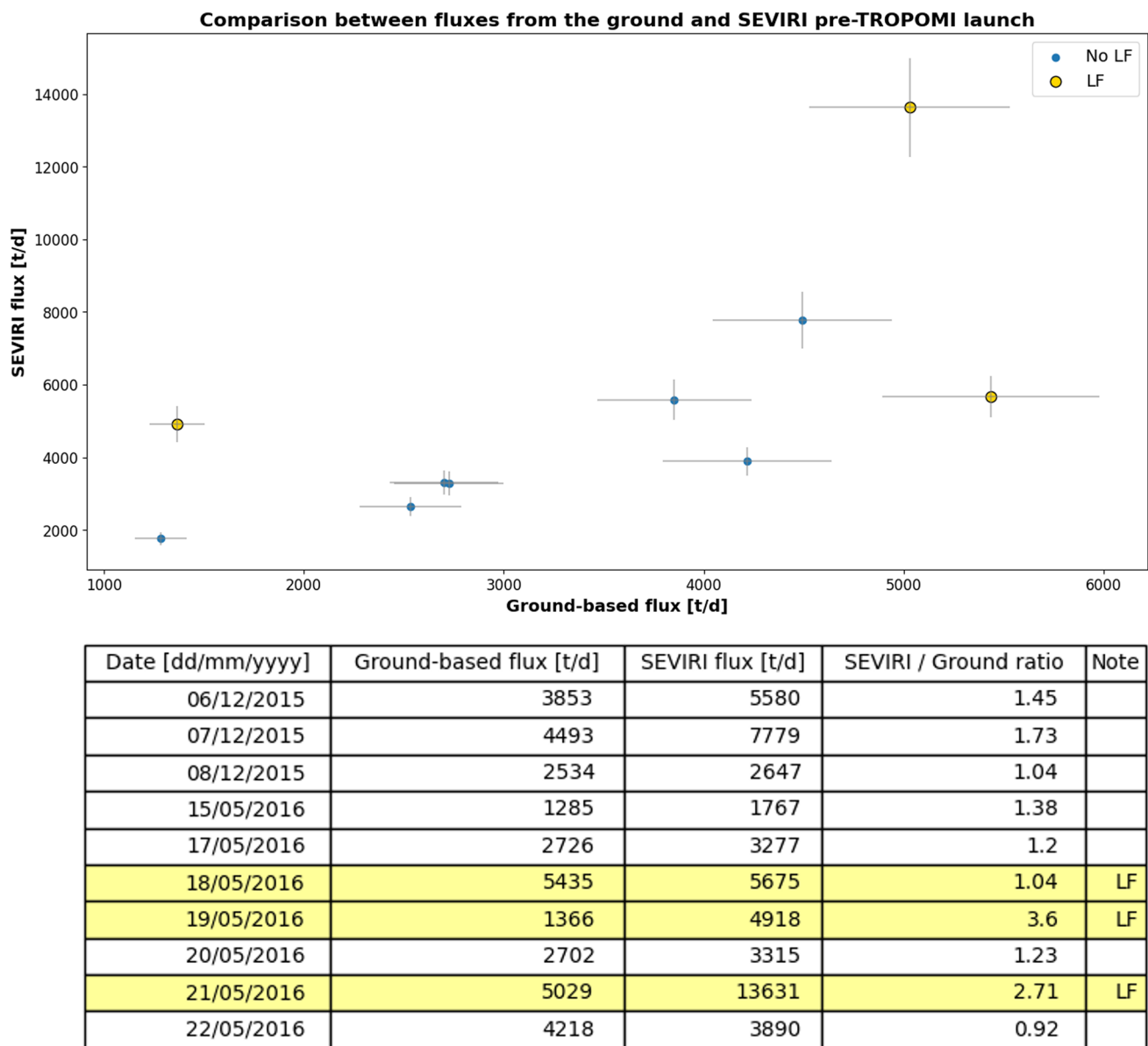
data retrieved from the UV camera system. The results are illustrated in Fig. 7, which includes a table of the computed values and a scatter plot showing results from both methods ( $\pm 1$  standard deviation). Different colors are used to highlight dates on which lava fountain episodes occurred.

