Seasonal and interannual variability of atmospheric ammonia over Guatemala driven by land use, biomass burning, and meteorological circulation

Christian Saravia[1], Pedro Saravia[2], and Katja Trachte[1]

[1]Department of Atmospheric Process, Brandenburg University of Technology (BTU) Cottbus-Senftenberg, Burger Chaussee 2, LG 4/3 Campus Nord, 03044, Cottbus, Germany
[2]Universidad de San Carlos de Guatemala, Escuela Regional de Ingeniería Sanitaria (ERIS), Ciudad Universitaria, 11° avenida Zona 12, Ciudad de Guatemala, Guatemala

Correspondence to: Christian Saravia (saravchr@b-tu.de)

Abstract.

Ammonia (NH_3) is a key atmospheric precursor of fine particulate matter, an indicator of agricultural and biomass burning emissions. In Central America, NH_3 variability remains largely unquantified. This study presents the first integrated spatiotemporal assessment of atmospheric NH_3 over Guatemala (2015–2023) using concatenated IASI A/B/C observations, combined with fire activity, land cover, and meteorology dataset. Annual NH_3 columns remained relatively stable, reflecting a persistent agricultural source dominated by biomass burning. Significant anomalies occurred in 2016, 2020, and 2023, with 2020 showing the highest annual and monthly NH_3. A clear seasonal is observed with maxima in April–May coincided with the regional fire season, followed by a rapid decline after rainy season. The spatial hotspots were consistently detected in northern (Petén–Quiché) and southern (Escuintla) agricultural regions. The most extreme episode in April 2020 recorded 957 active fires over ~1,486 km^2, largely within the Maya Biosphere Reserve. This episode occurred under elevated temperatures and short-term dry conditions, despite high annual precipitation, demonstrating the importance of seasonal variability. These results indicate that Guatemala's variability in NH_3 total columns reflects a stable agricultural condition with superimposed fire-driven peaks, modulated by climatic anomalies.

1 Introduction

Atmospheric ammonia (NH_3) utilizes a considerable influence on air quality and ecological integrity through its potential for long-range transport and interaction with prevailing meteorological conditions (Zhou et al., 2019). As a reactive nitrogen (Nr) compound, NH_3 plays a fundamental role in the global nitrogen cycle and a variety of biogeochemical processes, representing a dominant form of nitrogen present in terrestrial and atmospheric systems (Sutton et al., 2007, 2013; Whitburn et al., 2016b). Despite its relatively short atmospheric lifetime ranging from several hours to a few days due to its high deposition efficiency and conversion into particulate ammonium, current surface-based monitoring approaches remain inadequate for providing accurate global emission estimates, often introducing substantial uncertainties (Dammers et al., 2016; Herrera et al., 2022).

NH_3 is also a key component in atmospheric chemistry and in the coupling of nitrogen and carbon cycles within ecosystems, with broad consequences regarding climate regulation, agricultural sustainability, air quality and public health. NH_3 emissions originate from both natural and anthropogenic activities, with the latter contributing the majority of the global NH_3 burden. The agricultural sector remains the principal source, accounting for over 81% of total anthropogenic emissions globally (Van Damme et al., 2021; Wyer et al., 2022), while additional anthropogenic contributions stem from residential combustion, vehicular exhaust, industrial production, and wastewater treatment systems (Abeed et al., 2022; Dragosits et al., 2002; Sutton et al., 2007). Although agriculture particularly using fertilizers and manure remains the dominant source of atmospheric NH_3. Nonagricultural sources such as vehicular and industrial emission may be also contribute and are significantly underestimated (Chen et al., 2024; Chen and Wang, 2025; Farren et al., 2020; Gu et al., 2023; Zhou et al., 2017).

In recent decades, satellite remote sensing has significantly advanced the detection of atmospheric NH_3, leading to the development of several global NH_3 measurement datasets, notably from the Infrared Atmospheric Sounding Interferometers (IASI) instrument. For this study, we also include fire-based emission datasets such as the Global Fire Emissions Database (Giglio et al., 2006, 2013; van der Werf et al., 2010, 2017), the Global Fire Assimilation System (Remy and Kaiser, 2014) developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), and two fire products from the National Aeronautics and Space Administration (NASA), based on Fire Radiative Power (FRP) measurements (Fu et al., 2020; Li et al., 2020; Remy and Kaiser, 2014; Vermote et al., 2009; Wooster et al., 2003).

Central America's climate is significantly shaped by the two oceans it borders, with the vast Pacific Ocean, spanning nearly half the Earth's circumference at the equator, being especially crucial for climate regulation by El Niño brings drier conditions to Guatemala, while La Niña produces more precipitation (Bardales Espinoza et al., 2019) Guatemala's geomorphological attributes and geospatial coordinates inherently facilitate a multitude of microclimatic zones and pronounced climatic heterogeneity, the variability has been amplified in recent years by the nation's persistent susceptibility to extreme meteorological phenomena, including prolonged arid periods and intense tropical cyclones, both of which are intensified by the overarching impacts of anthropogenic climate change (Alfaro Marroquín and Gómez, 2019). Guatemala's climate deviates from the typical four-season delineation observed in the Northern Hemisphere. Instead, it is characterized by two distinct periods: the wet season, spanning from May to October, and the dry season, occurring from November to April (INSIVUMEH, 2018; Orrego León et al., 2021).

Furthermore, these climate condition directly influence and intensify of biomass burning events, particularly during dry season, Guatemala is exposed to a variety of threats, with wildfires being one of the main threats in recent decades (CONRED, 2025). Guatemala has experienced increasing concern from fire-related activities that are strongly tied to agricultural expansion, shifting cultivation, and deforestation. These practices, often used to clear land for crops or grazing, are typically intensified during the dry months, aligning with peak fire activity (Liu et al., 2024b; Monzón-Alvarado et al., 2012). Guatemala consistently reports a high number of fire hotspots (CONRED, 2025), especially in years dominated by El Niño-induced drought conditions (Chuvieco et al., 2019; CONRED, 2025; Giglio et al., 2013). The recurrence of such fires in forested and agro-pastoral zones not only transforms land cover but also releases large quantities of reactive trace gases and aerosols, including atmospheric NH_3 into the atmosphere (Andreae, 2019; Pohl et al., 2022; Wyer et al., 2022). Despite this, the role of biomass burning as a driver of NH_3 emissions remains underexamined in Central American air quality studies.

Despite the increasing availability of satellite-based datasets for monitoring atmospheric NH_3, there remains a significant lack of regional-scale studies in Central America, particularly in Guatemala, where land use dynamics and biomass burning are likely to play an important role in shaping substantially to atmospheric NH_3 patterns. Previous research has primarily examined individual drivers, such as meteorological circulation and fire season in Central America (Corona-Núñez and Campo, 2023; Liu et al., 2024a), or continental scale assessment of NH_3 variability (Clarisse et al., 2009; Van Damme et al., 2021; Herrera et al., 2022; Luo et al., 2022; Zhu et al., 2015). However, integrated regional analysis that simultaneously consider concatenated NH_3, fire activity, land cover and meteorological variables remain limited.

This study investigates the monthly spatiotemporal dynamics of atmospheric NH_3 total column over Guatemala from 2015 to 2023, using three satellite-based observations from IASI onboard of the Meteorological Operational satellite programme (MetOp), MetOp-A, MetOp-B, and MetOp-C, in combination with land cover classification from the Environmental Systems Research Institute (ESRI), fifth-generation global reanalysis (ERA5) meteorological data, fire activity from Moderate Resolution Imaging Spectroradiometer (MODIS), and vertical profiles global reanalysis of NH_3 from Copernicus Atmosphere Monitoring Service (CAMS). The research aims to identify spatial hotspots and the interannual and seasonal variability in NH_3. In addition, spatial clustering using k-means algorithm is applied to partition NH_3 patterns and explore their heterogeneity, with a particular focus on land cover types and the influence of fire-pixel activity. To ensure the reliability of the fire data, fire-pixels from MODIS with a confidence level ≥70% were included in the analysis. A case study in 2020 further examines a period of anomalous NH_3 of the total column variability in relation to extreme fire events linked to agriculture and meteorological conditions.

2 Data and Methods

2.1 Study location

The Republic of Guatemala, a Central American country situated between latitudes 13.5°N to 17.8°N and longitudes 88.2°W to 92.2°W. According to the National Institute of Statistics of Guatemala (INE, 2020), the country is administratively divided into 22 departments, which differ in terms of land use, population density, and economic activity. Guatemala encompasses a diverse range of ecological regions, topographical variations, and land use patterns. Its landscape is characterized by a complex zone of agricultural lands, forested highlands, volcanic zones, and rapidly urbanizing areas. Agriculture remains a cornerstone of the Guatemalan economy and landscape with extensive cultivation of crops such as maize, beans, coffee, sugarcane, oil palm, and bananas (FAO, 2019; Hervas, 2019; Lopez-Ridaura et al., 2019). Fertilizer application and livestock farming are particularly prevalent in rural regions. Meanwhile, increasing urbanization and industrialization, especially around Guatemala City and its metropolitan zone, have introduced additional anthropogenic activities, such as vehicular exhaust, industrial activity, and waste treatment processes.

Guatemala experiences a pronounced dry season (typically November to April) and rainy season (May to October) (Alfaro Marroquín and Gómez, 2019; Bardales Espinoza et al., 2019; INSIVUMEH, 2018; Orrego León et al., 2021), which strongly modulate fire activity, atmospheric transport conditions, and deposition processes relevant to NH_3 dispersion. Frequent wildfires, especially in the Petén department (northern area of Guatemala) and central highlands during the dry season, contribute further to the atmospheric burden of reactive nitrogen species. Topographically, Guatemala varies from sea level to 3,000 m above sea level (a.s.l) in the central plateau, and with volcanic peaks that reach 4,200 m a.s.l. (IGM, 2002). Figure 1 shows the digital elevation model (DEM) of the topographic surface in meters over Guatemala using the European Space Agency, 2024).

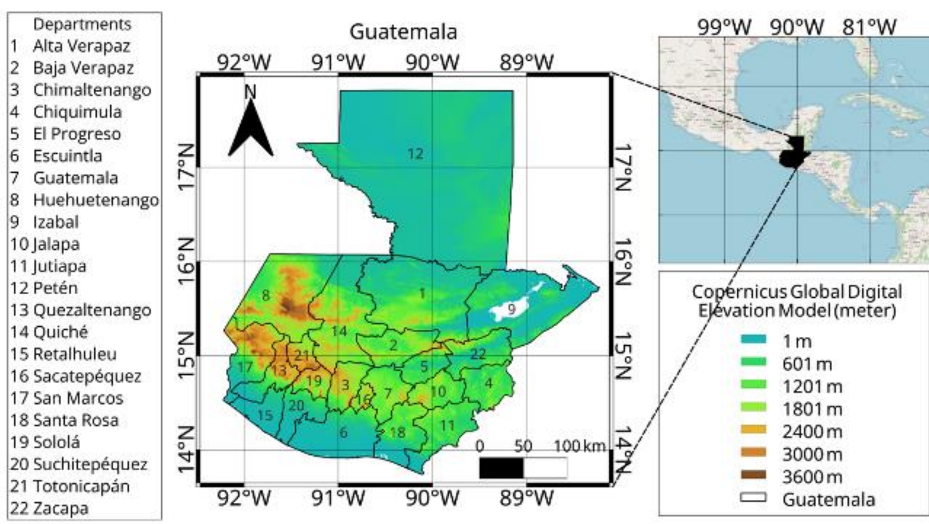

Figure 1: Departments of Guatemala and elevation (m) from Copernicus Global Digital Elevation Model.

2.2 IASI NH_3 satellite-based

This study applies a multi-step analytical framework to investigate the spatiotemporal variability of satellite-based atmospheric NH_3 over Guatemala from 2015 to 2023. The analysis is based on a temporally concatenated monthly NH_3 total column Level 3 (L3) observations, from the IASI instrument onboard the MetOp A/B/C satellites launched in 2006, 2012, and 2018, respectively (Clarisse et al., 2009, 2019; Coheur et al., 2009). The concatenation produces the dataset, which serves as the basis for all spatial distributions, time series, climatological analyses, clustering, and correlation, incorporating both morning and night observations for enhanced representativeness and discarded negative values. While IASI-B maintains the spatial resolution of sensors A and C, integrating all three sensors could improve both temporal and spatial coverage, thereby yielding more accurate and robust results. While the study period spans 108 months, the concatenated analysis incorporates a total of 228 sensor months, corresponding of IASI A (January 2015–December 2020), B (January 2015–December 2023), and C (January 2020–December 2023).

