Improved monitoring of shipping NO\textsubscript{2} with TROPOMI: decreasing NO\textsubscript{x} emissions in European seas during the COVID-19 pandemic

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Abstract. TROPOMI (TROPOspheric Monitoring Instrument) measurements of tropospheric NO\textsubscript{2} columns provide powerful information on emissions of air pollution by ships on open sea. This information is potentially useful for authorities to help determine the (non-)compliance of ships with increasingly stringent NO\textsubscript{x} emission regulations. We find that the information quality is improved further by recent upgrades in the TROPOMI cloud retrieval and an optimal data selection. We show that the superior spatial resolution of TROPOMI allows for the detection of several lanes of NO\textsubscript{2} pollution ranging from the Aegean Sea near Greece to the Skagerrak in Scandinavia, which have not been detected with other satellite instruments before. Additionally, we demonstrate that under conditions of sun glint TROPOMI’s vertical sensitivity to NO\textsubscript{2} in the marine boundary layer increases by up to 60\%. The benefits of sun glint are most prominent under clear-sky situations when sea surface winds are low but slightly above zero (±2 m s\textsuperscript{-1}). Beyond spatial resolution and sun glint, we examine for the first time the impact of the recently improved cloud algorithm on the TROPOMI NO\textsubscript{2} retrieval quality, both over sea and over land. We find that the new FRESCO+ (Fast Retrieval Scheme for Clouds from the Oxygen A band) wide algorithm leads to 50 hPa lower cloud pressures, correcting a known high bias, and produces 1–4×10\textsuperscript{15} molec. cm\textsuperscript{-2} higher retrieved NO\textsubscript{2} columns, thereby at least partially correcting for the previously reported low bias in the TROPOMI NO\textsubscript{2} product. By training an artificial neural network on the four available periods with standard and FRESCO+ wide test retrievals, we develop a historic, consistent TROPOMI NO\textsubscript{2} data set spanning the years 2019 and 2020. This improved data set shows stronger (35 %–75 %) and sharper (10 %–35 %) shipping NO\textsubscript{2} signals compared to co-sampled measurements from OMI. We apply our improved data set to investigate the impact of the COVID-19 pandemic on ship NO\textsubscript{2} pollution over European seas and find indications that NO\textsubscript{x} emissions from ships reduced by 10 %–20 % during the beginning of the COVID-19 pandemic in 2020. The reductions in ship NO\textsubscript{2} pollution start in March–April 2020, in line with changes in shipping activity inferred from automatic identification system (AIS) data on ship location, speed, and engine.

1 Introduction

Emissions of nitrogen oxides (NO\textsubscript{x} = NO + NO\textsubscript{2}) have several primary and secondary effects on air quality, human health, and the environment. NO\textsubscript{x} is a toxic gas itself (WHO, 2003) and contributes to the formation of secondary pollutants and ozone. Ozone close to the Earth’s surface is a toxic pollutant which can lead to respiratory problems and has negative effects on plant growth and crop yield (e.g., Wang and Mauzerall, 2004). NO\textsubscript{x} also contributes to acid deposition and eutrophication, harming sensitive ecosystems (European Environment Agency, 2019).

The international shipping sector is a strong source of NO\textsubscript{x} and other air pollutants to the atmosphere (e.g., Eyring et al., 2010). Previous studies suggest that international ship-
Satellite instruments have observed enhancements of NO₂ column densities over major shipping routes, e.g., from GOME (Beirle et al., 2004), SCIAMACHY (Richter et al., 2004), and OMI (Vinken et al., 2014b; Marmer et al., 2009). These satellite measurements have recently been continued with new observations from the TROPOMI (TROPOspheric Monitoring Instrument) sensor. With a pixel size of 3.5 km × 5.5 km TROPOMI provides a spatially more resolved evaluation of NO₂ pollution patterns compared to its predecessors GOME (40 km × 320 km), SCIAMACHY (30 km × 60 km), and OMI (13 km × 24 km). Indeed, previous studies demonstrated TROPOMI’s capability to pinpoint emissions from the mining industry (Griffin et al., 2019), emissions patterns within cities (Beirle et al., 2019; Lorente et al., 2019), emissions along a gas pipeline in Siberia (van der A et al., 2020), and even from individual ships in the Mediterranean Sea (Georgoulas et al., 2020). Ding et al. (2020) used TROPOMI NO₂ columns and inverse modeling to show NOₓ emission reductions during the COVID-19 lockdown over urban centers and regions with strong maritime transport.

While the aforementioned studies demonstrate the large potential of TROPOMI and its high resolution, retrieval problems remain. Validation studies (e.g., Griffin et al., 2019; Verhoelst et al., 2021) suggest a 15%–40% low bias in TROPOMI tropospheric vertical NO₂ (Nₓv,trop) columns relative to independent in situ and MAX-DOAS (multi-axis differential optical absorption spectroscopy) measurements. Cloud properties present one of the leading sources of uncertainty in trace gas retrieval from space (Boersma et al., 2004; Lorente et al., 2017), and cloud heights used until (and including) v1.3 of the operational TROPOMI retrieval algorithm have been suggested to be biased low (Compernolle et al., 2021). To address this bias in cloud heights, the Royal Dutch Meteorological Institute (KNMI) recently updated the FRESCO+ (Fast Retrieval Scheme for Clouds from the Oxygen A band) cloud retrieval by widening the spectral window, which is supposed to improve the sensitivity to low clouds.

The here-presented study presents and assesses the impact of steps towards an improved monitoring of shipping NO₂ with TROPOMI. First, we demonstrate TROPOMI’s capability to detect ship emissions applying a typical data selection and compare it to OMI’s. We examine previous suggestions of improved retrieval sensitivity over sun glint scenes (Georgoulas et al., 2020). Additionally, we evaluate the new FRESCO+ wide cloud pressure retrieval and its impact on the TROPOMI NO₂ columns in v1.4–2.1 of the operational TROPOMI NO₂ algorithm. Based on our findings, we create a data set of historical TROPOMI NO₂ columns consistent with the v1.4 data allowing for otherwise challenging trend analysis. We conclude with an application of our findings to quantify the effects of the COVID-19 pandemic on ship pollution, a unique opportunity to assess the relationship between the anticipated emission reductions and observed NO₂ columns.

2 Methods and materials

2.1 TROPOMI and OMI NO₂ column measurements

The European TROPOMI (Vreeken et al., 2012) is on board the Sentinel-5 Precursor launched in October 2017.
TROPOMI has a push-broom design with a 2-D detector, which measures back-scattered radiation from the Earth’s atmosphere for viewing zenith angles up to 57°, in the spectral region from UV to shortwave infrared. The instrument is equipped with a polarization scrambler, simplifying the radiative transfer analysis. The width of the TROPOMI swath is about 2600 km, which results in daily (near-)global coverage with about 25 million measurement points. In band 4, where NO₂ is retrieved, TROPOMI provides 450 measurements across-track, with a minimal width of 3.5 km.

The design of OMI is similar to that of TROPOMI, but OMI measures in a smaller spectral range (270–500 nm) (Levett et al., 2006, 2018). Another important difference is that OMI has only 60 across-track measurements, with the smallest pixels having a width of 25 km. Along track, the resolution of TROPOMI is 7 km (5.5 km since August 2019), compared to 13 km for OMI. Combined, the area of the smallest TROPOMI pixel is 19 km², while it is 325 km² for OMI, a factor of 17 improvement in spatial resolution. Both instruments are in a sun-synchronous ascending orbit and have an Equator overpass time of about 13:30.

Clouds have several relevant effects on NO₂ and is therefore similar in many aspects. On the other hand, especially spatial resolution, signal-to-noise, and the retrieval of cloud properties differ as highlighted in Table 1.