Since the UV camera system relies on solar ultraviolet radiation, thus providing reliable  $\text{SO}_2$  measurements only under daylight conditions, flux calculations were restricted to daytime SEVIRI images to enable a meaningful comparison with ground-based data. The SEVIRI-based plume proxy was generated from the 11 multispectral channels used as neural-network input, namely, 0.6, 0.8, 1.6, 3.9, 6.2, 7.3, 8.7, 9.7, 10.8, 12.0, and 13.4  $\mu\text{m}$ .

The comparison shows an excellent correlation, which decreases on days when lava fountaining episodes occur. For most analyzed days, the ratio between SEVIRI and ground-based measurements is greater than unity, indicating that the SEVIRI-based estimates tend to be systematically higher than the UV camera measurements.

Figure 8 presents an example from 22 May 2016, showing the volcanic plume predicted at four different instants, spaced 5 min apart, along with the corresponding VCD values for each pixel expressed in  $\text{mol}/\text{m}^2$ .

To evaluate the practical impact of the retrieval choice on the final high-temporal-resolution  $\text{SO}_2$  estimates, we compared  $\text{SO}_2$  fluxes derived from the custom height-adaptive VCD product with those obtained using the operational TROPOMI COBRA VCD product, consistent with the plume height computed from SEVIRI. This additional complexity is motivated by the fact that the customized data retrieval procedure combines SCD, averaging kernels, and plume height information derived from SEVIRI, thus yielding a training-target  $\text{SO}_2$  column that is consistent with the altitude estimated for each TROPOMI overpass, instead of relying on a fixed operational height scenario. Results are reported in the Appendix section (Fig. 13) and show that the custom corrected VCD generally produces higher  $\text{SO}_2$  fluxes than the operational product, with a mean relative difference of 15.3% and a median of 17.5%. The flux ratio averages 1.15 (median: 1.17), although individual cases range from 0.61 to 1.74, indicating that the retrieval choice has a moderate but non-negligible and event-dependent effect on the final  $\text{SO}_2$  flux estimates. This result suggests that part of the positive bias observed in the SEVIRI-derived fluxes may originate from the choice of the TROPOMI reference retrieval used for training. However, the persistence of discrepancies relative to the ground-based measurements indicates that this cannot be the only contributing factor and that residual differences also reflect the known underestimation of UV camera fluxes under some conditions, together with the intrinsic limitations of the SEVIRI observations and of the machine-learning retrieval.



**Fig. 7** Comparison between daily  $\text{SO}_2$  fluxes (in t/d) retrieved from UV camera measurements and SEVIRI observations before the TROPOMI launch (2015–2016), computed using the developed neural network. On the top panel, daily flux values are reported with  $\pm 1$

standard deviation. Yellow markers indicate days during which lava fountaining (LF) episodes occurred. Daily  $\text{SO}_2$  fluxes are also reported on the bottom table, together with the SEVIRI/ground-based flux ratio, and the lava fountain events (LF) are highlighted in yellow