IASI works with a cross-track scanning swath approximately 2200 km wide and provides measurements with a nadir pixel diameter of about 12 km. Positioned aboard sun-synchronous polar-orbiting satellites, the instrument enables near-global coverage twice daily during both daytime and nighttime corresponding to local solar overpass times of approximately 09:30 and 21:30, respectively (Clarisse et al., 2010; Van Damme et al., 2017; Whitburn et al., 2017). The NH_3 dataset was obtained from version 4 (v4.0.0R) (L3) of the ANNI-NH_3 retrieval product (Clarisse et al., 2023), and regridded to a 0.25° × 0.25° spatial resolution. A major enhancement in this version is the incorporation of the vertical column averaging kernel (AK), which is essential for aligning satellite retrievals with chemistry-transport model simulations by mitigating the influence of the priori NH_3 vertical profiles applied during retrieval. While spatial patterns remain consistent with previous versions, total column values are approximately 15–20% higher due to improvements in the high-resolution infrared retrieval configuration (HRI). Version 4 offers improved uncertainty characterization and enhanced temporal uniformity of the dataset from 2007 to 2023 (Clarisse et al., 2023). The retrieval algorithm estimates a hyperspectral range index from IASI spectra and converts it into NH_3 total column densities using an artificial neural network (Van Damme et al., 2021; Franco et al., 2018; Whitburn et al., 2017). The uncertainty was quantified using the standard error and the relative uncertainty was derived from the distribution of the observation within of each grid cell (Text S1).

Additionally, NH_3 vertical profiles data were obtained from the ECMWF, Atmospheric Composition Reanalysis 4 (EAC4), produced by the CAMS. This global reanalysis provides NH_3 with mass fraction in the air, provided as a mass mixing ratio (kg kg^{-1}), the model is defined by 60 hybrid sigma-pressure levels. It provides a detailed representation of the atmospheric structure, particularly near the surface (~0–100 m) where most emissions occur (Inness et al., 2019). These reanalysis datasets incorporate satellite observations and model simulations to provide globally consistent, spatially and temporally resolved atmospheric composition data (Flemming et al., 2017; Inness et al., 2019). In our study, the CAMS analysis of vertical structure and latitudinal distribution of NH_3 during a specific period of interest, rather than for a quantitative comparison with satellite of total column densities.

2.3 Cluster analysis of NH_3

An unsupervised clustering approach was applied to classify NH_3 total columns field based on their statistical similarity. Clustering is a type of unsupervised machine learning that groups large datasets based on their similarity, allowing for more manageable and interpretable analyses (Ahmad and Dey, 2007; Pham et al., 2005). This analytical approach is particularly beneficial when there is limited or no prior knowledge about the underlying structure of the data (Gašparović et al., 2019). Among clustering methods, the k-means algorithm is one of the most commonly applied and reliable techniques. It partitions data into a predefined number of k clusters by iteratively determining central points, or centroids, for each group (Pham et al., 2005). The algorithm requires the number of clusters to be specified in advance (Ahmad and Dey, 2007; Mahata et al., 2020). K-means operates using the squared Euclidean distance as its primary metric (Spencer, 2013), which quantifies the separation between two points within a Euclidean space of any dimension (Li et al., 2022). The Euclidean distance between two points, p and q, in a j-dimensional space is mathematically expressed as $d(p,q)$.

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \ldots + (p_j - q_j)}^2 \tag{1}$$

The k-means algorithm divides a dataset into k clusters by aiming to minimize the variance within each group (Li et al., 2022). It operates on a set of input samples X=$\{x^1, \ldots, x^n\}$, where each X^m=$\{x_1^m, x_2^m, \ldots, x_j^m\}$ represents an observation composed of j variables, and $m \epsilon X$=$\{1, \ldots, n\}$, with n being the total number of observations. These samples are categorized into k clusters $(S_1, S_2, \ldots S_k)$ with the goal of minimizing the total intra-cluster variance $\left(S_{i=1,\ldots,k}\right)$, as described in Equation (2):

$$\underset{S}{argmin} = \sum_{i=1}^{k} \sum_{X \in S_i} ||X - \mu_i||^2 \tag{2}$$

The notation $||X - \mu_i||$ represents the squared Euclidean distance between each data point (X) and its assigned cluster centroid μ_i within a multidimensional Euclidean space (Li et al., 2022). In this study, k-means clustering was utilized to examine the spatiotemporal patterns of NH_3 throughout the specified timeframe (Anne Fouilloux, 2018; Pedregosa et al., 2011). To determine the most suitable number of clusters k, the elbow method was employed. This approach assesses the Cluster Sum of Squares (CSS) to identify the point at which the inclusion of additional clusters no longer significantly improves the model performance (Umargono et al., 2019).

2.4 ESRI land cover class map

The ESRI Land Use Land Cover (LULC) 2020 dataset, released in June 2021, was developed using deep learning models trained on more than 5 billion manually labelled pixel samples derived from the European Space Agency's Sentinel-2 satellite imagery with 10 m spatial resolution (Karra et al., 2021), enables land cover mapping at both national and local scales.

According to (ESRI, 2021) these training samples were collected from 24,000 image tiles globally, each measuring 510 × 510 pixels, and reflect a wide range of land surface types. The LULC 2020 product is classified into nine classes: Water, Trees, Flooded vegetation, Crops, Built area, Bare ground, Snow/Ice, Clouds, and Rangeland (Karra et al., 2021). In this study, the analysis was restricted to classes related to Water, Trees, Flooded vegetation, Crops, Built area, and Rangeland.

2.5 Meteorological data from ERA-5

Meteorological variables used in this study were obtained from the ERA5 reanalysis (Soci et al., 2024) dataset provided by ECMWF, (Hersbach et al., 2020). Originally available at a horizontal resolution of approximately 31 km, the data were resampled to a 0.25° × 0.25° grid and both spatially and temporally to match the IASI NH_3 observation times and locations. The selected meteorological parameters were subsequently used in statistical analysis with atmospheric NH_3, these variables include 2 m air temperature (t2m), 10 m wind speed (ws), boundary layer height (BLH), relative humidity (derived using 2 m air temperature and dew point temperature), and total precipitation (tp). Pearson correlation matrix coefficient were calculated between monthly meteorological variables means and total column means of NH_3, including total fire counts per month, to quantify their linear relationship.

2.6 Fires

Active fire detections were obtained from MODIS Aqua/Terra Thermal Anomalies/Fire Locations product (MOD14/MYD14). Data was accessed via the Fire Information for Resource Management System (FIRMS) Near Real-Time (NRT), collection 6.1 (Giglio et al., 2021a). These data are produced by NASA´s Land, Atmosphere Near-real-time Capability for EOS (LANCE) and provide global active fire information at a nominal spatial resolution of 1 km.

MODIS fire detection recognizes thermal anomalies in individual pixels using mid-infrared radiance signals. It assigns each detected fire´s geographic location to the center of the corresponding 1 × 1 km^2 spatial resolution (Giglio et al., 2003, 2006; Justice et al., 2010). Each detection includes fire location, detection confidence, and FRP. Detection confidence, indicating the likelihood of an active fire in a pixel, is classified as low level: 0% to < 30%, nominal level: 30% to < 80%, high level: 80% to 100% (Giglio et al., 2016, 2021b, a; Hantson et al., 2013).

To reduce false detections, and ensure strong fire identification, only fire pixels with nominal to high confidence levels ≥70% were retained for analysis, in accordance with recommendations from previous studies (Giglio et al., 2016, 2021b, a; Hantson et al., 2013). Fire activity was quantified using fire counts, defined as the number of detected fire pixels, which serve as a proxy for fire occurrence and spatiotemporal variability. Monthly fire counts were aggregated for each year to characterize seasonal and interannual variability in fire activity.

FRP served as an indicator of fire intensity with energetic significance providing as an additional filtering. Moreover, it quantifies the rate of radiative energy released from combustion and is directly related to biomass consumption (Wooster et al., 2003). In this study only fire detections with FRP values ≥40 Megawatt (MW) were included, thereby excluding low-intensity or small-scale fires to ensure consistency between temporal statistics and spatial fire distribution.

FRP is derived from MODIS 4 μm radiance measurement using the methodology proposed by Wooster et al., 2003 in equation (3):

$$FRP = \frac{\sigma \times A_{pixel}}{\alpha \times \tau_4} (L_4 - L_{4b}) \quad (3)$$

A_{pixel} is the fire pixel area σ = 5.6704 × 10^{-8} Wm^{-2} K^{-4} is the Stefan–Boltzmann constant, α = 3.0 × 10^{-9} Wm^{-2} $sr^{-1}m^{-1}k^{-4}$ is the MODIS empirical constant, τ_4 is the atmospheric transmittance at 4 μm, and $L_4 - L_{4b}$ are radiances at 4 μm of the fire and background pixels, respectively (Wooster et al., 2003).

The burned analysis for this work was obtained by MODIS MCD64A1 Version 6.1 product, which combines observations from both Terra and Aqua platforms to produce a monthly global dataset gridded at 500 m that provides per-pixel burned-area and quality information (Giglio et al., 2018). The MCD64A1 MODIS burned area product integrates surface reflectance data with active fire detections to identify burned pixels based on temporal changes in a burn-sensitive vegetation index derived from shortwave infrared bands (bands 5 and 7) and spatial texture metrics (Dong et al., 2013; Freeborn et al., 2011; Giglio et al., 2003, 2021b; Justice et al., 2010). For each pixel, the product provides the estimated burn date as the ordinal day of the year, as well as quality assurance layers and uncertainty metrics. Pixels identified as unburned, water, or missing data are assigned to distinct flag values (Giglio et al., 2016).

3 Results

3.1 Spatiotemporal variability of NH_3

Fig. 2 shows the annual variability of NH_3 total column over Guatemala from the period 2015 to 2023. The respective boxplots show the distribution of monthly NH_3 values within each year. The medians reveal a NH_3 with a minimum of 2.90 × 10^{15} molecules cm^{-2} in 2021 and a maximum of 2.33 × 10^{16} molecules cm^{-2} in 2020 (Table S1). While the median values show an increase of NH_3 notable during 2020 (4.66 × 10^{15} molecules cm^{-2}) and 2023 (4.33 × 10^{15} molecules cm^{-2}). Consistently, the standard deviation varied considerably between years, reaching a peak in 2020 of 5.83 × 10^{15} molecules cm^{-2}.

The spatial distribution of NH_3, exhibited a consistent area-wide pattern characterized by elevated values in specific areas. Persistent hotspots are observed in the northern (Petén), north-central (Quiché, Alta Verapaz, and Izabal), and along the southern coastal department of Escuintla. Conversely, lower annual mean NH_3 dominate in the central midlands, including the departments of Totonicapán, Sololá, Chimaltenango, Sacatepéquez, Guatemala, Jalapa, and Jutiapa. Interannual variability in hotspot intensity is evident, with particularly values over Petén, Alta Verapaz and Quiché in 2016 and more widespread increases across Petén, Quiché, Alta Verapaz, Izabal and Escuintla in 2020. Notably, even in years with lower annual means such as 2018, increased NH_3 total column were still evident in Petén, Alta Verapaz, Izabal and Escuintla.