Clouds have several relevant effects on NO₂ retrieval. Clouds shield the lower part of the atmosphere which is most influenced by anthropogenic emissions including those from shipping. Therefore, data users are typically advised to consider scenes with cloud radiance fractions below 50 % (Eskes et al., 2019). Initial validation of TROPOMI NO₂ v1.2–1.3 pointed out that the FRESCO+ algorithm retrieves cloud heights close to the surface heights, leading to overestimations in the TROPOMI NO₂ AMFs and, consequently, underestimations of the tropospheric NO₂ columns (Verhoelst et al., 2021). Accurate knowledge of cloud fraction and height is key for high-quality trace gas column retrievals (e.g., Boersma et al., 2004; van Geffen et al., 2021a). A detailed description of the TROPOMI and OMI cloud algorithms and recent updates therein is given in the following subsection.

2.2 Improved TROPOMI FRESCO+, OMI, and VIIRS cloud retrievals

FRESCO+ (Fast Retrieval Scheme for Clouds from the Oxygen A band) retrieves cloud pressures from the relative depth of O₂–A band measurements (Koelemeijer et al., 2001; Wang et al., 2008) using three spectral windows at 758–759 nm (continuum, no absorption), 760–761 nm (strong absorption), and 765–766 nm (moderate absorption). In the algorithm, clouds are assumed to be Lambertian reflectors with a fixed albedo of 0.8, consistent with assumptions for the NO₂ AMF calculation. The surface albedo assumed in the cloud pressure retrieval is from the GOME-2 minimum Lambertian-equivalent reflectivity (LER) climatology at 758 and 772 nm (Tilstra et al., 2017), which is a potential source of uncertainty in the cloud pressure retrieval as the resolution and overpass time of GOME-2 are different from TROPOMI. FRESCO+ has been compared to other cloud data sets by Compernolle et al. (2021), who reported on tendencies in FRESCO+ to overestimate cloud pressures.

To address the high-bias in TROPOMI FRESCO+ cloud pressures, a new version of the FRESCO+ algorithm was introduced and implemented in the operational NO₂ retrieval with the introduction of TROPOMI v1.4 in December 2020. This version, called FRESCO+ wide, uses a wider spectral window for the cloud retrieval (765–770 nm, see Table 1), which includes the flank of the absorption band, where oxygen absorption is weaker than in the center of the O₂–A band (761 and 765 nm). Adding weaker O₂ absorption features improves the sensitivity to clouds low in the atmosphere. This is not possible from the strong O₂ absorption at 761 nm, which is so close to saturation that it becomes difficult to use its absorption depth in order to distinguish between bright reflecting layers at the Earth’s surface and reflecting surfaces in the lower atmosphere.

Prior to the implementation of FRESCO+ wide in the operational TROPOMI NO₂ retrieval in December 2020, KNMI produced four periods with TROPOMI NO₂ test data based on FRESCO+ wide, the so-called diagnostic data set 2B (DDS-2B). DDS-2B contains data from four v1.2–v1.3
Table 1. Retrieval settings for the TROPOMI and OMI NO$_2$ retrievals used in this work.

<table>
<thead>
<tr>
<th></th>
<th>TROPOMI v1.2–1.3</th>
<th>TROPOMI v1.4–2.1*</th>
<th>OMI QA4ECV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Data availability</strong></td>
<td>ESA science hub</td>
<td>ESA science hub</td>
<td>qa4ecv.eu</td>
</tr>
<tr>
<td><strong>Spatial resolution at nadir</strong></td>
<td>3.5 km × 5.5 km</td>
<td>3.5 km × 5.5 km (3.5 km × 7 km)</td>
<td>13 km × 25 km</td>
</tr>
<tr>
<td><strong>$N_s$</strong></td>
<td><strong>Fitting window</strong></td>
<td><strong>Signal-to-noise ratio</strong></td>
<td>Daily</td>
</tr>
<tr>
<td></td>
<td>405–465 nm</td>
<td>~ 1500</td>
<td>5</td>
</tr>
<tr>
<td><strong>DOAS polynomial degree</strong></td>
<td>5</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td><strong>Intensity offset correction</strong></td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Destriping</strong></td>
<td>Yes (since v1.2)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>AMF</strong></td>
<td>Surface albedo</td>
<td>OMI minimum LER at 440 nm (0.5°)</td>
<td>OMI minimum LER at 440 nm (0.5°)</td>
</tr>
<tr>
<td></td>
<td>A priori NO$_2$ profiles</td>
<td>TM5-MP at 1° × 1°</td>
<td>TM5-MP at 1° × 1°</td>
</tr>
<tr>
<td><strong>Cloud retrieval</strong></td>
<td>FRESCO+</td>
<td>FRESCO+ wide</td>
<td>OMCLDO2</td>
</tr>
<tr>
<td><strong>Cloud pressure</strong></td>
<td>Narrow O$_2$–A band (758, 761, and 765 nm)</td>
<td>Wide O$_2$–A band (758, 761 nm and 765–770 nm)</td>
<td>O$_2$–O$_2$ absorption feature (477 nm)</td>
</tr>
<tr>
<td><strong>Surface albedo in cloud pressure retrieval</strong></td>
<td>GOME-2 minimum LER at 758 and 772 nm (0.25° × 0.25°)</td>
<td>GOME-2 minimum LER at 758 and 772 nm (0.25° × 0.25°)</td>
<td>OMI minimum LER at 758 and 772 nm (0.5° × 0.5°)</td>
</tr>
</tbody>
</table>

* In addition to improved cloud parameters, TROPOMI v2.1 data has improved further through a better calibration of level-1 spectra, especially in the treatment of outliers and saturation (Ludewig et al., 2020), and through improvements in the NO$_2$ algorithm itself (van Geffen et al., 2021a). Version v2.1 is only used for production of the DDS-2B test data and not for publicly released data. Version v2.2, available publicly as of July 2021, is essentially the same as v2.1.

periods during 2018–2019 additionally processed with v2.1 of the TROPOMI algorithm. The most significant difference between the two is that v2.1 (and v1.4) uses cloud fractions and AMFs determined from the FRESCO+ wide cloud pressure instead of the FRESCO+ cloud pressures used in v1.2–v1.3 data.

Additionally, we use co-sampled cloud information from the Ozone Monitoring Instrument (OMI) on board of EOS-Aura. The OMI OMCLDO2 retrieval uses the relative depth of the O$_2$–O$_2$ absorption feature at 477 nm to retrieve cloud pressures (Acarreta et al., 2004; Veefkind et al., 2016). The general approach of using Lambertian reflectors is similar to the FRESCO+ algorithm, but an important difference is that the OMCLDO2-algorithm needs to account for Raman scattering and O$_3$ absorption and that the absorption strength of the O$_2$–O$_2$ features is proportional to the square of the O$_2$ concentration, making it more sensitive to low clouds compared to FRESCO+.