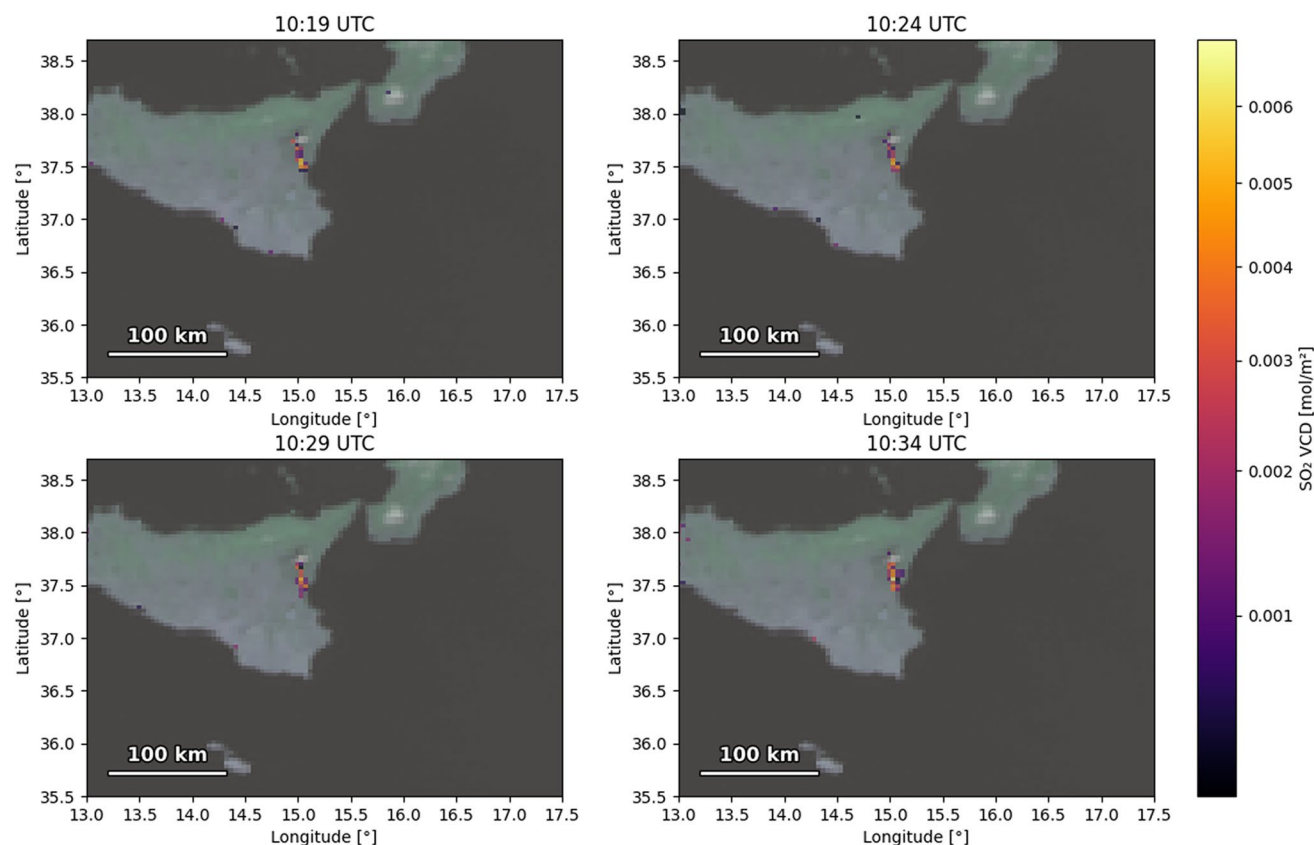
## Discussion and conclusions

In this work, we developed a new approach that combines the high temporal resolution of MSG-SEVIRI with the higher  $\text{SO}_2$  sensitivity of TROPOMI. A multilayer perceptron neural network was trained to reproduce TROPOMI-derived  $\text{SO}_2$  vertical column densities from SEVIRI spectral radiances, thus transferring the calibration and sensitivity of the hyperspectral LEO sensor to a GEO platform. This

integration significantly increases measurement density, provides  $\text{SO}_2$  maps at the denser SEVIRI spatial sampling, and makes near-continuous volcanic  $\text{SO}_2$  monitoring possible.

The application to Mount Etna shows that this approach delivers  $\text{SO}_2$  maps and flux time series that reasonably match those obtained with ground-based UV cameras during moderate degassing activity.

Although the trained neural network improves the capability of detecting  $\text{SO}_2$  in some early phases when

Predicted SO<sub>2</sub> plume - 22 May 2016

**Fig. 8** SO<sub>2</sub> plumes predicted at different times (every 5 min from 10:19 to 10:34 UTC) on 22 May 2016 on Etna. The color bar with the SO<sub>2</sub> VCD values in mol/m<sup>2</sup> is reported on the right. For display purposes, the maps are shown as zoomed subsets of the full analysis domain

SEVIRI radiances show only subtle signatures, plume detection may remain difficult when the volcanic cloud has low thermal contrast, limited vertical development, or only weak radiometric contrast across the SEVIRI channels (Prata and Kerkmann 2007; Corradini et al. 2020, 2021). In these cases, the ground-based UV camera may provide a clearer view of near-source degassing variability, whereas the satellite-based retrieval becomes more effective once the plume is sufficiently developed and spatially extended.