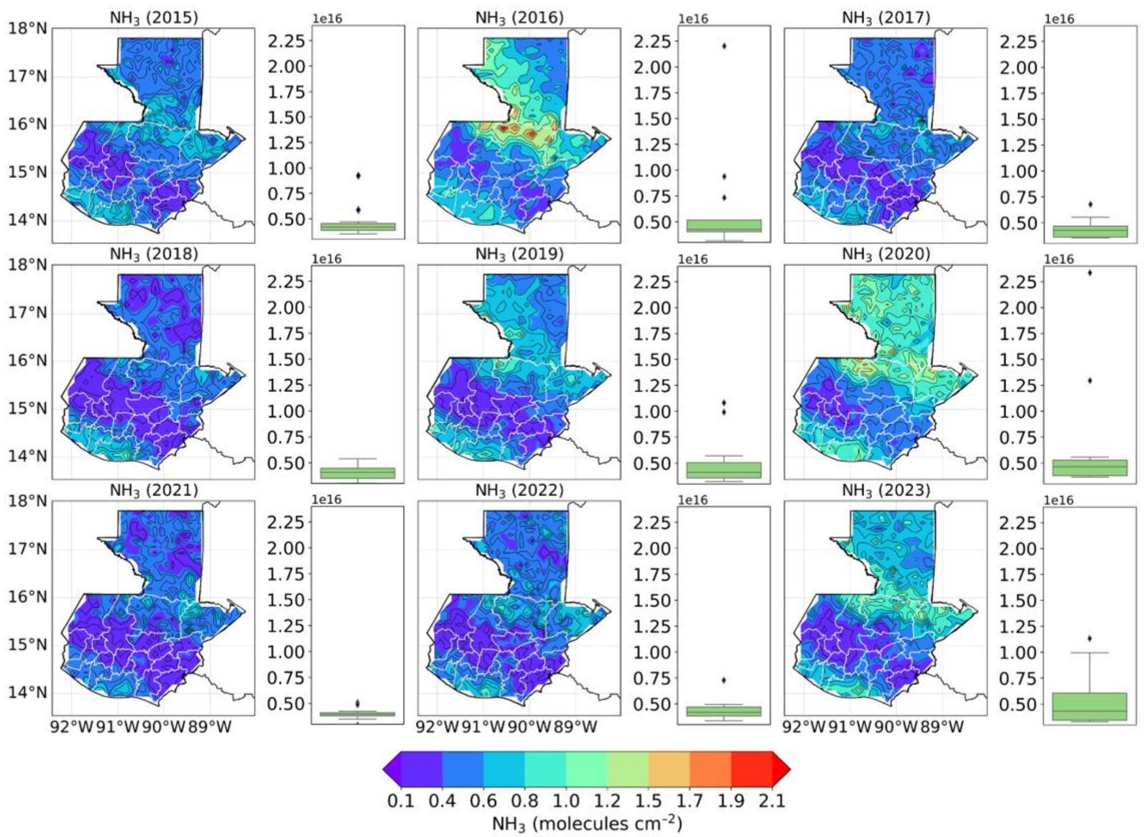

Figure 2: Annual means area-wide and boxplot distribution of monthly NH_3 total columns within each year ($\times 10^{16}$ molecules cm^{-2}) over Guatemala (2015–2023) from concatenated IASI A, B and C.

The monthly climatology variability of NH_3 total columns is illustrated by boxplots in Fig. 3, showing a distinct seasonal pattern. A minimum of 2.90×10^{15} molecules cm^{-2} observed in March. A substantial increase occurred in the month of April, with a median of 7.34×10^{15} molecules cm^{-2}, followed by May with a median of 7.27×10^{15} molecules cm^{-2} (Table S2). These months exhibit the greatest variability, reflected by a prominent outlier. The values started decreasing thereafter in the month of June with a median of 4.83×10^{15} molecules cm^{-2}. From July through December, the median stabilizes, ranging between 3.58×10^{15} molecules cm^{-2} (August) to 4.18×10^{15} molecules cm^{-2} (November).

The spatial distribution of monthly climatology mean NH_3 displays the distinct seasonal pattern across Guatemala. From January to March, NH_3 remain generally low over most of the country, with only limited area exhibiting elevated columns (Escuintla). A substantial increase in both the total column values and spatial coverage of NH_3 is observed in April, with widespread elevated areas particularly in the northern (Petén), north-central (Quiché, Alta Verapaz, and Izabal), and southern coastal area (Retalhuleu, Suchitepéquez, and Escuintla). Specific defined areas with highest values primarily in the departments of Quiché, Alta Verapaz and Escuintla is observed in the month of May. Subsequently, a sharp decline in NH_3 is evident across the country from June through December. During these months, the spatial distribution of NH_3 is characterized by few hotspots and generally uniform low values in the central midlands (Totonicapán, Sololá, Chimaltenango, Sacatepéquez, Guatemala, Jalapa, and Jutiapa).

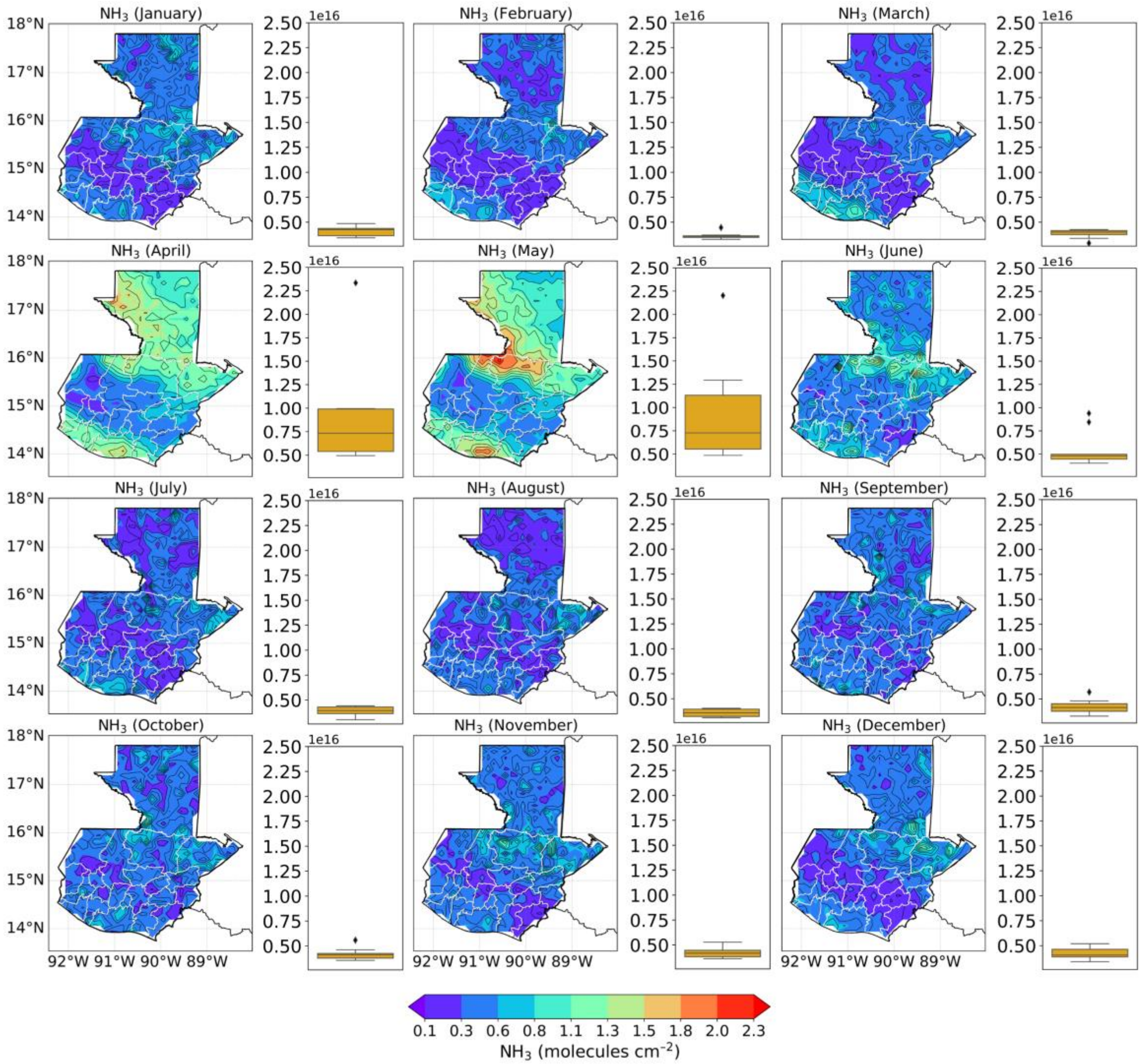

Figure 3: Monthly climatology area-wide and boxplot distribution of NH_3 total column for each calendar month (× 10^{16} molecules cm^{-2}) over Guatemala (2015–2023) from concatenated IASI A, B and C.

3.2 Land cover classification driven by NH_3 cluster k-means

The spatial distribution of NH_3 in Guatemala, based on the overall annual mean for the period 2015–2023, reveals six distinct hotspots, area 1 (Escuintla), 2 (Petén and Izabal), 3 (Alta Verapaz), 4 (Quiché and Alta Verapaz), 5 (Southwest of Petén) and 6 (Northwestern Petén) (Fig. 4a). Among these, the most prominent hotspot is area 4, which exhibits the highest annual mean NH_3 total column during the study period.

The k-means clustering partitions the country into three emission zones (Fig. 4b), each with distinct land cover profiles when integrated with ESRI data (Fig. 4c). Cluster 1 with smallest area (~28,254 km^2) (red) associated to the highest NH_3, is located in the northern (Petén), central-north (Quiché, Alta Verapaz, Izabal), and southern regions (Escuintla, Suchitepéquez, Retalhuleu and San Marcos) is dominated by cropland (16.7%; 4710.8 km^2) and rangeland (24.5%; 6934.2 km^2). Tree cover remains extensive (53.2%; 15,024.6 km^2), while built-up areas are limited (3.4%; 948.6 km^2) as shown in Fig. 4d. The complete land cover distribution across clusters is provided in Table 1.

Cluster 2 with a largest extend area around 45,662 km^2 (yellow) represents moderate zones forming a transition around Cluster 1 and extending into northern (Petén), central-north (Huehuetenango, Quiché, Alta Verapaz, Santa Rosa, Izabal), and south (Quetzaltenango, Escuintla, Suchitepéquez, Retalhuleu, Santa Rosa, Jutiapa and San Marcos) (Fig. 4e). It is dominated by tree cover (58.9%; 26,891.6 km^2) and rangeland (30.3%; 13,844.6 km^2), with a comparatively small share of cropland (6.0%; 2724.7 km^2). Built-up areas account for 2.8% (1261.8 km^2), slightly larger in absolute terms than in Cluster 1.

The intermediate extent area Cluster 3 with ~34,640 km^2 (green), associated with the lowest NH_3, covers the central region with departments of Huehuetenango, San Marcos, Totonicapán, Sololá, Chimaltenango, Sacatepéquez, Guatemala, El Progreso, Jalapa, Chiquimula and Jutiapa. This cluster is characterized by high rangeland cover (34.3%; 11,893.3 km^2) and substantial tree cover (47.1%; 16,298.9 km^2), while cropland is minimal (3.1%; 1088.6 km^2) (Fig. 4f). Notably, built-up areas occupy the largest proportion across clusters (14.8%; 5137.1 km^2).

Table 1: Land cover composition of percentage and area for the different cluster in Guatemala.

	Cluster 1		**Cluster 2**		**Cluster 3**	
LCC	**Percentage %**	**Area km^2**	**Percentage %**	**Area km^2**	**Percentage %**	**Area km^2**
Water	1.94	548.97	1.78	812.44	0.64	221.61
Trees	53.16	15,024.57	58.89	26,891.61	47.05	16,298.85
Flooded Veg.	0.31	86.77	0.28	127.16	0	0.63
Crops	16.67	4710.8	5.97	2724.67	3.14	1088.56
Built Areas	3.36	948.62	2.76	1261.81	14.83	5137.06
Rangeland	24.53	6934.19	30.32	13,844.63	34.33	11,893.31

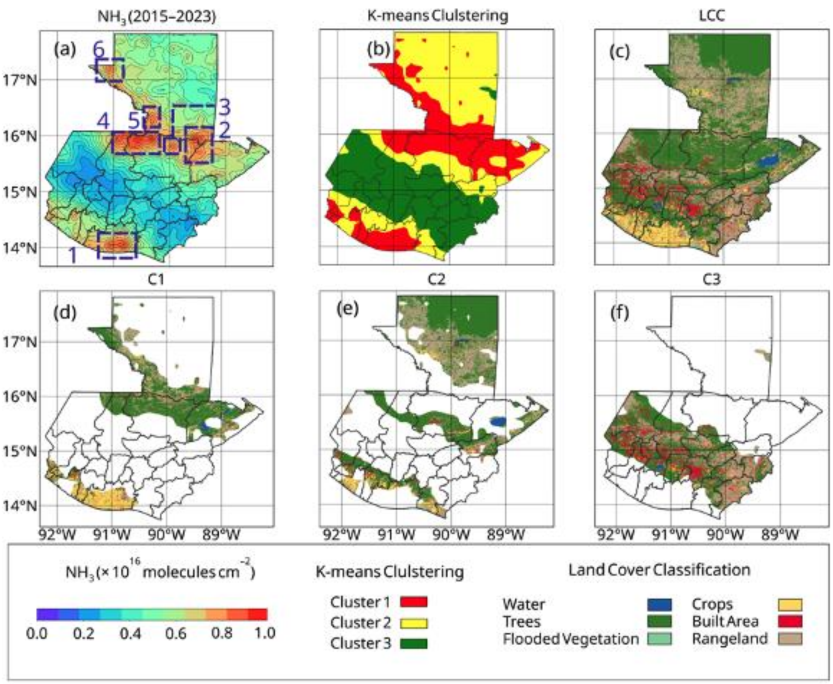

Figure 4: (a) Concatenated NH_3 total column (× 10^{16} molecules cm^{-2}) (2015–2023), (b) k-means cluster analysis with Cluster 1 (red color), Cluster 2 (yellow color) and Cluster 3 (green color). (c) ESRI Land Use Land Cover across Guatemala, categorized into three clusters based on k-means combined with land cover types: water, trees, flooded vegetation, crops, built area, and rangeland, (d) C1 related to cluster 1, (e) C2 to cluster 2, and (f) C3 to cluster 3.