We also use cloud information from VIIRS (Visible Infrared Imager Radiometer Suite) on board of the SUOMI National Polar-orbiting Partnership (SNPP) as a completely independent means of verification. SNPP orbits the Earth in a sun-synchronous, ascending node with full daily global coverage and observes the same scenes as TROPOMI within 3 min. We use NASA’s CLDPROP L2 VIIRS-SNPP cloud product (Platnick et al., 2017) with a resolution of 750 m at nadir, which provides a cloud mask, cloud (top) pressure, cloud optical thickness (COT), and cloud water phase for each pixel retrieved. The VIIRS retrieval derives a cloud top temperature using an optimal estimation approach in the thermal infrared spectral bands M14–M16 (8.5–12.3 µm). In a subsequent step, these cloud top temperatures are converted to cloud pressures using numerical weather prediction temperature profiles (Heidinger and Li, 2017). In addition to the cloud top pressure, we use the VIIRS cloud optical thickness (COT) to generate (effective) cloud fractions that can be compared directly to the TROPOMI cloud fractions. First, we derive a geometrical cloud fraction by calculating the share of cloudy VIIRS pixels per grid cell. Then, we translate this geometrical cloud fraction $f_{c,\text{geo}}$ into an effective cloud...
fraction \( f_{c, \text{eff}} \) using
\[
f_{c, \text{eff}} = f_{c, \text{geo}} \cdot a_{c}/0.8, \tag{1}
\]
with \( a_{c} \) being the cloud albedo. The cloud albedo is calculated from the VIIRS COT and a previously established empirical relationship between cloud optical thickness and cloud albedo for liquid water clouds (Buriez, 2005; Boersma et al., 2016).3

To evaluate the improvements in the FRESCO+ wide retrieval, we compare daily gridded, co-sampled cloud data from (partly) cloudy pixels seen by TROPOMI (FRESCO+ and FRESCO+ wide), OMI, and VIIRS over parts of the Mediterranean Sea (37.0–41.25° N, 2.0–8.0° W), the Bay of Biscay (43.5–47.5° N, 10.0–3.0° E), and Northwest Europe (50.0–53.0° N, 4.0–9.0° W). These regions represent different surface types (land and ocean), climatological conditions, and pollution levels. We define partly cloudy pixels as all pixels with an effective cloud fraction \( f_{c} \geq 0.05 \). For TROPOMI we additionally apply sufficient quality of retrieval (\( f_{\text{QA}} \geq 0.5 \)) and a pressure difference between surface pressure and cloud pressure of at least 7 hPa. The last filter is applied to filter out “ghost” clouds coming from sun glint viewing geometries (see Sect. 2.3 below). For OMI, we use the OMCLDO2 cloud properties and take only pixels with solar and viewing zenith angles smaller than 80° into account. As Eq. (1) is valid for liquid water clouds only, we select liquid water clouds and reject ice clouds, as indicated by the VIIRS cloud water phase. Around 25%–30% of VIIRS pixels are missed due to this filter.

2.3 Sun glint in the TROPOMI NO\(_x\) retrieval

The term sun glint refers to particular satellite viewing geometries, under which the ocean acts as a mirror by reflecting sun light directly to the satellite instrument. In the TROPOMI data product pixels that are potentially in sun glint mode are identified based on the combination of their solar and viewing zenith and azimuth angles. The sun glint condition is fulfilled when the scattering angle \( \Theta \) is smaller than a threshold angle \( \Theta_{\text{max}} \):
\[
\Theta = \arccos \left[ \cos \phi \cos \phi_{0} - \sin \phi \sin \phi_{0} \cos (\phi_{0} - \phi) \right] \leq \Theta_{\text{max}}, \tag{2}
\]
with \( \phi \) and \( \phi_{0} \) the solar and viewing zenith angles and \( \phi \) and \( \phi_{0} \) the solar and viewing azimuth angles, respectively (see Fig. S1). For the TROPOMI data products the maximum threshold angle has been set at 30°. Smaller angles are used before, e.g., for SCIAMACHY and GOME-2 (Loots et al., 2017). The TROPOMI algorithm treats the enhanced albedo as a partially cloudy scene with the cloud pressure located at or close to the sea surface.

2.4 Relationship between NO\(_x\) emissions and columns

When studying NO\(_x\) columns to investigate emission trends, the non-linearity of NO\(_x\) chemistry needs to be taken into account. For example, the lifetime of NO\(_x\) depends on the background O\(_3\) level, the available sun light, and NO\(_x\) concentrations themselves (Jacob, 1999). We use a (modeled) \( \beta \) factor to express the sensitivity of relative NO\(_x\) column changes to changes in the relative emission strength following the approach in Vinken et al. (2014a) with
\[
\beta = \frac{\Delta N/N}{\Delta E/E}, \tag{3}
\]
where \( \Delta E/E \) represents the imposed relative change in NO\(_x\) emission flux and \( \Delta N/N \) the relative change in subsequently simulated tropospheric NO\(_x\) columns. Here we use \( \beta \) values from Vinken et al. (2014b) modeled with GEOS-Chem at 0.5° × 0.67° and accounting for plume-in-grid chemistry. These \( \beta \) values have a similar spatial resolution as the spatially averaged TROPOMI NO\(_x\) signals from ships (see Fig. 9). As we are interested in European seas only, we average \( \beta \) in the area 35–40° N and 5° E–10° W for Gibraltar and 30–37° N and 15–35° W for the Eastern Mediterranean. We use the resulting \( \beta \) value to estimate relative changes in NO\(_x\) emissions (\( E_{2020} - E_{2019} \)) as
\[
\frac{E_{2020} - E_{2019}}{E_{2019}} = \beta \cdot \frac{N_{\text{obs},2020} - N_{\text{obs},2019}}{N_{\text{obs},2019}}, \tag{4}
\]
where \( (N_{\text{obs},2020} - N_{\text{obs},2019})/N_{\text{obs},2019} \) is the observed relative change in NO\(_x\) columns.

2.5 AIS data and ship-specific data

To relate the TROPOMI NO\(_x\) columns to shipping activity, we use data from the automatic identification system (AIS) for shipping. Since 2005, the International Maritime Organization (IMO) requires all ships with a gross tonnage over 300 and all passenger ships to carry an AIS transponder. These transponders broadcast static (e.g., identity, size) and dynamic (e.g., position, speed, course) information of the ship, which can be received by other ships, shore stations, and satellites (International Maritime Organization (IMO), 2014). Here we use historical AIS data available to the Dutch Human Environment and Transport Inspectorate (ILT) to assess changes in shipping activity over densely traveled European shipping lanes in 2019 and 2020. We use AIS data of ships in a part of the shipping lane in the Eastern Mediterranean (31.91–34.53° N and 25.91–27.67° E) and close to the Strait of Gibraltar (35.0–37.0° N and 4.0–2.5° W). Furthermore, we use information on ship dimensions from the official ship registrations (https://gisis.imo.org/Public/Default...
aspx, last access: 20 December 2021) to calculate a ship emission proxy \( E \) from ship length \( L \) and ship speed \( v \) as \( E \propto L^2 \cdot v^3 \), as used, for example, in Georgoulas et al. (2020). For the areas and times under study, ship-specific data were available only for 50\% (Gibraltar) and 70\% (Eastern Mediterranean) of the ships.

3 Results

We start with demonstrating TROPOMI’s capabilities to detect shipping \( \text{NO}_2 \) by applying established data selection criteria. Next, we show steps to optimize monitoring of ship emissions by making use of sun glint (Sect. 3.2) and recent improvements in the cloud retrieval (Sect. 3.3) and compare the improved TROPOMI data to OMI data in Sect. 3.4. We end with an application of our findings to quantify \( \text{NO}_2 \) emission reductions from shipping due to COVID in 2020 in Sect. 3.5.