Quantitative comparisons showed good correspondence between SEVIRI-derived fluxes and ground-based measurements outside ash-rich paroxysms, with residual biases largely explained by viewing geometry differences, light dilution or temporary obscuration of the plume in UV imagery. Furthermore, comparisons with previously published SEVIRI retrieval methods (e.g., Corradini et al. 2020) indicated that the approach proposed here maintains methodological consistency while adding finer temporal resolution,

improving the tracking of plume dispersion and flux variations throughout an eruptive event.

The trained network was also applied to SEVIRI data acquired before the launch of Sentinel-5P, to reconstruct SO<sub>2</sub> fluxes for earlier years. For this analysis, we selected periods of moderate activity, characterized by subterminal eruptions, without intense lava fountaining except for three cases, thus ensuring more stable comparisons with UV camera data and reducing discrepancies caused by ash interference. The agreement observed in these study cases confirms that the method can reliably extend volcanic SO<sub>2</sub> time series also before 2018, opening the door to multiyear analyses of degassing trends from 2004 (when MSG-SEVIRI started to be operational).

A further strength of the proposed framework is its ability to fill important monitoring gaps at regional to continental scale within the SEVIRI field of view. This is particularly valuable during intense eruptive phases, when ground-based UV camera measurements may be degraded or interrupted

by ash-rich, optically thick plumes, and for volcanoes where routine ground-based SO<sub>2</sub> surveillance is unavailable. In such cases, the geostationary satellite perspective provides a unique opportunity to maintain high-temporal-resolution tracking of plume evolution and SO<sub>2</sub> flux variability over broad areas.

An additional advantage of the GEO-based framework is that, unlike ground-based UV cameras, it is not restricted to daylight observations. Indeed, although the quantitative comparison with UV camera fluxes in this study was limited to daytime for consistency with the ground-based reference dataset, the SEVIRI-based retrieval has also been applied to late-afternoon and nighttime scenes. This capability is illustrated by the examples reported in the Appendix, where predicted SO<sub>2</sub> plumes remain clearly detectable beyond daylight hours, although showing higher uncertainty values.

By incorporating coincident satellite and ground-based observations during training, future versions of the model could learn to account for instrument-specific biases while preserving the complementary strengths of each observing system. Such an approach has the potential to improve the robustness of SO<sub>2</sub> flux retrievals under challenging observing conditions, particularly during periods of partial cloud cover or rapidly evolving volcanic activity.

The TROPOMI-calibrated framework could also help mitigate the well-known row-anomaly issues affecting the Aura/OMI instrument (Dobber et al. 2008; Schenkeveld et al. 2017) and may be extended to Suomi-NPP/NOAA-20/21 OMPS measurements (Flynn et al. 2014; Li et al. 2017). During periods of overlap with TROPOMI observations, machine learning models could be trained to reproduce TROPOMI-equivalent SO<sub>2</sub> VCDs from OMI or OMPS inputs and then applied to earlier time periods, improving the consistency of long-term SO<sub>2</sub> records. In addition, high-temporal-resolution GEO-derived VCDs could support gap filling and temporal interpolation around LEO overpass times. Although this approach would not replace instrument-level radiometric corrections, it could reduce row-dependent gaps and biases, helping to improve the continuity and homogeneity of pre-TROPOMI volcanic SO<sub>2</sub> time series.

In conclusion, the proposed method successfully combines the positive characteristics of LEO and GEO satellites through artificial intelligence, resulting in enhanced temporal and spatial resolution in volcanic SO<sub>2</sub> monitoring, reliable flux estimates in conditions where ground-based or LEO data are unavailable, along with the possibility of reconstructing degassing trends before the Sentinel-5P launch.