3.3 Fires

In order to connect the previously described NH_3 patterns Fig. 5 shows the annual distribution of active fires in Guatemala during the study period. The fire activity shows a marked interannual variability. The area-wide total annual fire counts peaked in 2016 (1779 fires), and 2017 (1783), while the minimum was observed in 2022 (807) (Table S4). Fire frequency declined substantially in 2018, reflecting a reduction in both annual counts and monthly extremes. Fire activity increased again in 2019 (median 32) and in 2023 (median 58). The year 2020 is characterized by increased temporal variability, including with the highest single month fire count with 957 fires. Fire occurrences increase slightly in 2021 (median 30) and reached their lowest in 2022 (median 19), before recovering in 2023 (median 59).

The spatial distribution of detected fires is consistent with the temporal variability in fire counts, showing pronounced interannual differences in both fire occurrence and spatial heterogeneity. Years with elevated fire occurrence (2016, 2017, 2019, 2020, and 2023), showed widespread spatial extents of fires detections, with recurrent hotspots concentrated primarily in the northern (Petén) and along the southern area (Escuintla, Suchitepéquez, Retalhuleu, and Santa Rosa). In contrast, years of reduced fire activity, including 2018, 2021 and 2022, showed decreased detections, and reduce spatial confined distribution of fires.

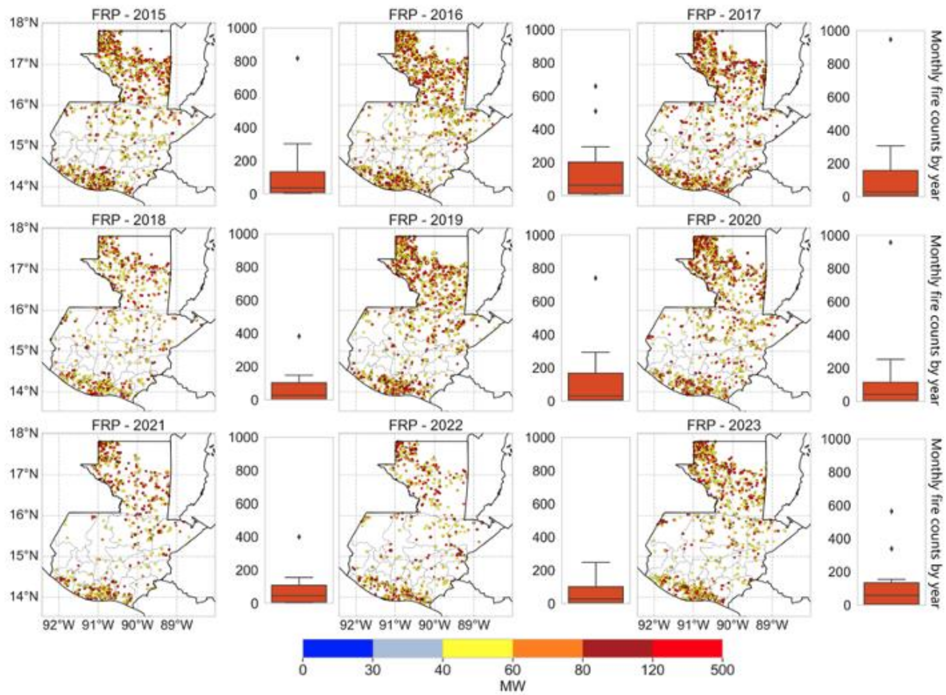

Figure 5: Annual distribution of monthly fire counts over Guatemala (2015–2023), MODIS fire detection filtered by nominal confidence level ≥70% and FRP ≥40 MW, the boxplots represent the area-wide monthly fire count for each year.

The monthly climatology of fire activity in Guatemala (Fig. 6). The boxplots show a clear seasonal pattern in detected fires. Fire activity is relatively low at the starting of the year, with median of 78 in January, and 105 in February (Table S5). A substantial rise occurs in March (median 211), while April marks the peak with a maximum of 957. Consequently, the month of May demonstrated a decrease of number of fires (median 238). Moreover, an observed sharply declining in June (median 15), and the lowest fire activity occurs in September (median 3). Finally, slight increase is observed at the end of the year in December (median of 46).

The spatial distribution of FRP across Guatemala also confirms this seasonal pattern and shows the shifts in fire location and intensity. During the early months of the year, fire activity is concentrated mainly along the southern areas (Escuintla, Suchitepéquez, Retalhuleu, and Santa Rosa). As the fire season advances, the activity shifts northward with central-north (Huehuetenango, Quiché, Alta Verapaz, Santa Rosa, Izabal), and northern (Petén). In November and December, the fire remerged in the southern coast (Escuintla, Suchitepéquez, and Retalhuleu).

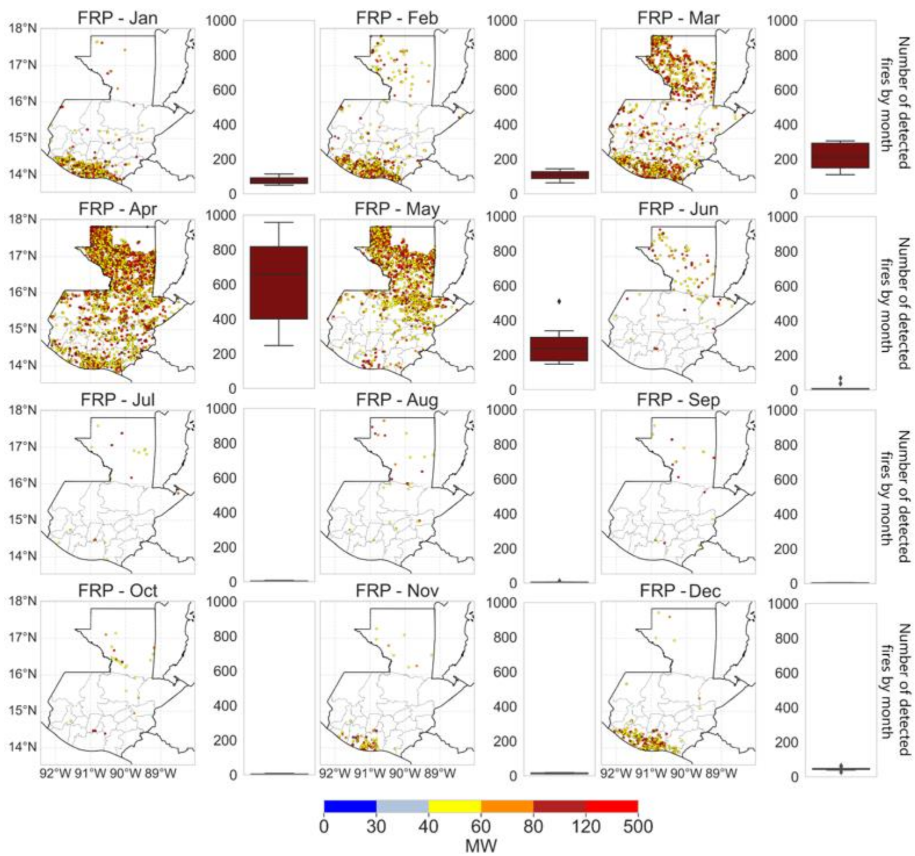

Figure 6: Monthly climatology of detected fires over Guatemala (2015–2023), MODIS fire detection filtered by nominal confidence level ≥70% and FRP ≥40 MW, the boxplots represent the area-wide distribution of number of detected fires for each month across all years.

3.4 Meteorology

Figure 7 illustrates the variability of meteorological variables derived from monthly scales over Guatemala from ERA5. Fig. 7 (a,c), exhibit the BLH and precipitation. The BLH shows fluctuations with the highest median recorded in 2019 (524 m), in contrast to the lowest median observed in 2017 (415 m) which also demonstrated the minimum value (305 m) (Table S6). The maximum vertical value was detected during 2020 (791 m) indicated a large data range. At the monthly scale, April shows the highest BLH (median 671 m) and lowest during October (median 348 m). Furthermore, the precipitation indicates that the annual distribution of monthly totals presents the highest median values recorded in 2020 (69 mm) and 2022 (55 mm), while the lowest median is observed in 2019 (34 mm) which also shows the minimum value (7.5 mm). The maximum monthly exceeds 130 mm (2017 and 2022). The monthly climatology presents peaks medians precipitation in the month of June (97 mm), and September (95 mm), while the lowest in February (13 mm).

Fig. 7(b,e) presents the air temperature and relative humidity. The warmest median temperature during the year 2023 (22.8°C), whereas the maximum temperature was detected during 2020 (27.9°C). The coldest temperature was recorded during 2018 with 20.2°C. Additional, the warmest month is May (median 26.4°C) and the coldest is January (21.9°C). Relative humidity showed the highest median observed during 2016 (81%), while the lowest median year was 2019 (76%), the minimum year detected was 2020 with 63%, this also showed the largest vertical values. The years 2017 and 2022 exhibit the maximum values with 87%. The month medians indicate the lowest in April (mean 71%) and the highest in October (mean 84%).

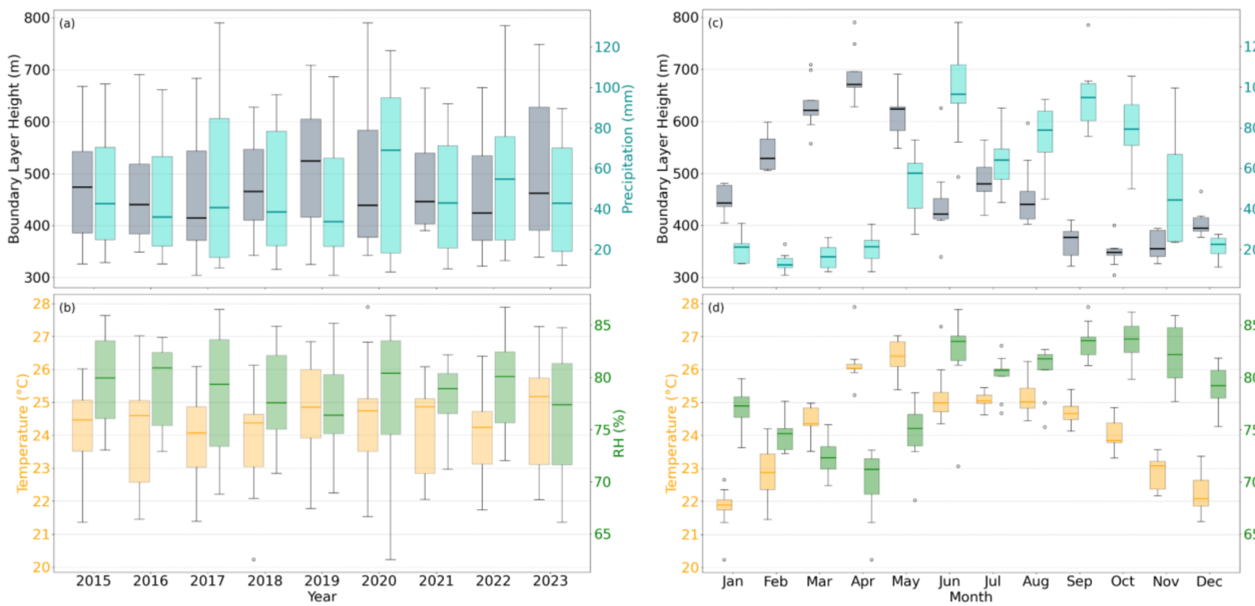

Figure 7: Boxplot distribution of meteorological variables over Guatemala (2015–2023) from ERA5 reanalysis, (a, c) show boundary layer height (m) (gray) and precipitation (mm) (turquoise), (b, d) relative humidity (%) (green) and temperature (°C) (yellow).

3.5 Case Study of NH_3

NH_3 anomalies were observed in Guatemala in April 2020, marking the highest recorded monthly mean (Fig. S4). This peak is particularly remarkable as it occurred shortly after the implementation of COVID-19 lockdown measures (March 2020). The monthly mean spatial distribution of concatenated NH_3 in April 2020 (2.3×10^{16} molecules cm^{-2}), indicates distinct hotspots concentrated in the northern (Petén), north-central (Quiché) and southern (Escuintla) areas. The highest values were observed in the department of Petén, reaching up to (6.4×10^{16} molecules cm^{-2}) (Fig. 8). The corresponding environmental conditions, including wind vectors meter per second (m s^{-1}), with a strong easterly wind (~3 m s^{-1}) dominated the northern region, facilitating long-range transport of NH_3, while central Guatemala experienced moderate to stagnant wind conditions.