3.1 Detection of \( \text{NO}_2 \) pollution over European shipping lanes

TROPOMI detects unprecedented spatial detail in shipping \( \text{NO}_2 \) over busy shipping routes. Figure 1 shows the summertime mean (May–September 2019) \( \text{NO}_2 \) columns from TROPOMI and OMI averaged to a common \( 0.0625^\circ \times 0.0625^\circ \) grid, as well as CAMS/STEAM \( \text{NO}_2 \) emissions (Granier et al., 2019; Johansson et al., 2017) for the same period. We find a clear signal of shipping \( \text{NO}_2 \) in the TROPOMI data west of Portugal and from the Strait of Gibraltar to the east. There are further indications of enhanced \( \text{NO}_2 \) related to shipping in the Bay of Biscay from the tip of Brittany towards the northwest of Spain, and in the Eastern Mediterranean from the south of Sicily towards the Suez Canal. Previous studies reported \( \text{NO}_2 \) enhancements over these shipping lanes with other satellites (e.g., by OMI; Vinken et al., 2014b). Additionally, we see a clear \( \text{NO}_2 \) enhancement in the Aegean Sea between Istanbul and the Greek islands, as well as around Denmark, as shown in Fig. 2, which to our knowledge have not been observed by satellite instruments previously. Furthermore, (clear) hints of shipping activity can be seen in the Baltic Sea, the eastern Aegean Sea, the Adriatic Sea, northeast of Corsica, the British Channel, and several forks in the Eastern Mediterranean and southeast of Sicily, which are present in using AMF (see Appendix B) as wind-induced waves are expected to change the reflectivity. Fig. 4a shows the relationship between effective scene albedo and wind speed for scenes with small scattering angles \( \Theta \leq 15^\circ \). For very low wind speeds the mean scene albedo is almost as high for non-sun glint scenes and smaller than for all other wind speeds. For wind speeds between 1.5 and \( 2.0 \text{ m s}^{-1} \) we find an effective scene albedo of almost 0.25, which is approximately double compared to the average for these scattering angles and more than 5 times as high as for non-sun glint scenes. For higher wind speeds the scene albedo decreases to around 0.10. In Fig. 4b the effect on the averaging kernel profile is shown. As ex-
Figure 1. Summertime (May–September) mean tropospheric NO\textsubscript{2} columns from TROPOMI (a) and OMI (b) over European seas in 2019. Panel (c) shows the summertime mean NO\textsubscript{x} emissions from the CAMS/STEAM emission inventory (Granier et al., 2019; Johansson et al., 2017). The gray and pink rectangles in the center panel indicate areas used in Sect. 3.2 and 3.4, respectively.

Figure 2. The 2019 summertime mean (May–September) tropospheric NO\textsubscript{2} columns from TROPOMI (a, c) and summertime mean NO\textsubscript{x} emissions from the CAMS/STEAM emission inventory (b, d; Granier et al., 2019; Johansson et al., 2017) of shipping lanes around Denmark (a, b) and the eastern Aegean Sea (c, d) for the first time detected with satellites.

Expected low wind speeds lead to the smallest AK in the lower atmosphere, whereas wind speeds between 1.5 and 2.0 m s\textsuperscript{-1} show the largest AKs close to the sea surface. This relationship can be understood in terms of wind-induced sea surface roughness (Cox and Munk, 1956). Both very low and strong winds limit the probability that a scattering angle $\Theta \leq \Theta_{\text{max}}$ leads to sun glint effects at the sensor: For very low wind speeds, the sea surface is effectively flat, leading to sun glint only for very small scattering angles $\Theta \ll \Theta_{\text{max}}$, whereas for strong winds the sea surface is so rough that the sun light is reflected in all directions, making the reflections towards the satellite instrument unlikely.
Additionally, we find that sun glint scenes can be used with confidence for detecting ship pollution signals from UV–Vis spectrometers such as TROPOMI, and the usage of sun glint data should be encouraged. The (normalized) tropospheric slant columns \( N_{\text{trop,geo}} = N_s \text{trop} / M_{\text{geo}} \) (see Appendix B) observed under sun glint conditions are 20%–25% higher than under non-sun glint conditions as shown in Fig. 5a. Vertical profiles of \( \text{NO}_2 \) over oceans typically feature enhancements from ships within the marine boundary layer and small background levels above (e.g., Chen et al., 2005b; Boersma et al., 2008; see Fig. 1). Therefore, it is no surprise that the AK increases in the lower atmosphere lead to small but detectable increases in (tropospheric) slant columns over the study region covering a frequently traveled shipping lane.

The enhanced slant columns are correctly accounted for by increased AKs leading to reliable retrievals under sun glint. Figure 5b compares the tropospheric vertical columns reported in the official TROPOMI \( \text{NO}_2 \) product sampled under sun glint compared to non-sun glint conditions. The differences between the distributions are only small. Mean values for scene albedo, (normalized) tropospheric slant columns, and tropospheric vertical columns reported in the official TROPOMI \( \text{NO}_2 \) product for different scattering angles are summarized in Table 2.

3.3 Cloud properties

Here we evaluate TROPOMI’s capability to retrieve realistic cloud parameters retrieved from the 405–465 nm continuum reflectances and effective cloud pressures from the \( \text{O}_2-A \) band (Table 1), addressing recent improvements in the FRESCO+ algorithm to avoid overestimated cloud pressures (Compernolle et al., 2021). These improvements in
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3.3.1 Cloud fractions

We find that improved TROPOMI cloud fractions are of sufficient quality to support the TROPOMI NO$_2$ AMF calculation. They show good correlation with independent data such as from OMI and VIIRS. TROPOMI v1.2 and v2.1 cloud fractions are very similar, with the new v2.1 cloud fractions being slightly smaller. More details can be found in Appendix D1.

3.3.2 Cloud pressure

FRESCO+ wide cloud pressures are a clear improvement over the FRESCO+ data used in v1.2–1.3. Figure 6 shows a comparison of gridded, co-sampled cloud pressure distributions from TROPOMI v1.2 (FRESCO+), TROPOMI v2.1 (FRESCO+ wide), OMI QA4ECV, and VIIRS over the Bay of Biscay between 1 and 7 July 2018. As expected, the improved TROPOMI v2.1 cloud pressures are $\approx 40$ hPa lower than for v1.2, in line with their enhanced sensitivity, and show more realistic, elevated clouds. It is apparent that OMI cloud pressures are generally lower and show a flatter distribution than the other products. TROPOMI v2.1 and v1.2 show similar distributions as VIIRS, with v1.2 pressures higher by 50 hPa in the median and v2.1 moving closer to VIIRS with a difference of 2 hPa relative to VIIRS. We find similar agreement between TROPOMI and independent data over the Mediterranean Sea and Northwest Europe as shown in Table D2. FRESCO+ wide cloud pressures agree best but remain higher than VIIRS in the median (both FRESCO cloud pressure distributions show a larger tail towards low pressures compared to VIIRS, possibly caused by filtering for liquid water clouds in VIIRS). This is in line with expectations as VIIRS’s infrared cloud retrieval is mostly sensitive

### Table 2

<table>
<thead>
<tr>
<th></th>
<th>Non-sun glint</th>
<th>Sun glint</th>
<th>Super sun glint</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective scene albedo</td>
<td>0.03 ± 0.02</td>
<td>0.08 ± 0.05</td>
<td>0.11 ± 0.05</td>
</tr>
<tr>
<td>$N_{\text{Trop,geo}}$ (molec. cm$^{-2}$)</td>
<td>(0.65 ± 0.28) $\times 10^{15}$</td>
<td>(0.80 ± 0.30) $\times 10^{15}$</td>
<td>(0.83 ± 0.30) $\times 10^{15}$</td>
</tr>
<tr>
<td>$N_{\text{v,trop}}$ (molec. cm$^{-2}$)</td>
<td>(1.06 ± 0.42) $\times 10^{15}$</td>
<td>(1.05 ± 0.40) $\times 10^{15}$</td>
<td>(1.06 ± 0.38) $\times 10^{15}$</td>
</tr>
</tbody>
</table>

cloud retrievals lead to an inconsistency in the tropospheric NO$_2$ column record.