Since the current implementation performs better for moderate to strong plume conditions, an important next step will be to specifically refine the method for continuous/passive degassing, as this would substantially increase its value for routine volcanic surveillance beyond eruptive episodes. Future work will focus on expanding the training dataset to include a wider range of degassing scenarios, especially high-emission events, which could also be better investigated exploiting the new Flexible Combiner Imager (FCI) onboard the Meteosat Third Generation geostationary satellites. This sensor collects data across 16 spectral channels, with spatial resolution ranging from 0.5 to 2 km<sup>2</sup> at nadir. The infrared bands at 3.8  $\mu$ m and 10.5  $\mu$ m are particularly relevant for volcanic monitoring, as they are acquired in high-resolution mode, providing a spatial resolution of about 1 km<sup>2</sup> at nadir and a temporal sampling interval of 10 min.

Beyond Mount Etna, the framework is readily exportable to other volcanoes worldwide monitored by GEO satellites, such as Himawari-8 (AHI) over Japan or GOES-16/17 (ABI) in the Americas. The use of SEVIRI's multi-band radiances and open neural network architectures ensures that the method is not volcano-specific but can be rapidly retrained for different geographic contexts or instrument datasets. Implementation at volcano observatories is technically straightforward and only requires daily use of calibrated satellite radiances with an automatically trained neural network, which can be easily integrated into existing monitoring routines. With minimal computational requirements and full compatibility with current satellite data streams, this approach has strong potential to enhance global volcanic surveillance.

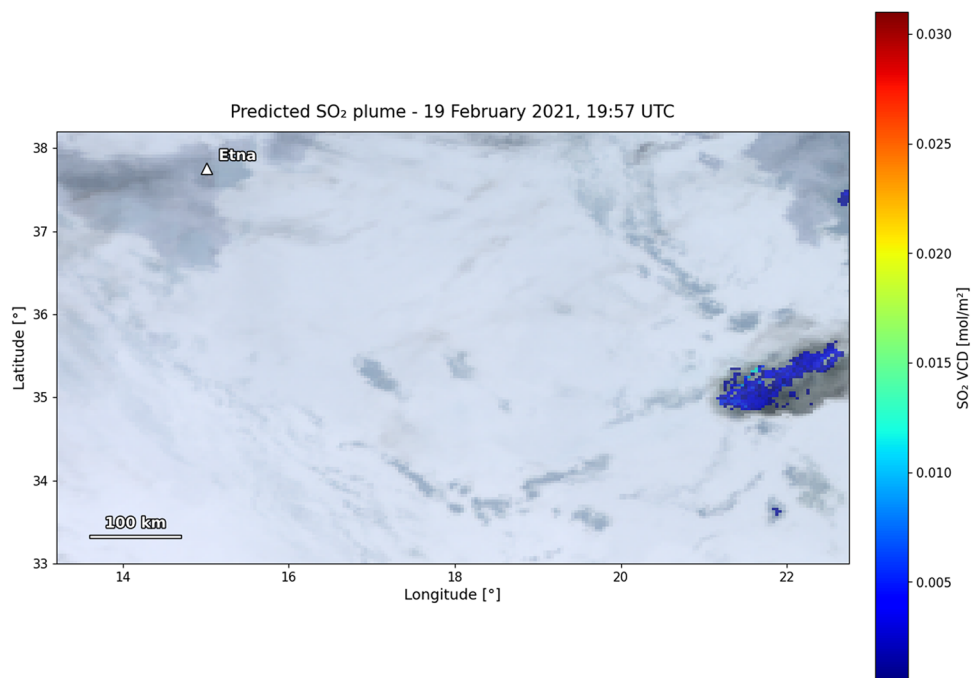
Furthermore, the presented approach could in principle be extended to other atmospheric constituents, provided that they exhibit a sufficiently informative spectral signature in the geostationary radiances and that reliable reference products are available for training. In the volcanic context, this perspective may be particularly relevant for species or plume components that can be constrained from complementary satellite observations, although SO<sub>2</sub> remains the most suitable target for the present implementation.