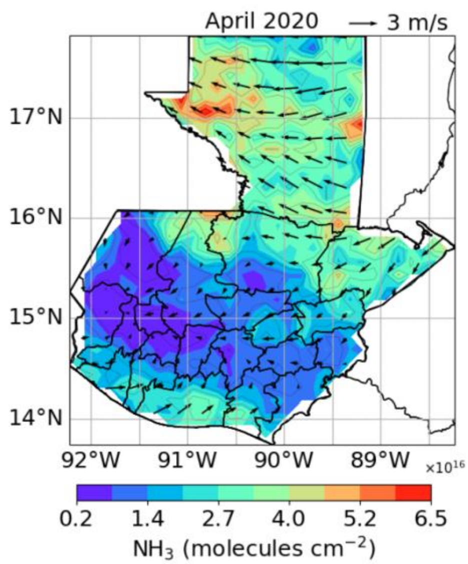

Figure 8: Monthly mean area-wide of NH_3 total column ($\times 10^{16}$ molecules cm^{-2}) from the concatenated IASI A, B and C, and wind mean vectors from ERA5 over Guatemala (April 2020).

Figure 9a shows the vertical and latitudinal distribution of atmospheric NH_3 over Guatemala using zonal means and area averaged vertical profiles in mass mixing ratios (kg kg^{-1}). The zonal mean cross-section of NH_3 throughout the atmosphere (vertical axis, model level 60 to 44) along the latitudes of Guatemala as a zonal mean during April 2020. It highlights a greater abundance of NH_3 in both the northern and southern areas. Furthermore, the NH_3 vary with both latitude and altitude, the highest NH_3 are observed at lower model levels primarily confined near the surface (below approximately level 56). The highest NH_3 values are found between 14°N and 15°N latitude.

Fig. 9b further illustrates the area average vertical profiles of NH_3 for April (blue line), spring (March – May, green line) and the annual mean 2020 (black dashed line). The vertical profile of NH_3 shows the April 2020 mean (blue line) with ~1.0×10^{-9} kg kg^{-1}, the spring mean (March–May 2020, green line) of ~0.9×10^{-9} kg kg^{-1} and the annual mean for 2020 (black dashed line) with ~0.5×10^{-9} kg kg^{-1} respectively.

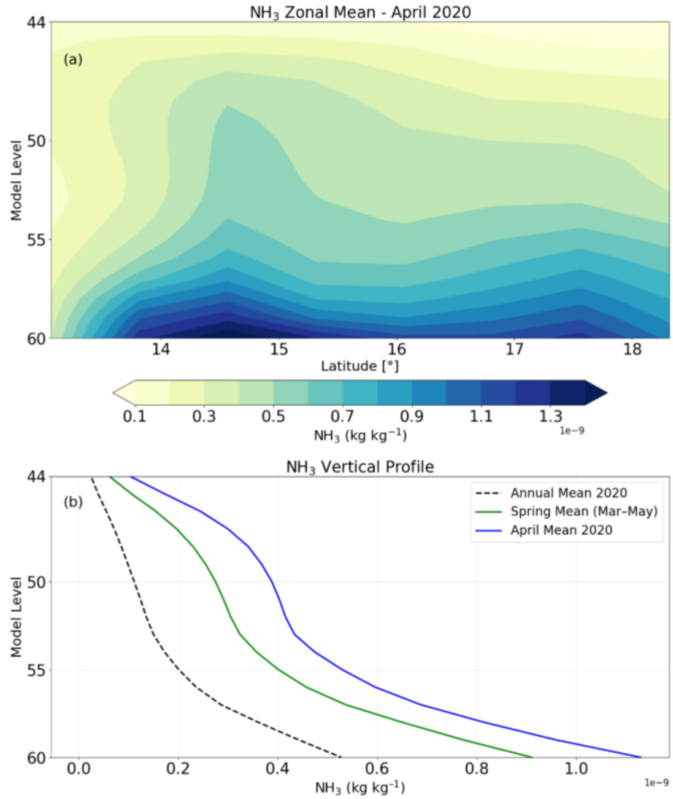

Figure 9: (a) zonal mean of NH_3 mass mix ratio (kg kg^{-1}) across latitudinal bands (model level 60 to 44) for April 2020 and (b) vertical profile of NH_3 mass mix ratio (kg kg^{-1}) for April (blue line), spring (March – May, green line) and annual mean 2020 (black dashed line) over Guatemala from global reanalysis CAMS.

3.6 Fire activity April 2020

Fire activity in spring 2020 showed an anomalous peak compared to the long-term pattern (Fig. 10). As mentioned above, March to May indicate a general increase phase in fire activities in Guatemala. April 2020 recorded the highest monthly total number of detected fires across Guatemala throughout the entire study period (957). The spatial distribution of FRP distribution illustrates widespread, affecting specifically in the northwestern (Petén) accounting for 674 detected fires (Table S7, Fig.S7), central-north (Quiché, Alta Verapaz, Izabal), and southern areas (Escuintla, Santa Rosa, and Jutiapa). The corresponding burned areas patterns further confirm the extension of the fire's activities during the month, with the most extensive land burned occurred in the department of Petén.

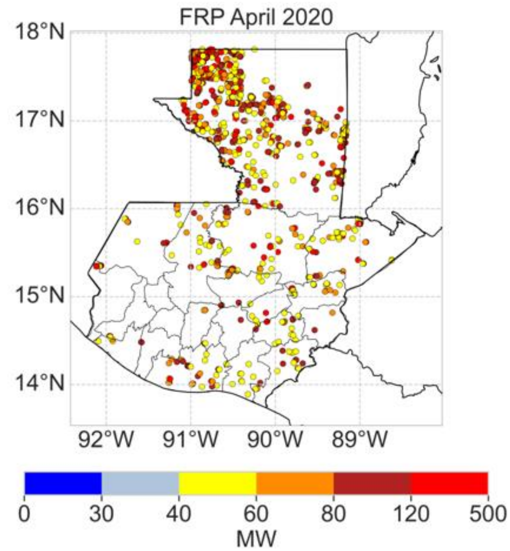

Figure 10: April 2020 shows the spatial distribution of area-wide of fires detected over the study period over Guatemala (2015–2023), using MODIS fire detection filtered by nominal confidence level ≥70% and FRP ≥40 MW.

4 Discussion

4.1 Dynamics of NH_3 over Guatemala

The variability of NH_3 total columns over Guatemala is a result of the interaction between persistent agricultural sources, episodic biomass burning, and meteorological modulation. Although annual medians are relatively stable ($3.95–4.66 \times 10^{15}$ molecules cm^{-2}, Table S1), high maximum values and the increase of variability over some specific years (2016, 2019, 2020, 2023) indicating that episodic processes occur on top of a stable background. This stability suggests that background NH_3 values are largely controlled by persistent agricultural sources, consistent with previous studies showing that agricultural practices dominate global NH_3 emissions (McDuffie et al., 2020; Sutton et al., 2013).

The spatially increased NH_3 columns are consistently observed in the Petén and Escuintla departments, which are dominated by mixed agricultural landscapes (crops and rangeland). Comparable patterns have been reported in other agricultural regions, including South Asia (Abeed et al., 2022), and Western Europe (Van Damme et al., 2018). Cluster analysis also supports the patterns by identifying the highest columns that are associated with intensive crop areas. Notable, the cluster 1 with the highest NH_3 represents the smallest spatial extent, indicating that the total column intensity rather than area coverage. In contrast, the central highlands exhibit lower NH_3 columns despite the presence of urban areas (Huehuetenango, Quiché, and San Marcos. Fig. 4) suggesting that urban areas could play a secondary role on the national scale.

A pronounced seasonal cycle demonstrates the role of atmospheric conditions in modulating both the NH_3 and the removal process. The increase in NH_3 during the months of March–April–May (MAM, mean 7.49×10^{15} molecules cm^{-2}) coincides with the regional fire season (mean total fire count 3321), and also increases the variability where events of high columns of NH_3 appeared. Additionally, the positive moderate association between temperature (r=0.50, Fig. S5) suggests that higher temperatures enhance volatilization.

The decline of NH_3 from June onwards defines a transition dominated by the atmospheric removal process where the monthly means NH_3 decreased by 42% between May and June (Table S2). This coincides with the rainy season (Fig. S4), when fire activity reduces, and wet deposition becomes more effective, as reported for Central America by Ríos and Raga, (2018). This further supported by the negative correlation with relative humidity (r=–0.44), and weak correlation with total precipitation (r=–0.08). The seasonal pattern also expresses spatial distribution, with increased NH_3 extending hotspots during the peak months (April–May) indicating that the NH_3 source become more distributed in the Northern (Petén, Alta Verapaz, Quiché), and southern (Escuintla) (Fig. 3), likely associated with agricultural burning and land preparation practices. A moderate positive correlation with BLH (r=0.47), suggests that enhanced vertical mixing contributes to increasing column NH_3 detected by satellite observations. These findings are similar related with global studies showing strong seasonal patterns in NH_3, reflecting crops application timing and biomass burning (Van Damme et al., 2018, 2021; Fortems-Cheiney et al., 2016; Saravia and Trachte, 2025).

4.2 Fires, biomass burning, and extreme events over Guatemala

Fires represent an important driver of interannual variability in NH_3 over Guatemala. Years with enhanced fire occurrence, such as 2016, 2017, and 2019, coincide with elevated NH_3 columns. In contrast to the years with reduced fire counts 2018 and 2022 correspond to lower NH_3 levels. The strong positive relationship between NH_3 and fire activity (r=0.65) supports the role of biomass burning as a major episodic source. The spatial distribution of fires further reinforces this link, with recurrent hotspots in northern Guatemala (Petén) and southern coast (Escuintla). Petén shows the strongest area of fire activity, including the officially designated protected areas that correspond to the large Maya Biosphere reserve (CONAP, 2016). The observed pattern of fire activity is predominantly anthropogenic. Previous studies indicate that most fires globally are human induced (FAO, 2007), and in Central America lighting occurrence is minimal during the dry season (November–April) (Kucieńska et al., 2010) when fire activity is highest.

Interannual variability in fire activity is modulated by meteorological conditions. Periods with increased fires are generally associated with the increase of temperature (r=0.42) and atmospheric conditions such as BLH (r=0.76). For example, extreme temperature conditions (2016, 2020, 2023), consistent with INSIVUMEH (2023) ground observations, linked it with the episode of El Niño Southern Oscillation (ENSO), which modulates temperature and precipitation conditions in the region of Central America (Anderson et al., 2023). Similar patterns were reported for Amazonia, where NH_3 emission from biomass burning exhibit strong spatial and temporal variability, with interannual peak linked to severe droughts and late fire-season activity, highlighting the influence of ENSO events (Anderson et al., 2023; Whitburn et al., 2016b), and Southeast Asia, particularly Indonesia, largely human-induced fires for land clearing burned extensive tropical forest and peatlands (Chang et al., 2021; Whitburn et al., 2016b).

The neutral ENSO during April 2020 event provides a clear example of extreme conditions of NH_3, fires and meteorological conditions. That period coincides with the highest fire activity during the study period (957) (Fig. S6), coinciding with the maximum NH_3 column (2.33×10^{16} molecules cm^{-2}), indicating strong biomass burnings (Fig. S7). Although 2020 recorded the highest annual median precipitation (69 mm) (Table S6), April 2020 was characterized with one of lowest monthly precipitations (9 mm) (Fig. S4), consistent with short dry conditions within the year. Elevated temperatures (27.9° C.) likely enhanced volatilization from the fire and agricultural sources, while relatively dry atmospheric conditions reduced the process of removal. Boundary layer height (791 m) also contributed to the observed values, with enhanced vertical mixing increasing the NH_3 in the vertical column, the confinement to the lower troposphere was visible predominantly where the agricultural areas source was detected (Fig. 9). Despite the COVID-19 restriction, NH_3 reached the highest value during this period. Similar increases in atmospheric NH_3 during lockdown conditions have been reported in previous studies, attributed to the persistence of agricultural burnings (Evangeliou et al., 2025; Lovarelli et al., 2021; Viatte et al., 2021; Xu et al., 2022)

4.3 Implications and consistency of dataset NH_3

The dataset concatenated sensor implemented a total of 228 months of observation data over the 108 months of the study period, providing stable observations for NH_3 variability over Guatemala. The comparison during the overlapping period shows strong correlation between sensors, with R^2 above 0.9 and regression slopes close to 1 (Fig. S9). This indicates inter sensor differences are relatively small compared to the observed variability over time. The biases represent a small fraction of the mean NH_3 column, supporting the use of a concatenated dataset for long term analysis. This is supported by the monthly L3 total column for individual IASI sensors (Fig. S3 and Table S3), this aligns with previous studies time series for the three sensors and the consistency over 10 different remote regions (Clarisse et al., 2023, Van Damme et al., 2014).