### Figure 5

(a) Probability distribution of tropospheric NO$_2$ columns ($N_{\text{trop}}/M_{\text{geo}}$) over the Central Mediterranean north of Libya in June–July–August 2018 (see grey rectangle in Fig. 1c) taken under non-sun glint, sun glint ($\theta \leq 30^\circ$), and super sun glint ($\theta \leq 20^\circ$). (b) Probability distribution of tropospheric NO$_2$ columns in the official TROPOMI NO$_2$ product ($N_{\text{trop}}/M_{\text{trop}}$) for the same data selection.

### Figure 6

Probability distribution function of effective cloud pressures from TROPOMI v1.2, TROPOMI v2.1, OMI, and VIIRS for 1–6 July 2018 over the Bay of Biscay. Only cloud pressures for cloud fractions between 0.05 and 0.20 were selected as these are most relevant for AMF calculations for mostly clear-sky pixels.

to the cloud top (Platnick et al., 2017), whereas FRESCO’s O$_2$–A band retrieval is more sensitive to the center of a cloud (e.g., Sneep et al., 2008). Around 25%–30% of VIIRS cloud retrievals in the areas studied here are ice water clouds and therefore not included in the analysis. As these clouds appear at higher altitudes, improved cloud pressures have only a little influence on the NO$_2$ columns (see Sect. 3.3.3).

### 3.3.3 Effect of improved cloud pressure on TROPOMI NO$_2$ columns

The improved cloud pressures lead to increases in NO$_2$ columns of up to 40% depending on area and season. The left panels of Fig. 7 show the change in tropospheric NO$_2$ columns as a function of cloud pressure over the Bay of Biscay and Northwest Europe in summer. We see that NO$_2$ columns increase most for locations that had the highest original v1.2 cloud pressures and that the improvements are strongest when cloud pressures are reduced most (light blue dots). The increase over the Bay of Biscay is smaller (up to $0.1 \times 10^{15}$ molec. cm$^{-2}$) than over Northwest Europe (up to $1.0 \times 10^{15}$ molec. cm$^{-2}$), reflecting the higher pollution levels over the mainland. We see similar patterns with stronger improvements in winter, as shown in the right panels of Fig. 7. The increased v2.1 NO$_2$ columns indicate that the v1.2 TROPOMI NO$_2$ product suffers from a “cloud shielding” effect: NO$_2$ columns are underestimated due to clouds that are situated too low within the polluted boundary layer, and improved v2.1 cloud pressures (at least partly) resolve the low bias in v1.2 NO$_2$ columns. For this analysis, we compared the TROPOMI v2.1 columns retrieved with improved cloud information to the TROPOMI v1.2 NO$_2$ columns. We used 10 d in four different seasons (27 June–6 July 2018, 28 December 2018–5 January 2019, 25 March–5 April 2019, and 13–23 September 2019) for which both v2.1 test data and v1.2 operational data were available to us as part of the DDS-2B. Our comparison focused on mostly clear-sky situations ($f_c < 0.2$), which are most relevant for the detection of near-surface pollution sources.

We trained a deep neural network (DNN) to predict v2.1 columns for the full TROPOMI mission period up to December 2020 and thereby created a consistent data set. The DNN-predicted v2.1 (hereafter v2.1p) reduces the mean difference to the retrieved v2.1 NO$_2$ columns to $< 0.01 \times 10^{15}$ molec. cm$^{-2}$ (original v2.1–v1.2 mean difference was $0.12 \times 10^{15}$ molec. cm$^{-2}$) over the three areas (see Sect. 2.2) of study during the four periods, suggesting considerable skill in the DNN approach. Details can be found in Appendix E.

Figure 8 shows the averaged NO$_2$ columns from v2.1p over the summer of 2019 and winter of 2019/2020. The difference map in the right panels indicates that predicted v2.1 NO$_2$ columns are higher by up to $0.5 \times 10^{15}$ molec.cm$^{-2}$, especially over the most polluted seas such as the English Channel and shipping lanes. We find a stronger impact of the improved cloud pressures in the winter season, reflecting that NO$_2$ pollution is confined in a thinner marine boundary layer in that season.

### 3.4 Comparison of TROPOMI and OMI NO$_2$ columns in shipping lanes

TROPOMI detects a more pronounced and narrower region of ship NO$_2$ pollution than OMI. On average, TROPOMI v2.1p detects 45% higher peak NO$_2$ values than OMI. TROPOMI data allow the attribution of 14% more NO$_2$ to shipping lane enhancements and over 23% to narrower shipping lanes. To quantitatively investigate TROPOMI’s capability to detect NO$_2$ over shipping lanes under different measurement conditions and compare it to OMI’s, we created average NO$_2$ cross sections over busy shipping lanes. We studied NO$_2$ enhancements in summer 2019 (June–August) over shipping lanes in the Bay of Biscay, from Sicily to the Suez Canal, and east of Gibraltar, the regions visually defined in Fig. 1c. First, we defined the location of the shipping lanes according to the emission data shown in Fig. 1c. Then, we calculated the average NO$_2$ columns along the shipping lane and parallel to it, taking care to exclude NO$_2$ columns measured over land. In that way we created an average cross section of NO$_2$ over shipping lanes. In the last step, we performed a background correction by subtracting a linear NO$_2$ background to isolate the NO$_2$ enhancements caused by shipping. The orbital data were gridded to regular grids of $0.0625^\circ \times 0.0625^\circ$ and $0.125^\circ \times 0.125^\circ$ resolution for TROPOMI and OMI, respectively. For TROPOMI only pixels with $f_{QA} > 0.75$ were taken into account. For OMI, a consistent filtering was applied, including maximal solar and viewing zenith angles of 80° and maximal cloud radiance fractions of 0.5. The resulting cross sections are shown in Fig. 9. Table 4 summarizes the peak value, the area under the curve (i.e., the total NO$_2$ attributed to shipping) and the full width at half maximum (FWHM) for the three shipping lanes. It should be noted that the grid used for OMI is 2 times coarser than the one used for TROPOMI. Gridding TROPOMI to the coarser grid used for OMI only changes the results slightly, indicating that the improved spatial resolution of TROPOMI indeed improves the detection of NO$_2$.
from narrow ship lanes and is in line with the finding of new shipping lanes shown in Fig. 2.

As already seen in Fig. 8, the v2.1p data set shows slightly higher NO\textsubscript{2} compared to the TROPOMI v1.2–v1.3 data, especially in the center of the lane, while background NO\textsubscript{2} is less affected by the correction. The impact of the DNN is larger in winter than in summer as discussed before.

For the Bay of Biscay it is also apparent that the NO\textsubscript{2} peak is shifted to the east for all data sets. As the location is defined by an emission inventory based on AIS data (and therefore real ship location), this is likely an effect of dominant westerly winds.

We conclude that TROPOMI provides a significant improvement for the detection of shipping NO\textsubscript{2} with sharper and more pronounced shipping lanes in seasonal averages. The improved v2.1p TROPOMI data increase the signal further.

3.5 Reductions in ship NO\textsubscript{x} emissions during the COVID-19 pandemic

Emission proxies derived from AIS data and from TROPOMI NO\textsubscript{2} suggest emission reductions from shipping in 2020 compared to 2019 as depicted in Fig. 10c and f. While in the first 3 months of 2020 the ship emissions were generally higher compared to 2019, both emission proxies show reductions starting in April and lasting until the end of the year. This reduction can be linked to the COVID-19 pandemic, which led to economic lockdowns in many countries of the world. Europe had its most stringent measures in spring and autumn 2020.