Future developments could also benefit from the integration of new infrared satellite sensors, including upcoming missions such as MetOp-SG IASI-NG, which will provide SO<sub>2</sub> total column measurements and may offer additional training and validation opportunities. Taken together, these perspectives indicate that artificial-intelligence-based radiance inversion can become a valuable component of continuous, automated SO<sub>2</sub> monitoring systems at regional to global scale.

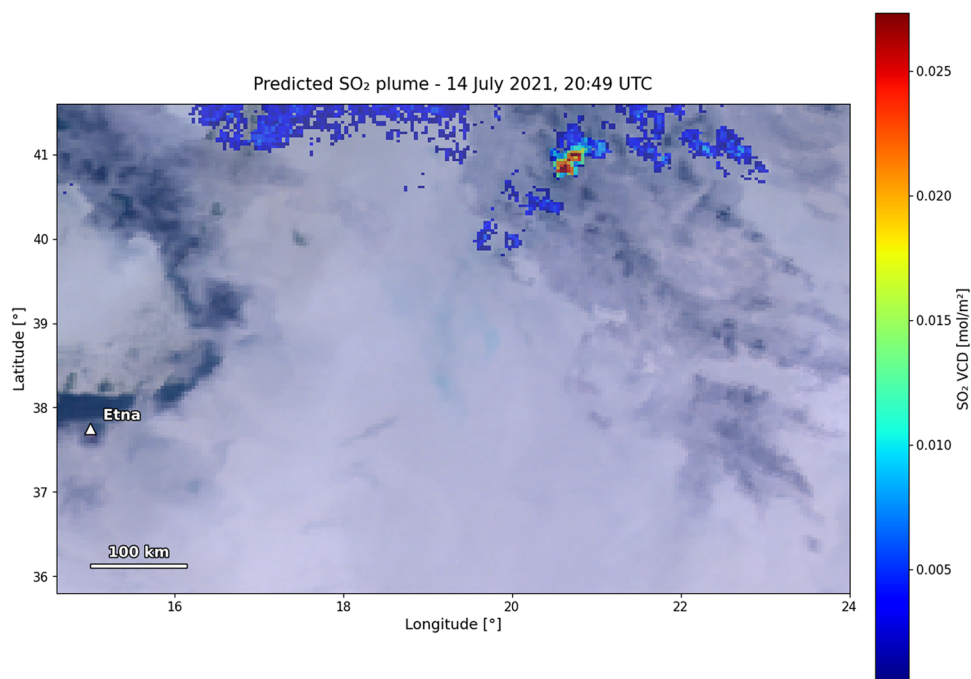
## Appendix

Figures 9, 10, 11, 12 and 13.