The observation sampling density stays relatively stable over time, ranging between 1.85–2.65 obs. grid cell $month^{-1}$ with annual pixel counts mean (978–1492) (Table S10). The year 2020, which exhibits the highest NH_3 is associated with the lower observation density (1.97 obs. grid cell $month^{-1}$), indicating that the observed maximum is not driven by added more sampling. This is further supported by the absence of a significant relationship between frequency of the sampling and NH_3 (R^2=0.028), confirming that the observed variability is not an object of the sampling bias. Moreover, the standard errors (Table S9) remain small relative to the magnitude of interannual variability, that indicates the observed differences between years exceed the measurement uncertainty and robustness of the NH_3 column patterns. The seasonal scale presents a clear pattern, the maximum columns coincide with the period months of high sampling (MAM), while the lower columns during the rainy season occur under reduced observation density with 17% of reduction, likely due to increased cloud cover. The lower sampling detected is located over high altitude such as Sierra de las Minas (Fig. S10), that is associated with persistent cloud forest (Chaluleu, 2020; Holder, 2003, 2006).

Finally, the use of L3 dataset, based on averaging L2 retrievals, ensures that the observation keeps the original retrieval signal. Guatemala's tropical location further provides a favorable thermal contrast condition for infrared retrievals, supporting the NH_3 measurements detection despite a relatively moderate background total column.

5 Conclusion

This study provides the first integrated spatiotemporal assessment of concatenated IASI A/B/C of NH_3 total column with day and night overpassing over Guatemala (2015–2023). Using multi-satellite observations combined with fire, land cover, and meteorological reanalysis data. The results reveal distinct seasonal and interannual patterns, with NH_3 driven by a stable agricultural baseline, onto which the episodic biomass burning events are superimposed during the dry season.

Spatiotemporal highest NH_3 total columns are detected and restricted to the north (Petén and Quiché) and southern (Escuintla). These hotspots coincide with areas of intensive cropland and rangeland practices. The disproportionate small but high intensity agricultural cluster, suggest that localized land use practice is the primary control on Guatemala atmospheric nitrogen budget. Conversely, the secondary role of urban emission is evident in lower NH_3 in the central high–middle lands despite the high population densities. Seasonally, a peak in NH_3 occurs during MAM months, strongly correlated with fire activity and elevated temperatures. The decline of NH_3 (42%) in June demonstrates a transition from the rainy season. April 2020 exemplified the linking between fire activity and NH_3, when nearly 1,500 km^2 burned areas were affected (Fig. S7).

Finally, the robustness of this study demonstrated by stable observation density and correlation between sampling frequency and NH_3. The favorable thermal contrast is tropics that allow IASI to detect signals even at moderate background values. These findings provide a baseline for future air quality policies and nitrogen deposition studies, also to understand the role of NH_3 as a precursor to particulate matter in Central America, highlighting the importance of integrating satellite observation with ground-based monitoring and evaluation to better constrain the impact of land management and the atmosphere.

Data availability

Monthly atmospheric ammonia column products from the Infrared Atmospheric Sounding Interferometer (IASI A/B/C), versioned Level-3 data cover global grids, AERIS-IASI portal: https://iasi.aeris-data.fr/nh3/. Monthly meteorology variables are provided by the ERA5 reanalysis dataset (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels-monthly-means?tab=download). Active fire detections MODIS-Aqua/Terra from the NASA-Earth Observing System's Fire Information for Resource Management System (FIRMS) database (https://firms.modaps.eosdis.nasa.gov/). Burned area monthly L3 global 500m grid V061 (https://www.earthdata.nasa.gov/data/catalog/lpcloud-mcd64a1-061). Atmospheric Composition Global Reanalysis 4 (EAC4), produced by the Copernicus Atmosphere Monitoring Service (CAMS) (https://ads.atmosphere.copernicus.eu/datasets/cams-global-reanalysis-eac4?tab=overview).

Author contributions

Conceptualization, C.S. and K.T.; methodology, C.S. and K.T.; formal analysis, C.S.; investigation, C.S. and P.S.; resources, C.S. and P.S.; data curation, C.S.; writing (original draft preparation), C.S.; writing (review and editing), C.S., P.S., and K.T.; visualization, C.S.; supervision, K.T.

Competing interest

The authors declare that they have no conflict of interest.

Financial support

This research received no external funding.

References

Abeed, R., Viatte, C., Porter, W. C., Evangeliou, N., Clerbaux, C., Clarisse, L., Van Damme, M., Coheur, P.-F., and Safieddine, S.: Estimating agricultural ammonia volatilization over Europe using satellite observations and simulation data, EGUsphere, https://doi.org/10.5194/egusphere-2022-1046, 2022.

Ahmad, A. and Dey, L.: A k-mean clustering algorithm for mixed numeric and categorical data, Data Knowl. Eng., 63, 503–527, https://doi.org/10.1016/j.datak.2007.03.016, 2007.

Alfaro Marroquín, G. and Gómez, R.: Antecedentes y contexto del cambio climático en Guatemala, in: Primer reporte de evaluación del conocimiento sobre cambio climático en Guatemala, edited by: Castellanos, E. J., Paiz-Estévez, A., Escribá, J., Rosales-Alconero, M., and Santizo, A., Editorial Universitaria UVG, Guatemala, 2–19, 2019.

Anderson, T. G., McKinnon, K. A., Pons, D., and Anchukaitis, K. J.: How Exceptional Was the 2015–2019 Central American Drought?, Geophys. Res. Lett., 50, https://doi.org/10.1029/2023GL105391, 2023.

Andreae, M. O.: Emission of trace gases and aerosols from biomass burning – an updated assessment, Atmos. Chem. Phys., 19, 8523–8546, https://doi.org/10.5194/acp-19-8523-2019, 2019.

Anne Fouilloux: annefou/metos_python: Working with Spatio-temporal data in Python (v2018.0.0), https://doi.org/doi.org/10.5281/zenodo.1165281, 2018.

Bardales Espinoza, W. A., Castañón, C., and Herrera Herrera, J. L.: Clima de Guatemala, tendencias observadas e índices de cambio climático, in: Primer reporte de evaluación del conocimiento sobre cambio climático en Guatemala, vol. 1, edited by: Castellanos, E. J., Paiz-Estévez, A., Escribá J., Rosales-Alconero M., and Santizo A., Editorial Universitaria UVG, Guatemala, 20–39, 2019.

Chaluleu, C. A.: Fototrampeo en bosques nubosos y latifoliados de la Reserva de la Biósfera Sierra de las Minas, Revista Mesoamericana de Biodiversidad y Cambio Climático–Yu'am, 4, 44–65, 2020.

Chang, Y., Zhang, Y.-L., Kawichai, S., Wang, Q., Van Damme, M., Clarisse, L., Prapamontol, T., and Lehmann, M. F.: Convergent evidence for the pervasive but limited contribution of biomass burning to atmospheric ammonia in peninsular Southeast Asia, Atmos. Chem. Phys., 21, 7187–7198, https://doi.org/10.5194/acp-21-7187-2021, 2021.

Chen, J., Cheng, M., Krol, M., de Vries, W., Zhu, Q., Liu, X., Zhang, F., and Xu, W.: Trends in anthropogenic ammonia emissions in China since 1980: A review of approaches and estimations, Front. Environ. Sci., 11, https://doi.org/10.3389/fenvs.2023.1133753, 2023.

Chen, P. and Wang, Q.: Underestimated industrial ammonia emission in China uncovered by material flow analysis, Environmental Pollution, 368, 125740, https://doi.org/10.1016/j.envpol.2025.125740, 2025.

Chen, P., Wang, Q., Shao, M., and Liu, R.: Significantly underestimated traffic-related ammonia emissions in Chinese megacities: Evidence from satellite observations during COVID-19 lockdowns, Chemosphere, 361, 142497, https://doi.org/10.1016/j.chemosphere.2024.142497, 2024.

Chuvieco, E., Mouillot, F., van der Werf, G. R., San Miguel, J., Tanase, M., Koutsias, N., García, M., Yebra, M., Padilla, M., Gitas, I., Heil, A., Hawbaker, T. J., and Giglio, L.: Historical background and current developments for mapping burned area from satellite Earth observation, Remote Sens. Environ., 225, 45–64, https://doi.org/10.1016/j.rse.2019.02.013, 2019.

Clarisse, L., Clerbaux, C., Dentener, F., Hurtmans, D., and Coheur, P.-F.: Global ammonia distribution derived from infrared satellite observations, Nat. Geosci., 2, 479–483, https://doi.org/10.1038/ngeo551, 2009.

Clarisse, L., Shephard, M. W., Dentener, F., Hurtmans, D., Cady-Pereira, K., Karagulian, F., Van Damme, M., Clerbaux, C., and Coheur, P.: Satellite monitoring of ammonia: A case study of the San Joaquin Valley, Journal of Geophysical Research: Atmospheres, 115, https://doi.org/10.1029/2009JD013291, 2010.

Clarisse, L., Van Damme, M., Clerbaux, C., and Coheur, P.-F.: Tracking down global NH3 point sources with wind-adjusted super resolution, Atmos. Meas. Tech., 12, 5457–5473, https://doi.org/10.5194/amt-12-5457-2019, 2019.

Clarisse, L., Franco, B., Van Damme, M., Di Gioacchino, T., Hadji-Lazaro, J., Whitburn, S., Noppen, L., Hurtmans, D., Clerbaux, C., and Coheur, P.: The IASI NH_3 version 4 product: averaging kernels and improved consistency, Atmos. Meas. Tech., 16, 5009–5028, https://doi.org/10.5194/amt-16-5009-2023, 2023.

Coheur, P.-F., Clarisse, L., Turquety, S., Hurtmans, D., and Clerbaux, C.: IASI measurements of reactive trace species in biomass burning plumes, Atmos. Chem. Phys., 9, 5655–5667, https://doi.org/10.5194/acp-9-5655-2009, 2009.

CONAP: Ley de Áreas Protegidas y su Reglamento, Decreto No. 4-89 y sus Reformas, Decretos No. 18-89, 110-96 y 111-97 del Congreso de la República de Guatemala, 114, 2016.

CONRED: Protocolo Nacional Temporada de Incendios Forestales y No Forestales, Guatemala, 3–83 pp., 2025.

Corona-Núñez, R. O. and Campo, J. E.: Climate and socioeconomic drivers of biomass burning and carbon emissions from fires in tropical dry forests: A Pantropical analysis, Glob. Chang. Biol., 29, 1062–1079, https://doi.org/10.1111/gcb.16516, 2023.

Van Damme, M., Clarisse, L., Heald, C. L., Hurtmans, D., Ngadi, Y., Clerbaux, C., Dolman, A. J., Erisman, J. W., and Coheur, P. F.: Global distributions, time series and error characterization of atmospheric ammonia (NH3) from IASI satellite observations, Atmos. Chem. Phys., 14, 2905–2922, https://doi.org/10.5194/acp-14-2905-2014, 2014.

Van Damme, M., Whitburn, S., Clarisse, L., Clerbaux, C., Hurtmans, D., and Coheur, P.-F.: Version 2 of the IASI NH3 neural network retrieval algorithm: near-real-time and reanalysed datasets, Atmos. Meas. Tech., 10, 4905–4914, https://doi.org/10.5194/amt-10-4905-2017, 2017.

Van Damme, M., Clarisse, L., Whitburn, S., Hadji-Lazaro, J., Hurtmans, D., Clerbaux, C., and Coheur, P.-F.: Industrial and agricultural ammonia point sources exposed, Nature, 564, 99–103, https://doi.org/10.1038/s41586-018-0747-1, 2018.

Van Damme, M., Clarisse, L., Franco, B., Sutton, M. A., Erisman, J. W., Wichink Kruit, R., van Zanten, M., Whitburn, S., Hadji-Lazaro, J., Hurtmans, D., Clerbaux, C., and Coheur, P.-F.: Global, regional and national trends of atmospheric ammonia derived from a decadal (2008–2018) satellite record, Environmental Research Letters, 16, 055017, https://doi.org/10.1088/1748-9326/abd5e0, 2021.