We created daily 0.0625° × 0.0625° maps of TROPOMI data using v2.1p NO\textsubscript{2} columns as described in Sect. 3.3.3 with \( f_{QA} \geq 0.75 \). We calculate the area under the cross section as a measure for shipping NO\textsubscript{2} for monthly mean NO\textsubscript{2} columns for the shipping lanes of Gibraltar and the Mediterranean defined in Fig. 1c. Monthly TROPOMI shipping NO\textsubscript{2} for 2019 and 2020 can be seen in Fig. S2c. Figure 10d shows the relative change in shipping NO\textsubscript{2} from 2019 to 2020 in the Strait of Gibraltar. Using \( \beta \) values and the approach de-
Figure 8. Effect of DNN correction: (a) corrected TROPOMI data for summer (May–September) 2019, (b) change in NO$_2$ columns by the correction for the same period (v2.1p–v1.3), (c) corrected TROPOMI data for winter (November–April) 2019/2020, and (d) change in NO$_2$ columns by the correction for the same period (v2.1p–v1.3). Land areas are whitened out for clarity.

Figure 9. Mean enhancement cross sections in June–August 2019. TROPOMI v1.2–v1.3 in black, the improved TROPOMI v2.1p in green, and OMI in grey. Shaded areas indicate the 95% confidence interval.

scribed Sect. 2.4 and shown in Fig. 10e, we arrive at the TROPOMI-based relative change in emission changes shown in Fig. 10f.

The uncertainty in our top-down NO$_x$ emission changes follows from the following: (i) the sensitivity of TROPOMI shipping NO$_2$ to the area of study ($\sigma_{\text{area}} = 5\%$), (ii) the inter-year differences on monthly averaged NO$_2$ columns over the areas of study caused by meteorology, and (iii) the combined spatial and temporal spread of $\beta$ as a result of differences in the chemical regime caused, for example, by differences in atmospheric composition and radiation ($\sigma_{\beta} = 0.15$). Figures 10d and F1d show $\sigma_{\text{area}}$ in panel (e) uncertainties (ii) and (iii) are used, while for panel (f) a full error propagation of all uncertainties listed above was performed. A full discussion on the uncertainty estimates can be found in Sect. S4.
Table 4. Statistics for the NO$_2$ enhancement cross section over the Mediterranean shipping lane.

<table>
<thead>
<tr>
<th>Shipping lane</th>
<th>Product</th>
<th>Max (10$^{15}$ molec. cm$^{-2}$)</th>
<th>Area under curve (10$^{15}$ km molec. cm$^{-2}$)</th>
<th>FWHM (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bay of Biscay</td>
<td>TROPOMI v1.2–v1.3</td>
<td>0.189</td>
<td>11.34</td>
<td>54.6</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1p</td>
<td>0.195</td>
<td>11.72</td>
<td>54.6</td>
</tr>
<tr>
<td></td>
<td>OMI</td>
<td>0.113</td>
<td>7.75</td>
<td>59.2</td>
</tr>
<tr>
<td>Strait of Gibraltar</td>
<td>TROPOMI v1.2–v1.3</td>
<td>0.534</td>
<td>24.47</td>
<td>41.3</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1p</td>
<td>0.562</td>
<td>26.18</td>
<td>41.7</td>
</tr>
<tr>
<td></td>
<td>OMI</td>
<td>0.418</td>
<td>28.83</td>
<td>63.8</td>
</tr>
<tr>
<td>Mediterranean</td>
<td>TROPOMI v1.2–v1.3</td>
<td>0.148</td>
<td>8.80</td>
<td>52.3</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1p</td>
<td>0.153</td>
<td>9.19</td>
<td>52.6</td>
</tr>
<tr>
<td></td>
<td>OMI</td>
<td>0.113</td>
<td>8.56</td>
<td>70.2</td>
</tr>
</tbody>
</table>

Figure 10. (a) Relative change in monthly mean of daily number of ships passing the Strait of Gibraltar between 2019 and 2020 inferred from AIS data. (b) Same but with average ship speed. (c) Relative change in emission proxy ($v^3 \cdot L^2$). (d) Relative change in TROPOMI shipping NO$_2$. (e) Monthly $\beta$ values from Vinken et al. (2014b) with month-to-month variability imposed by monthly values from Verstraeten et al. (2015). Uncertainty intervals represent the temporal and spatial variability in $\beta$ (see discussion in the text). (f) Relative change in top-down emissions from shipping. Error bars represent the propagated uncertainties in TROPOMI shipping NO$_2$, $\beta$, and differences in meteorological conditions between 2019 and 2020 (see discussion in the text).

Additionally, we used AIS data to calculate an AIS-based emission proxy as described in Sect. 2.5. We filtered for days with TROPOMI coverage of at least 50 % of each study area. AIS data indicate that the number of ships passing per month through the Strait of Gibraltar has reduced from March 2020 onwards relative to 2019 (Figs. 10a and S2a). The average speed of the ships passing through the shipping lanes is lower between May–September 2020 compared to the same period in 2019 as well (Figs. 10b and S2b). This is in agreement with a study by Millefiori et al. (2020) who found an increase in container ship speed in May and June in 2019 which is absent in 2020 leading to a relative decrease. Finally, Fig. 10c shows the relative change in AIS-deduced emission proxy from 2019 to 2020. Similar results for the shipping lane in the Mediterranean can be found in Figs. F1 and S3.

Several studies report changes in ship activity in 2020 using AIS data. In addition to the 5 % decrease in ship speed in the Mediterranean between March and April 2020 compared to 2019 mentioned above, Millefiori et al. (2020) reported global mobility of container ships to have decreased by 10 % between March and June 2020 compared to the previous year. March et al. (2021) find increases in traffic density for January and February 2020 with decreases in March–June, with western Europe showing very strong reductions. Both studies show strong variations by vessel category and geographical distribution. Doumbia et al. (2021) find a global...
enhances the signal strength from spectral fitting of NO that sun glint drives higher apparent scene reflectivity, which
quent steps in the TROPOMI retrieval procedure. We find
examined how sun glint viewing geometries affect subse-
ual ship’s NO
These newly found lanes of pollution coincide with busy sail-
Denmark and Norway, which are not detected by OMI and
NO
evaluated the high-resolution TROPOMI NO
columns provide valuable information on ship air pol-
emissions over European
seas in 2019–2020. Satellite observations of tropospheric
pollution. In European
waters alone, TROPOMI finds six new lanes with enhanced
NO2 ranging from the Aegean Sea to the Skagerrak between
Denmark and Norway, which are not detected by OMI and
which have not previously been reported in the literature.
These newly found lanes of pollution coincide with busy sail-
ing routes and bottom-up emission proxies.
To better understand the recent detection of an individ-
ual ship’s NO2 plume under conditions of sun glint, we
examined how sun glint viewing geometries affect subse-
quent steps in the TROPOMI retrieval procedure. We find
that sun glint drives higher apparent scene reflectivity, which
enhances the signal strength from spectral fitting of NO2
columns along the average light path by 20 %–30 % over
clear-sky shipping lanes. In such situations, the vertical sen-
sitivity to NO2 within the marine boundary layer increases by
up to 60 %. This effect is especially strong when sea surface
wind speeds are low but non-zero. When winds are strong,
the wash causes sunlight to be reflected in other directions
than directly towards the satellite, leading to little gain in ver-
tical sensitivity. We find that the TROPOMI NO2 algorithm
accounts for these effects so that data within and outside of
sun glint geometries can be used with confidence. Never-
theless, our work clearly indicates that optimal spectral fit-
ting can be accomplished for small scattering angles (< 15°)
and sea surface wind speeds of 1.5–3 m s−1. Although se-
lecting a subset fulfilling these sampling criteria reduces the
amount of available data sharply, our findings indicate that
sun glint conditions are beneficial for quantifying previously
undetectable small NOx emission sources over open sea and
holding promise for also detecting other trace gases with
UV–Vis satellite instruments over water, where surface re-
lectivity and vertical sensitivity are generally small.
In November 2020, KNMI implemented an improved
FRESCO+ cloud retrieval called FRESCO+ wide in the op-
erational TROPOMI NO2 algorithm. We find here that this
new FRESCO+ wide cloud retrieval provides some 50 hPa
lower cloud pressures which agree better with coinciding
cloud top heights from the VIIRS sensor than the standard
FRESCO+. We show that the improved cloud pressures lead
to a more realistic description of vertical sensitivities in the
TROPOMI NO2 algorithm and at least partly address the
known low bias in the tropospheric NO2 product prior to
November 2020, thus not only solving a known issue in the
TROPOMI NO2 retrieval but also increasing signal strength.
We then trained a neural network on a limited data set of
simultaneously available standard and improved cloud and
NO2 retrievals. Based on four different training sets, the neu-nal network learned the statistical relationship between stan-
dard FRESCO+ cloud pressures and other parameters and
the new tropospheric NO2 columns. We used the neural net-work to predict updated NO2 columns for the entire 2019–
2020 TROPOMI NO2 record. The neural network predicts
a general increase in tropospheric NO2 columns. Increases
are particularly strong (up to 4×1015 molec. cm−2) in the
most polluted regions of Europe in wintertime. Our predicted
(v2.1p) TROPOMI data set enables the consistent analysis of
temporal changes in NO2 during the COVID year 2020 and
is useful to other data users until the TROPOMI NO2 repro-
cessing scheduled for 2022 has been completed.
We compared changes in our v2.1p TROPOMI NO2
columns between 2019 and 2020 to changes in the number
of ships, their speed, and their size obtained from AIS data
in the main European traffic lanes. From April 2020 onwards,
TROPOMI observes 25 % less NO2 pollution than in the year
before, in step with a 10 % reduction in the number of ships
and a 5 % speed reduction relative to 2019. Accounting for
non-linearity in local NOx chemistry, we infer an average
20 % reduction in top-down NOx emissions in the Strait of
Gibraltar from ships during months in which COVID mea-
sures were in force in Europe, and global mobility decreased