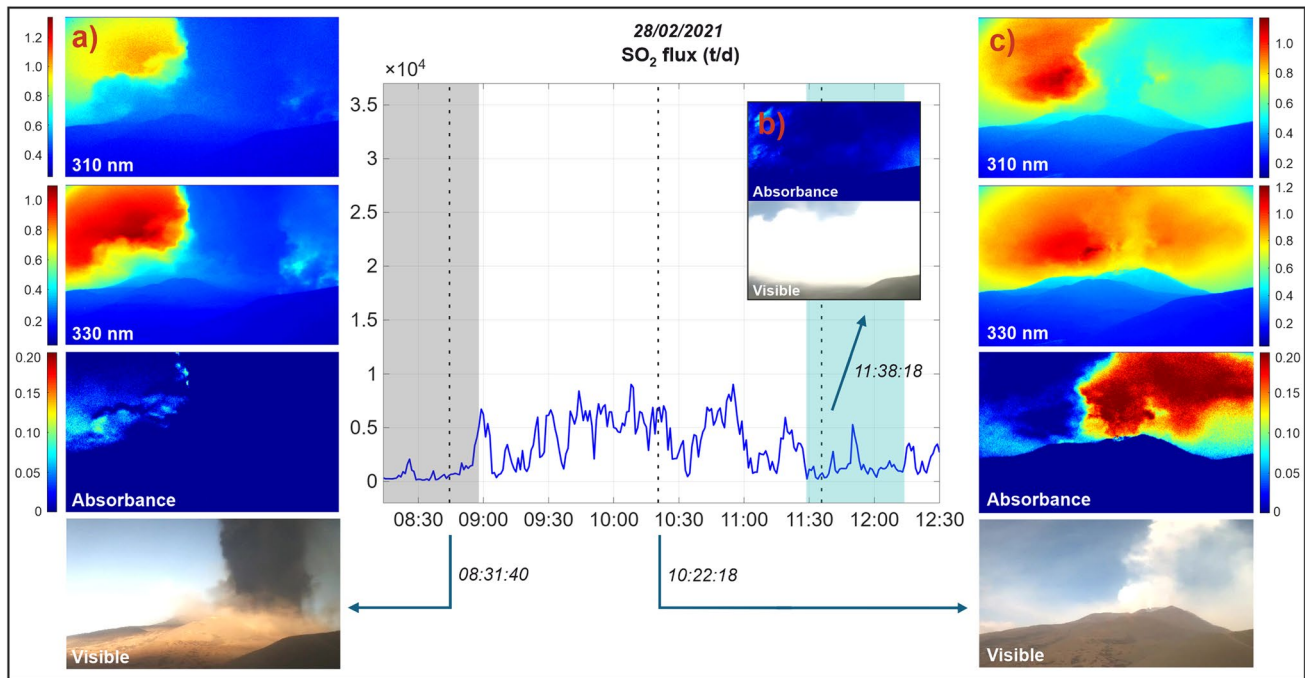
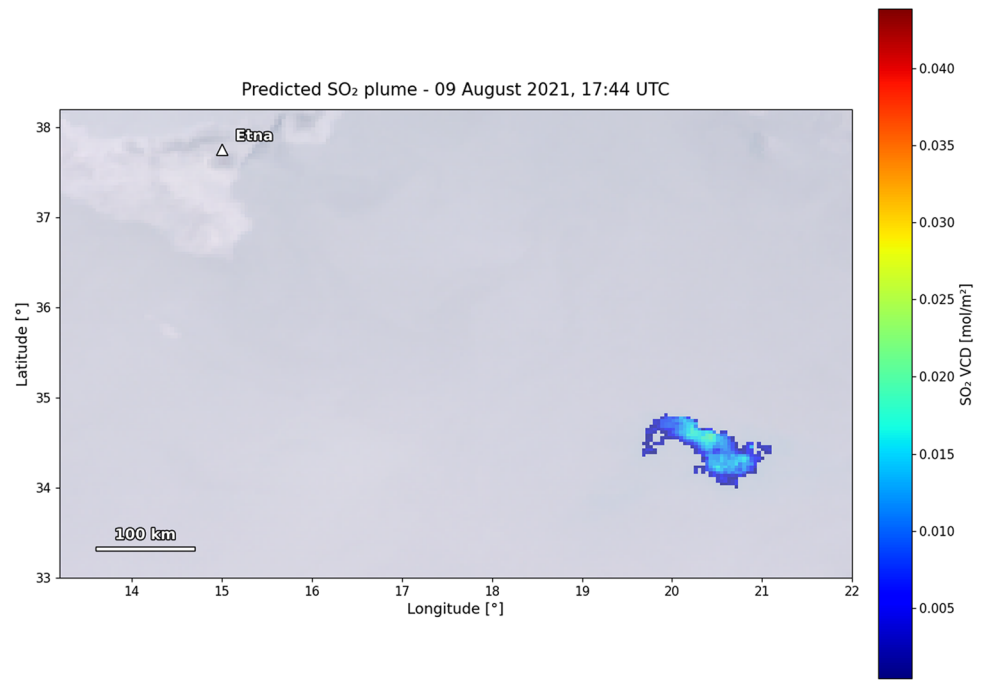
**Fig. 9** Predicted SO<sub>2</sub> plume on 19 February 2021 at 19:57 UTC on Etna. The color bar with the SO<sub>2</sub> VCD values in mol/m<sup>2</sup> is reported on the right



**Fig. 10** Predicted SO<sub>2</sub> plume on 14 July 2021 at 20:49 UTC on Etna. The color bar with the SO<sub>2</sub> VCD values in mol/m<sup>2</sup> is reported on the right