Van Damme, M., Clarisse, L., Stavrakou, T., Wichink Kruit, R., Sellekaerts, L., Viatte, C., Clerbaux, C., and Coheur, P. F.: On the weekly cycle of atmospheric ammonia over European agricultural hotspots, Sci. Rep., 12, https://doi.org/10.1038/s41598-022-15836-w, 2022.

Dammers, E., Palm, M., Van Damme, M., Vigouroux, C., Smale, D., Conway, S., Toon, G. C., Jones, N., Nussbaumer, E., Warneke, T., Petri, C., Clarisse, L., Clerbaux, C., Hermans, C., Lutsch, E., Strong, K., Hannigan, J. W., Nakajima, H., Morino, I., Herrera, B., Stremme, W., Grutter, M., Schaap, M., Wichink Kruit, R. J., Notholt, J., Coheur, P.-F., and Erisman, J. W.: An evaluation of IASI-NH3 with ground-based Fourier transform infrared spectroscopy measurements, Atmos. Chem. Phys., 16, 10351–10368, https://doi.org/10.5194/acp-16-10351-2016, 2016.

Dragosits, U., Theobald, M. R., Place, C. J., Lord, E., Webb, J., Hill, J., ApSimon, H. M., and Sutton, M. A.: Ammonia emission, deposition and impact assessment at the field scale: a case study of sub-grid spatial variability, Environmental Pollution, 117, 147–158, https://doi.org/10.1016/S0269-7491(01)00147-6, 2002.

ESRI: ESRI: Sentinel-2 2020 Global Land Use/Land Cover (LULC) Map, 12 pp., 2021.

European Space Agency: Copernicus Global Digital Elevation Model, https://doi.org/https://doi.org/10.5069/G9028PQB, 2024.

Evangeliou, N., Balkanski, Y., Eckhardt, S., Cozic, A., Van Damme, M., Coheur, P.-F., Clarisse, L., Shephard, M. W., Cady-Pereira, K. E., and Hauglustaine, D.: 10-year satellite-constrained fluxes of ammonia improve performance of chemistry transport models, Atmos. Chem. Phys., 21, 4431–4451, https://doi.org/10.5194/acp-21-4431-2021, 2021.

Evangeliou, N., Tichý, O., Svendby Otervik, M., Eckhardt, S., Balkanski, Y., and Hauglustaine, D. A.: Unchanged $PM_{2.5}$ levels over Europe during COVID-19 were buffered by ammonia, Aerosol Research, 3, 155–174, https://doi.org/10.5194/ar-3-155-2025, 2025.

FAO: Fire Management - Global Assessment 2006, 135 pp., 2007.

FAO: FAOSTAT. Countries by commodity, 2019.

Farren, N. J., Davison, J., Rose, R. A., Wagner, R. L., and Carslaw, D. C.: Underestimated Ammonia Emissions from Road Vehicles, Environ. Sci. Technol., 54, 15689–15697, https://doi.org/10.1021/acs.est.0c05839, 2020.

Flemming, J., Benedetti, A., Inness, A., Engelen, R. J., Jones, L., Huijnen, V., Remy, S., Parrington, M., Suttie, M., Bozzo, A., Peuch, V.-H., Akritidis, D., and Katragkou, E.: The CAMS interim Reanalysis of Carbon Monoxide, Ozone and Aerosol for 2003–2015, Atmos. Chem. Phys., 17, 1945–1983, https://doi.org/10.5194/acp-17-1945-2017, 2017.

Fortems-Cheiney, A., Dufour, G., Hamaoui-Laguel, L., Foret, G., Siour, G., Van Damme, M., Meleux, F., Coheur, P. -F., Clerbaux, C., Clarisse, L., Favez, O., Wallasch, M., and Beekmann, M.: Unaccounted variability in NH3 agricultural sources detected by IASI contributing to European spring haze episode, Geophys. Res. Lett., 43, 5475–5482, https://doi.org/10.1002/2016GL069361, 2016.

Franco, B., Clarisse, L., Stavrakou, T., Müller, J. -F, Van Damme, M., Whitburn, S., Hadji-Lazaro, J., Hurtmans, D., Taraborrelli, D., Clerbaux, C., and Coheur, P. -F: A General Framework for Global Retrievals of Trace Gases From IASI: Application to Methanol, Formic Acid, and PAN, Journal of Geophysical Research: Atmospheres, 123, https://doi.org/10.1029/2018JD029633, 2018.

Fu, Y., Li, R., Wang, X., Bergeron, Y., Valeria, O., Chavardès, R. D., Wang, Y., and Hu, J.: Fire Detection and Fire Radiative Power in Forests and Low-Biomass Lands in Northeast Asia: MODIS versus VIIRS Fire Products, Remote Sens. (Basel)., 12, 2870, https://doi.org/10.3390/rs12182870, 2020.

Gašparović, M., Zrinjski, M., and Gudelj, M.: Automatic cost-effective method for land cover classification (ALCC), Comput. Environ. Urban Syst., 76, 1–10, https://doi.org/10.1016/j.compenvurbsys.2019.03.001, 2019.

Giglio, L., Descloitres, J., Justice, C. O., and Kaufman, Y. J.: An Enhanced Contextual Fire Detection Algorithm for MODIS, Remote Sens. Environ., 87, 273–282, https://doi.org/10.1016/S0034-4257(03)00184-6, 2003.

Giglio, L., van der Werf, G. R., Randerson, J. T., Collatz, G. J., and Kasibhatla, P.: Global estimation of burned area using MODIS active fire observations, Atmos. Chem. Phys., 6, 957–974, https://doi.org/10.5194/acp-6-957-2006, 2006.

Giglio, L., Randerson, J. T., and van der Werf, G. R.: Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4), J. Geophys. Res. Biogeosci., 118, 317–328, https://doi.org/10.1002/jgrg.20042, 2013.

Giglio, L., Schroeder, W., and Justice, C. O.: The collection 6 MODIS active fire detection algorithm and fire products, Remote Sens. Environ., 178, 31–41, https://doi.org/10.1016/j.rse.2016.02.054, 2016.

Giglio, L., Boschetti, L., Roy, D. P., Humber, M. L., and Justice, C. O.: The Collection 6 MODIS burned area mapping algorithm and product, Remote Sens. Environ., 217, 72–85, https://doi.org/10.1016/j.rse.2018.08.005, 2018.

Giglio, L., Schroeder, W., Hall, J. V., and Justice, C. O.: MODIS Collection 6 and Collection 6.1 Active Fire Product User's Guide, 2021a.

Giglio, L., Justice, C., Boschetti, L., and Roy, D.: MODIS/Terra + Aqua Burned Area Monthly L3 Global 500 m SIN Grid V061, NASA EOSDIS Land Processes DAAC [data set], https://doi.org/https://doi.org/10.5067/MODIS/MCD64A1.061, 2021b.

Gu, C., Wang, S., Zhu, J., Dai, W., Liu, J., Xue, R., Che, X., Lin, Y., Duan, Y., Wenig, M. O., and Zhou, B.: Underestimated ammonia vehicular emissions in metropolitan city revealed by on-road mobile measurement, Environmental Research Letters, 18, 104040, https://doi.org/10.1088/1748-9326/acf94a, 2023.

Guo, Y., Hong, S., Feng, N., Zhuang, Y., and Zhang, L.: Spatial distributions and temporal variations of atmospheric aerosols and the affecting factors: a case study for a region in central China, Int. J. Remote Sens., 33, 3672–3692, https://doi.org/10.1080/01431161.2011.631951, 2012.

Hantson, S., Padilla, M., Corti, D., and Chuvieco, E.: Strengths and weaknesses of MODIS hotspots to characterize global fire occurrence, Remote Sens. Environ., 131, 152–159, https://doi.org/10.1016/j.rse.2012.12.004, 2013.

Herrera, B., Bezanilla, A., Blumenstock, T., Dammers, E., Hase, F., Clarisse, L., Magaldi, A., Rivera, C., Stremme, W., Strong, K., Viatte, C., Van Damme, M., and Grutter, M.: Measurement report: Evolution and distribution of NH3 over Mexico City from ground-based and satellite infrared spectroscopic measurements, Atmos. Chem. Phys., 22, 14119–14132, https://doi.org/10.5194/acp-22-14119-2022, 2022.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.: The ERA5 global reanalysis, Quarterly Journal of the Royal Meteorological Society, 146, 1999–2049, https://doi.org/10.1002/qj.3803, 2020.

Hervas, A.: Land, development and contract farming on the Guatemalan oil palm frontier, J. Peasant Stud., 46, 115–141, https://doi.org/10.1080/03066150.2017.1351435, 2019.

Holder, C. D.: Fog precipitation in the Sierra de las Minas Biosphere Reserve, Guatemala, Hydrol. Process., 17, 2001–2010, https://doi.org/10.1002/hyp.1224, 2003.

Holder, C. D.: The hydrological significance of cloud forests in the Sierra de las Minas Biosphere Reserve, Guatemala, Geoforum, 37, 82–93, https://doi.org/10.1016/j.geoforum.2004.06.008, 2006.

IGM: Mapa hipsometrico 2002, Guatemala, 2002.

INE: Encuesta Nacional Agropecuaria , Guatemala City, 2020.

Inness, A., Ades, M., Agustí-Panareda, A., Barré, J., Benedictow, A., Blechschmidt, A.-M., Dominguez, J. J., Engelen, R., Eskes, H., Flemming, J., Huijnen, V., Jones, L., Kipling, Z., Massart, S., Parrington, M., Peuch, V.-H., Razinger, M., Remy, S., Schulz, M., and Suttie, M.: The CAMS reanalysis of atmospheric composition, Atmos. Chem. Phys., 19, 3515–3556, https://doi.org/10.5194/acp-19-3515-2019, 2019.

INSIVUMEH: Variabilidad y cambio climático en Guatemala, Guatemala, 2018.

INSIVUMEH: Estado del Clima en Guatemala, 2023.

Justice, C. O., Giglio, L., Roy, D., Boschetti, L., Csiszar, I., Davies, D., Korontzi, S., Schroeder, W., O'Neal, K., and Morisette, J.: MODIS-Derived Global Fire Products, 661–679, https://doi.org/10.1007/978-1-4419-6749-7_29, 2010.

Karra, K., Kontgis, C., Statman-Weil, Z., Mazzariello, J. C., Mathis, M., and Brumby, S. P.: Global land use / land cover with Sentinel 2 and deep learning, in: 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, 4704–4707, https://doi.org/10.1109/IGARSS47720.2021.9553499, 2021.

Keeley, J. E.: Fire Management of California Shrubland Landscapes, Environ. Manage., 29, 395–408, https://doi.org/10.1007/s00267-001-0034-Y, 2002.

Kucieńska, B., Raga, G. B., and Rodríguez, O.: Cloud-to-ground lightning over Mexico and adjacent oceanic regions: a preliminary climatology using the WWLLN dataset, Ann. Geophys., 28, 2047–2057, https://doi.org/10.5194/angeo-28-2047-2010, 2010.

Li, F., Zhang, X., and Kondragunta, S.: Biomass Burning in Africa: An Investigation of Fire Radiative Power Missed by MODIS Using the 375 m VIIRS Active Fire Product, Remote Sens. (Basel)., 12, 1561, https://doi.org/10.3390/rs12101561, 2020.

Li, J., Hendricks, J., Righi, M., and Beer, C. G.: An aerosol classification scheme for global simulations using the K-means machine learning method, Geosci. Model Dev., 15, 509–533, https://doi.org/10.5194/gmd-15-509-2022, 2022.

Liu, Y., Qian, Y., Rasch, P. J., Zhang, K., Leung, L. R., Wang, Y., Wang, M., Wang, H., Huang, X., and Yang, X.-Q.: Fire–precipitation interactions amplify the quasi-biennial variability in fires over southern Mexico and Central America, Atmos. Chem. Phys., 24, 3115–3128, https://doi.org/10.5194/acp-24-3115-2024, 2024a.

Liu, Y., Chen, J., Shi, Y., Zheng, W., Shan, T., and Wang, G.: Global Emissions Inventory from Open Biomass Burning (GEIOBB): utilizing Fengyun-3D global fire spot monitoring data, Earth Syst. Sci. Data, 16, 3495–3515, https://doi.org/10.5194/essd-16-3495-2024, 2024b.

Lopez-Ridaura, S., Barba-Escoto, L., Reyna, C., Hellin, J., Gerard, B., and van Wijk, M.: Food security and agriculture in the Western Highlands of Guatemala, Food Secur., 11, 817–833, https://doi.org/10.1007/s12571-019-00940-z, 2019.