4 Discussion and conclusion

We used tropospheric NO2 column observations from the
TROPOMI sensor to optimally monitor ship NO2 pollution
and study the changes in ship NOx emissions over European
seas in 2019–2020. Satellite observations of tropospheric
NOx columns provide valuable information on ship air pol-
lution over open seas, which can be used to inform compli-
ance monitoring by flag states and national authorities. We
evaluated the high-resolution TROPOMI NO2 retrievals for
its potential to better detect ship NO2 pollution. In European
waters alone, TROPOMI finds six new lanes with enhanced
NO2 ranging from the Aegean Sea to the Skagerrak between
Denmark and Norway, which are not detected by OMI and
which have not previously been reported in the literature.
These newly found lanes of pollution coincide with busy sail-
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To better understand the recent detection of an individ-
ual ship’s NO2 plume under conditions of sun glint, we
examined how sun glint viewing geometries affect subse-
quent steps in the TROPOMI retrieval procedure. We find
that sun glint drives higher apparent scene reflectivity, which
enhances the signal strength from spectral fitting of NO2
columns along the average light path by 20 %–30 % over
clear-sky shipping lanes. In such situations, the vertical sen-
sitivity to NO2 within the marine boundary layer increases by

as a result of the pandemic. For future research, a full chemical transport modeling of AIS-based emissions and strict co-sampling of AIS and TROPOMI data can help with understanding the observed differences in top-down and bottom-up emission changes and reduce the error margins.

We showed that TROPOMI is a superior instrument to analyze relatively small enhancements in NO₂ pollution over dark European seas. Its vertical sensitivity to ship pollution is substantially enhanced for small scattering angles under cloud free conditions and low wind speeds. Such sun glint scenes should allow improved detection of other pollutants, such as formaldehyde and SO₂ as well. KNMI’s operational TROPOMI NO₂ product is subject to continuous improvement, which causes step changes in the publicly available data record until the official reprocessing has been finalized. Our improved (v2.1p) TROPOMI data set offers a consistent alternative that can be used over Europe in and after 2019 and may be applied to other regions of the world where consistent NO₂ time series are needed.
Appendix A: Zoomed-in NO₂ maps

Figure A1. Summertime mean (May–September) tropospheric NO₂ columns from TROPOMI (left panels) and summertime mean NOₓ emissions from the CAMS/STEAM emission inventory (right panels; Granier et al., 2019; Johansson et al., 2017).
Appendix B: \( N_{\text{TROP,geo}} \)

We calculate a geometric tropospheric vertical column density \( N_{\text{TROP,geo}} \) using

\[
N_{\text{TROP,geo}} = \frac{N_{\text{s,trop}}}{M_{\text{geo}}},
\]

(B1)

where \( N_{\text{s,trop}} \) is the tropospheric slant column density which can be calculated from the TROPOMI files using

\[
N_{\text{s,trop}} = N_{\text{s,tot}} - N_{\text{s,strat}} = N_{\text{s,tot}} - N_{\text{v,strat}} \cdot M_{\text{strat}},
\]

(B2)

where \( M, N_s, \) and \( N_v \) are mean air mass factor, slant column density, and vertical column density, respectively. The subscripts trop, tot, and strat indicate tropospheric, total, and stratospheric columns, respectively. \( M_{\text{geo}} \) can be calculated using the solar zenith angle \( \theta \) and the viewing zenith angle \( \theta_0 \) as

\[
M_{\text{geo}} = \frac{1}{\cos(\theta)} + \frac{1}{\cos(\theta_0)}.
\]

The resulting tropospheric column is shown in Fig. B1.

Figure B1. Mean of \( \text{NO}_2 \) columns calculated with geometrical AMF for summer 2019 (May–September); land areas have been whitened for clarity.

Appendix C: Spatial correlation to emissions

Figure C1. Scatter of binned summertime (May–September) 2019 tropospheric \( \text{NO}_2 \) columns vs. emissions from CAMS/STEAM for the same period at 0.1° x 0.1° in the Mediterranean. Error bars indicate the standard error of the bin. (a): TROPOMI; (b): OMI.
Appendix D: Cloud properties

Table D1. Evaluation of TROPOMI v2.1 cloud fractions over European shipping lanes (1–6 July 2018) against reference data.

<table>
<thead>
<tr>
<th>Shipping lane</th>
<th>Product</th>
<th>Mean bias</th>
<th>RMS</th>
<th>$R^2$</th>
<th>Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biscay</td>
<td>TROPOMI v2.1 vs. 1.2</td>
<td>-0.020</td>
<td>0.036</td>
<td>0.99</td>
<td>0.95 · x</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1 vs. OMI QA4ECV</td>
<td>0.002</td>
<td>0.124</td>
<td>0.78</td>
<td>0.01 + 0.97 · x</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1 vs. VIIRS</td>
<td>-0.062</td>
<td>0.181</td>
<td>0.66</td>
<td>-0.01 + 0.89 · x</td>
</tr>
<tr>
<td>Mediterranean</td>
<td>TROPOMI v2.1 vs. 1.2</td>
<td>-0.009</td>
<td>0.017</td>
<td>0.99</td>
<td>0.96 · x</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1 vs. OMI QA4ECV</td>
<td>0.00005</td>
<td>0.09</td>
<td>0.67</td>
<td>-0.011.05 · x</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1 vs. VIIRS</td>
<td>-0.050</td>
<td>0.147</td>
<td>0.60</td>
<td>0.02 + 0.65 · x</td>
</tr>
<tr>
<td>NW Europe</td>
<td>TROPOMI v2.1 vs. 1.2</td>
<td>-0.015</td>
<td>0.046</td>
<td>0.95</td>
<td>0.94 · x</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1 vs. OMI QA4ECV</td>
<td>-0.038</td>
<td>0.111</td>
<td>0.76</td>
<td>-0.01 + 0.91 · x</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1 vs. VIIRS</td>
<td>-0.026</td>
<td>0.156</td>
<td>0.64</td>
<td>0.04 + 0.74 · x</td>
</tr>
</tbody>
</table>