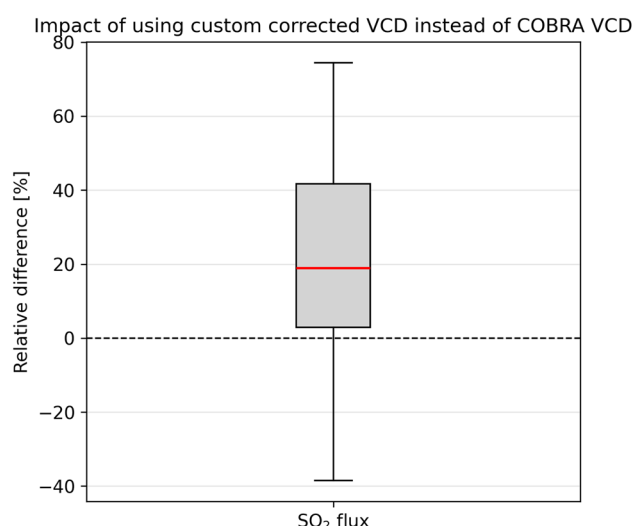


**Fig. 11** Predicted SO<sub>2</sub> plume on 09 August 2021 at 17:44 UTC on Etna. The color bar with the SO<sub>2</sub> VCD values in mol/m<sup>2</sup> is reported on the right



**Fig. 12** An example of some representative ground-based camera images acquired at Mt. Etna, used to illustrate the variety of conditions met by the UV camera, and the consequent multiple effects that can compromise the correct SO<sub>2</sub> flux measurements. **a** Ash-rich plume, **(b)** plume affected by unfavourable weather conditions (e.g., clouds between the plume and the camera), and **c** predominantly gas-rich SO<sub>2</sub> plume. Since SO<sub>2</sub> strongly absorbs UV radiation at 310 nm

but only weakly at 330 nm, SO<sub>2</sub>-rich plumes produce larger differential absorbances between the two channels, resulting in higher absorbance values and SO<sub>2</sub> fluxes. Conversely, ash-rich plumes and cloudy conditions enhance broadband light scattering and reduce the differential absorbance signal, leading to artificially low SO<sub>2</sub> absorbances and flux estimates



**Fig. 13** Boxplot of the relative differences in  $\text{SO}_2$  flux between estimates derived from the custom height-adaptive corrected VCD product and those based on the operational TROPOMI COBRA VCD product selected according to the SEVIRI-derived plume height. Positive values indicate higher fluxes obtained using the custom-corrected VCD

**Acknowledgements** The authors gratefully thank the Istituto Nazionale di Geofisica e Vulcanologia, Italy, grant Progetto INGV Pianeta Dinamico (code CUP D53J19000170001) funded by Italian Ministry MUR (“Fondo Finalizzato al rilancio degli investimenti delle amministrazioni centrali dello Stato e allo sviluppo del Paese”, legge 145/2018) - VT SAFARI 2023-24 and VT-CLAIM 2026-2029 subprojects.

**Author contribution** Conceptualization: G. G.; Methodology: G. G. and M. D.; Software: M. D.; Validation: A. A. and G. L.; Formal Analysis: M. D., A. A. and G. L.; Investigation: M. D., A. A. and G. L.; Resources: A. A. and G. G.; Data Curation: M. D. and G. L.; Writing—original draft preparation: M. D. and G. G.; Writing—review and editing: M. D., A. A., G. L. and G. G.; Visualization: M. D.; Supervision: A. A. and G. G.. All authors have read and agreed to the published version of the manuscript.

**Funding** Open access funding provided by Istituto Nazionale di Geofisica e Vulcanologia within the CRUI-CARE Agreement.

**Data availability** The Sentinel-5P TROPOMI Offline Level 2 product in netCDF-4 format was provided by the European Space Agency Copernicus Open Access Hub in the Sentinel-5P Pre-Operations Hub. The MSG-SEVIRI data were taken from the EUMETSAT User Portal. The wind dataset was made available by the European Centre for Medium-Range Weather Forecasts (ECMWF).

## Declarations

**Competing interests** The authors declare no competing interests.

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