Lovarelli, D., Fugazza, D., Costantini, M., Conti, C., Diolaiuti, G., and Guarino, M.: Comparison of ammonia air concentration before and during the spread of COVID-19 in Lombardy (Italy) using ground-based and satellite data, Atmos. Environ., 259, 118534, https://doi.org/10.1016/j.atmosenv.2021.118534, 2021.

Luo, Z., Zhang, Y., Chen, W., Van Damme, M., Coheur, P.-F., and Clarisse, L.: Estimating global ammonia (NH_3) emissions based on IASI observations from 2008 to 2018, Atmos. Chem. Phys., 22, 10375–10388, https://doi.org/10.5194/acp-22-10375-2022, 2022.

Mahata, K., Das, R., Das, S., and Sarkar, A.: Land Use Land Cover map segmentation using Remote Sensing: A Case study of Ajoy river watershed, India, Journal of Intelligent Systems, 30, 273–286, https://doi.org/10.1515/jisys-2019-0155, 2020.

Marais, E. A., Pandey, A. K., Van Damme, M., Clarisse, L., Coheur, P., Shephard, M. W., Cady-Pereira, K. E., Misselbrook, T., Zhu, L., Luo, G., and Yu, F.: UK Ammonia Emissions Estimated With Satellite Observations and GEOS-Chem, Journal of Geophysical Research: Atmospheres, 126, https://doi.org/10.1029/2021JD035237, 2021a.

Marais, E. A., Pandey, A. K., Van Damme, M., Clarisse, L., Coheur, P., Shephard, M. W., Cady-Pereira, K. E., Misselbrook, T., Zhu, L., Luo, G., and Yu, F.: UK Ammonia Emissions Estimated With Satellite Observations and GEOS-Chem, Journal of Geophysical Research: Atmospheres, 126, https://doi.org/10.1029/2021JD035237, 2021b.

McDuffie, E. E., Smith, S. J., O'Rourke, P., Tibrewal, K., Venkataraman, C., Marais, E. A., Zheng, B., Crippa, M., Brauer, M., and Martin, R. V.: A global anthropogenic emission inventory of atmospheric pollutants from sector- and fuel-specific sources (1970–2017): an application of the Community Emissions Data System (CEDS), Earth Syst. Sci. Data, 12, 3413–3442, https://doi.org/10.5194/essd-12-3413-2020, 2020.

Monzón-Alvarado, C., Cortina-Villar, S., Schmook, B., Flamenco-Sandoval, A., Christman, Z., and Arriola, L.: Land-use decision-making after large-scale forest fires: Analyzing fires as a driver of deforestation in Laguna del Tigre National Park, Guatemala, Applied Geography, 35, 43–52, https://doi.org/10.1016/j.apgeog.2012.04.008, 2012.

Orrego León, E. O., Hernández Quevedo, M. P., and Gómez Jordán, R. C.: Variabilidad del inicio, final y duración de la época lluviosa en Guatemala y su tendencia, Revista Mesoamericana de Biodiversidad y Cambio Climático–Yu'am, 5, 4–24, 2021.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., and Duchesnay, É.: Scikit-learn: Machine learning in Python, the Journal of machine Learning research, 12, 2825–2830, 2011.

Pham, D. T., Dimov, S. S., and Nguyen, C. D.: Selection of K in K-means clustering, Proc. Inst. Mech. Eng. C J. Mech. Eng. Sci., 219, 103–119, https://doi.org/10.1243/095440605X8298, 2005.

Pohl, V., Gilmer, A., Hellebust, S., McGovern, E., Cassidy, J., Byers, V., McGillicuddy, E. J., Neeson, F., and O'Connor, D. J.: Ammonia Cycling and Emerging Secondary Aerosols from Arable Agriculture: A European and Irish Perspective, Air, 1, 37–54, https://doi.org/10.3390/air1010003, 2022.

Remy, S. and Kaiser, J. W.: Daily global fire radiative power fields estimation from one or two MODIS instruments, Atmos. Chem. Phys., 14, 13377–13390, https://doi.org/10.5194/acp-14-13377-2014, 2014.

Ríos, B. and Raga, G. B.: Spatio-temporal distribution of burned areas by ecoregions in Mexico and Central America, Int. J. Remote Sens., 39, 949–970, https://doi.org/10.1080/01431161.2017.1392641, 2018.

Saravia, C. and Trachte, K.: Spatiotemporal Analysis of NH3 Emission Sources and Their Relation to Land Use Types in the Eastern German Lowlands, Atmosphere (Basel)., 16, 346, https://doi.org/10.3390/atmos16030346, 2025.

Soci, C., Hersbach, H., Simmons, A., Poli, P., Bell, B., Berrisford, P., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Radu, R., Schepers, D., Villaume, S., Haimberger, L., Woollen, J., Buontempo, C., and Thépaut, J.: The ERA5 global reanalysis from 1940 to 2022, Quarterly Journal of the Royal Meteorological Society, 150, 4014–4048, https://doi.org/10.1002/qj.4803, 2024.

Spencer, N. H.: Squared Euclidean Distances, in: Essentials of Multivariate Data Analysis, 95, 2013.

Sutton, M. A., Nemitz, E., Erisman, J. W., Beier, C., Bahl, K. B., Cellier, P., de Vries, W., Cotrufo, F., Skiba, U., Di Marco, C., Jones, S., Laville, P., Soussana, J. F., Loubet, B., Twigg, M., Famulari, D., Whitehead, J., Gallagher, M. W., Neftel, A., Flechard, C. R., Herrmann, B., Calanca, P. L., Schjoerring, J. K., Daemmgen, U., Horvath, L., Tang, Y. S., Emmett, B. A., Tietema, A., Peñuelas, J., Kesik, M., Brueggemann, N., Pilegaard, K., Vesala, T., Campbell, C. L., Olesen, J. E., Dragosits, U., Theobald, M. R., Levy, P., Mobbs, D. C., Milne, R., Viovy, N., Vuichard, N., Smith, J. U., Smith, P., Bergamaschi, P., Fowler, D., and Reis, S.: Challenges in quantifying biosphere–atmosphere exchange of nitrogen species, Environmental Pollution, 150, 125–139, https://doi.org/10.1016/j.envpol.2007.04.014, 2007.

Sutton, M. A., Reis, S., Riddick, S. N., Dragosits, U., Nemitz, E., Theobald, M. R., Tang, Y. S., Braban, C. F., Vieno, M., Dore, A. J., Mitchell, R. F., Wanless, S., Daunt, F., Fowler, D., Blackall, T. D., Milford, C., Flechard, C. R., Loubet, B., Massad, R., Cellier, P., Personne, E., Coheur, P. F., Clarisse, L., Van Damme, M., Ngadi, Y., Clerbaux, C., Skjøth, C. A., Geels, C., Hertel, O., Wichink Kruit, R. J., Pinder, R. W., Bash, J. O., Walker, J. T., Simpson, D., Horváth, L., Misselbrook, T. H., Bleeker, A., Dentener, F., and de Vries, W.: Towards a climate-dependent paradigm of ammonia emission and deposition, Philosophical Transactions of the Royal Society B: Biological Sciences, 368, 20130166, https://doi.org/10.1098/rstb.2013.0166, 2013.

Umargono, E., Suseno, J. E., and S. K., V. G.: K-Means Clustering Optimization using the Elbow Method and Early Centroid Determination Based-on Mean and Median, in: Proceedings of the International Conferences on Information System and Technology, 234–240, https://doi.org/10.5220/0009908402340240, 2019.

Vermote, E., Ellicott, E., Dubovik, O., Lapyonok, T., Chin, M., Giglio, L., and Roberts, G. J.: An approach to estimate global biomass burning emissions of organic and black carbon from MODIS fire radiative power, Journal of Geophysical Research: Atmospheres, 114, https://doi.org/10.1029/2008JD011188, 2009.

Viatte, C., Petit, J.-E., Yamanouchi, S., Van Damme, M., Doucerain, C., Germain-Piaulenne, E., Gros, V., Favez, O., Clarisse, L., Coheur, P.-F., Strong, K., and Clerbaux, C.: Ammonia and PM2.5 Air Pollution in Paris during the 2020 COVID Lockdown, Atmosphere (Basel)., 12, 160, https://doi.org/10.3390/atmos12020160, 2021.

van der Werf, G. R., Randerson, J. T., Giglio, L., Collatz, G. J., Mu, M., Kasibhatla, P. S., Morton, D. C., DeFries, R. S., Jin, Y., and van Leeuwen, T. T.: Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009), Atmos. Chem. Phys., 10, 11707–11735, https://doi.org/10.5194/acp-10-11707-2010, 2010.

van der Werf, G. R., Randerson, J. T., Giglio, L., van Leeuwen, T. T., Chen, Y., Rogers, B. M., Mu, M., van Marle, M. J. E., Morton, D. C., Collatz, G. J., Yokelson, R. J., and Kasibhatla, P. S.: Global fire emissions estimates during 1997–2016, Earth Syst. Sci. Data, 9, 697–720, https://doi.org/10.5194/essd-9-697-2017, 2017.

Whitburn, S., Van Damme, M., Clarisse, L., Bauduin, S., Heald, C. L., Hadji-Lazaro, J., Hurtmans, D., Zondlo, M. A., Clerbaux, C., and Coheur, P. -F: A flexible and robust neural network IASI-NH3 retrieval algorithm, Journal of Geophysical Research: Atmospheres, 121, 6581–6599, https://doi.org/10.1002/2016JD024828, 2016a.

Whitburn, S., Van Damme, M., Clarisse, L., Turquety, S., Clerbaux, C., and Coheur, P.-F.: Doubling of annual ammonia emissions from the peat fires in Indonesia during the 2015 El Niño, Geophys. Res. Lett., 43, 11,007-11,014, https://doi.org/10.1002/2016GL070620, 2016b.

Whitburn, S., Van Damme, M., Clarisse, L., Hurtmans, D., Clerbaux, C., and Coheur, P.-F.: IASI-derived NH3 enhancement ratios relative to CO for the tropical biomass burning regions, Atmos. Chem. Phys., 17, 12239–12252, https://doi.org/10.5194/acp-17-12239-2017, 2017.

Wolfe, R. E., Nishihama, M., Fleig, A. J., Kuyper, J. A., Roy, D. P., Storey, J. C., and Patt, F. S.: Achieving sub-pixel geolocation accuracy in support of MODIS land science, Remote Sens. Environ., 83, 31–49, https://doi.org/10.1016/S0034-4257(02)00085-8, 2002.

Wooster, M., Zhukov, B., and Oertel, D.: Fire radiative energy for quantitative study of biomass burning: derivation from the BIRD experimental satellite and comparison to MODIS fire products, Remote Sens. Environ., 86, 83–107, https://doi.org/10.1016/S0034-4257(03)00070-1, 2003.

Wyer, K. E., Kelleghan, D. B., Blanes-Vidal, V., Schauberger, G., and Curran, T. P.: Ammonia emissions from agriculture and their contribution to fine particulate matter: A review of implications for human health, J. Environ. Manage., 323, 116285, https://doi.org/10.1016/j.jenvman.2022.116285, 2022.

Xu, W., Zhao, Y., Wen, Z., Chang, Y., Pan, Y., Sun, Y., Ma, X., Sha, Z., Li, Z., Kang, J., Liu, L., Tang, A., Wang, K., Zhang, Y., Guo, Y., Zhang, L., Sheng, L., Zhang, X., Gu, B., Song, Y., Van Damme, M., Clarisse, L., Coheur, P.-F., Collett, J. L., Goulding, K., Zhang, F., He, K., and Liu, X.: Increasing importance of ammonia emission abatement in PM2.5 pollution control, Sci. Bull. (Beijing)., 67, 1745–1749, https://doi.org/10.1016/j.scib.2022.07.021, 2022.

Zhou, C., Zhou, H., Holsen, T. M., Hopke, P. K., Edgerton, E. S., and Schwab, J. J.: Ambient Ammonia Concentrations Across New York State, Journal of Geophysical Research: Atmospheres, 124, 8287–8302, https://doi.org/10.1029/2019JD030380, 2019.

Zhou, Y., Zhao, Y., Mao, P., Zhang, Q., Zhang, J., Qiu, L., and Yang, Y.: Development of a high-resolution emission inventory and its evaluation and application through air quality modeling for Jiangsu Province, China, Atmos. Chem. Phys., 17, 211–233, 2017.

Zhu, L., Henze, D. K., Bash, J. O., Cady-Pereira, K. E., Shephard, M. W., Luo, M., and Capps, S. L.: Sources and Impacts of Atmospheric NH3: Current Understanding and Frontiers for Modeling, Measurements, and Remote Sensing in North America, Curr. Pollut. Rep., 1, 95–116, https://doi.org/10.1007/s40726-015-0010-4, 2015.