D1 Cloud fractions

The improved (v2.1) and old (v1.2) cloud fractions have a strong correlation ($R^2 = 0.99$), but v2.1 cloud fractions are 5% lower on average; see Table D1. The spatiotemporal correlation between TROPOMI v2.1 and the well-established OMI QA4ECV cloud fraction product is also very high ($R^2 = 0.78$), with TROPOMI v2.1 cloud fractions 3% lower than OMI on average. TROPOMI v2.1 shows high correlation ($R^2 = 0.66$) and somewhat lower cloud fractions (−11%) compared to the co-sampled effective VIIRS cloud fractions. TROPOMI cloud fractions are especially lower for partly cloud-covered scenes, possibly resulting from biased surface albedos assumed in the TROPOMI retrieval (from the GOME-2 climatology at 0.5° resolution, see Table 1). We find a similar high correlation and small differences between TROPOMI and independent data over the Mediterranean Sea and Northwest Europe as shown in Table D1.

D2 Cloud pressures

Table D2. Evaluation of TROPOMI v2.1 cloud pressures against reference data for European shipping lanes.

<table>
<thead>
<tr>
<th>Shipping lane</th>
<th>Product</th>
<th>Median cloud pressure (hPa)</th>
<th>10th/90th percentile (hPa)</th>
<th>Geometric mean (hPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mediterranean</td>
<td>TROPOMI v1.2</td>
<td>980</td>
<td>684/1010</td>
<td>920</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1</td>
<td>947</td>
<td>653/978</td>
<td>889</td>
</tr>
<tr>
<td></td>
<td>OMI QA4ECV</td>
<td>781</td>
<td>509/903</td>
<td>739</td>
</tr>
<tr>
<td></td>
<td>VIIRS</td>
<td>935</td>
<td>743/976</td>
<td>896</td>
</tr>
<tr>
<td>NW Europe</td>
<td>TROPOMI v1.2</td>
<td>839</td>
<td>504/969</td>
<td>785</td>
</tr>
<tr>
<td></td>
<td>TROPOMI v2.1</td>
<td>861</td>
<td>590/955</td>
<td>812</td>
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<tr>
<td></td>
<td>OMI QA4ECV</td>
<td>740</td>
<td>474/862</td>
<td>712</td>
</tr>
<tr>
<td></td>
<td>VIIRS</td>
<td>863</td>
<td>702/993</td>
<td>853</td>
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An artificial neural network allows us to predict v2.1 columns for the full TROPOMI mission period up to December 2020. We find the predicted v2.1 columns to be close to actual retrieved v2.1 columns in a testing data set. Figure E1 illustrates the skill of the DNN approach to reliably predict v2.1 data: as a reduced major axis regression shows, the DNN-predicted v2.1 (hereafter v2.1p) NO\textsubscript{2} columns agree substantially better with the retrieved v2.1 NO\textsubscript{2} values ($N_{v2.1\,\text{true}} = 0.98 \times N_{v2.1\,\text{pred}} + 0.03 \times 10^{15}$ molec. cm\(^{-2}\), $R^2 = 0.98$, $n = 56219$) compared to the originally retrieved v1.2 NO\textsubscript{2} columns ($N_{v1.2\,\text{true}} = 0.87 \times N_{v1.2} + 0.09 \times 10^{15}$ molec.cm\(^{-2}\), $R^2 = 0.91$). The improvement from TROPOMI v1.2 to v2.1 is driven by the improved cloud pressures and associated changes in the tropospheric AMFs.

We trained the artificial DNN using the Python package Keras (Chollet and others, 2015) with three hidden layers. We divided the combined v1.2 and v2.1 data sets in three random subsets for training (60%), validation (20%), and testing (20%). The input parameters to predict TROPOMI (pseudo) v2.1 NO\textsubscript{2} columns are $N_{v,v1.2}$, $M_{trop}$, $f_{cl}$, $p_{cl}$, all viewing geometry parameters, surface albedo, and the $f_{QA}$ value (all from v1.2). The DNN was then trained to minimize the mean absolute difference between the predicted and actually retrieved v2.1 NO\textsubscript{2} columns from the training set. This means our prediction does not use FRESCO+ wide cloud pressures for dates outside the training set period. Rather, the DNN has been trained to predict new NO\textsubscript{2} columns based on the old FRESCO+ cloud pressures and other parameters. Our DNN application succeeds in reducing the mean difference between the predicted and retrieved v2.1 NO\textsubscript{2} columns to $<0.01 \times 10^{15}$ molec. cm\(^{-2}\) (original v2.1–v1.2 mean difference was $0.12 \times 10^{15}$ molec. cm\(^{-2}\)) over the three areas of study during the four periods, suggesting considerable skill in the DNN approach. Our improved data set consists of the original L2 TROPOMI NetCDF files with the predicted change in tropospheric NO\textsubscript{2} columns as additional variable.

To show that DNN is capable of capturing seasonal variations in NO\textsubscript{2} corrections and, more broadly, that we can use a generic DNN to correct historic TROPOMI v1.2 data, we train a DNN based on three seasons (summer, winter, and spring) and tested its predicted NO\textsubscript{2} columns against actually retrieved v2.1 data in autumn. This analysis is done for the three testing areas defined in Sect. 3.3. After application of DNN, the mean discrepancy between predicted and retrieved v2.1 NO\textsubscript{2} columns reduces to $<0.01 \times 10^{15}$ molec.cm\(^{-2}\) (original mean discrepancy: $0.09 \times 10^{15}$ molec.cm\(^{-2}\)), and $R^2$ improved from 0.82 to 0.97.
Appendix F: Ship NO$_2$ emission reductions during the COVID-19 pandemic

Figure F1. (a) Relative change in monthly mean of daily number of ships passing the Mediterranean shipping lane between 2019 and 2020. (b) Same but with average ship speed. (c) Relative change in emission proxy ($v^3 \cdot L^2$). (d) Relative change in TROPOMI shipping NO$_2$; the error bars indicate the sensitivity to changes in the area of study. (e) Monthly $\beta$ values as discussed in Sect. 2.4. Error bars represent uncertainty originating from the temporal and spatial variability (see discussion in the text). (f) Relative change in top-down emissions from shipping. Error bars represent the propagated uncertainties in TROPOMI shipping NO$_2$, $\beta$, and differences in meteorological conditions between 2019 and 2020 (see discussion in the text).

Data availability. The data can be made available upon request by contacting the author (christoph.riess@wur.nl). TROPOMI L2 NO$_2$ is publicly available via the Copernicus open-access hub (https://s5phub.copernicus.eu/dhus/#/home, van Geffen et al., 2019).

Supplement. The supplement related to this article is available online at: https://doi.org/10.5194/amt-15-1415-2022-supplement.

Author contributions. TCVWR, KFB, and JvV designed the study. TCVWR performed the data analysis with support from KFB, JvV, and WP. TCVWR wrote the manuscript with contributions from KFB, JvV, and WP. JvV made the AIS data available. MS developed the FRESCO+ wide algorithm, and JvG provided specifics on the TROPOMI NO$_2$ data versions and made the DDS-2B available. HE oversees the NO$_2$ retrieval improvements at KNMI. All authors reviewed the manuscript.

Competing interests. The contact author has declared that neither they nor their co-authors have any competing interests.

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