



## RESEARCH ARTICLE

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## Key Points:

- First 4D-Var inversion to include bi-directional flux of NH<sub>3</sub>, based on CrIS NH<sub>3</sub> and cross-validated with surface observations
- Bi-directional flux reduces posterior regional NH<sub>3</sub> emissions by 10%–20% annually (monthly up to 34%), compared to uni-directional emissions
- Posterior NH<sub>3</sub> emissions generally improve simulated seasonality and magnitude of NH<sub>3</sub> and NH<sub>x</sub> wet deposition

## Supporting Information:

Supporting Information may be found in the online version of this article.

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## 4D-Var Inversion of European NH<sub>3</sub> Emissions Using CrIS NH<sub>3</sub> Measurements and GEOS-Chem Adjoint With Bi-Directional and Uni-Directional Flux Schemes

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**Abstract** We conduct the first 4D-Var inversion of NH<sub>3</sub> accounting for NH<sub>3</sub> bi-directional flux, using CrIS satellite NH<sub>3</sub> observations over Europe in 2016. We find posterior NH<sub>3</sub> emissions peak more in springtime than prior emissions at continental to national scales, and annually they are generally smaller than the prior emissions over central Europe, but larger over most of the rest of Europe. Annual posterior anthropogenic NH<sub>3</sub> emissions for 25 European Union members (EU25) are 25% higher than the prior emissions and very close (<2% difference) to other inventories. Our posterior annual anthropogenic emissions for EU25, the UK, the Netherlands, and Switzerland are generally 10%–20% smaller than when treating NH<sub>3</sub> fluxes as uni-directional emissions, while the monthly regional difference can be up to 34% (Switzerland in July). Compared to monthly mean in-situ observations, our posterior NH<sub>3</sub> emissions from both schemes generally improve the magnitude and seasonality of simulated surface NH<sub>3</sub> and bulk NH<sub>x</sub> wet deposition throughout most of Europe, whereas evaluation against hourly measurements at a background site shows the bi-directional scheme better captures observed diurnal variability of surface NH<sub>3</sub>. This contrast highlights the need for accurately simulating diurnal variability of NH<sub>3</sub> in assimilation of sun-synchronous observations and also the potential value of future geostationary satellite observations. Overall, our top-down ammonia emissions can help to examine the effectiveness of air pollution control policies to facilitate future air pollution management, as well as helping us understand the uncertainty in top-down NH<sub>3</sub> emissions estimates associated with treatment of NH<sub>3</sub> surface exchange.

**Plain Language Summary** Atmospheric ammonia contributes to air pollutants and excessive deposition of reactive nitrogen that is detrimental to sensitive ecosystems. Ammonia is emitted mainly by agricultural livestock and fertilizer use. While surface measurements of NH<sub>3</sub> are sparse, satellite observations can provide near daily global coverage. Here we calculate monthly NH<sub>3</sub> emissions over Europe, the only region adopting NH<sub>3</sub> control policies, using an air quality model coupled with a process-based bi-directional NH<sub>3</sub> flux scheme and NH<sub>3</sub> measurements observed by the CrIS satellite instrument. Our CrIS-derived annual regional total anthropogenic NH<sub>3</sub> emissions are close (<2% difference) to statistic-based bottom-up estimates and are 10%–20% lower than when treating NH<sub>3</sub> exchange between the atmosphere and biosphere as one-way

emissions. Our top-down NH<sub>3</sub> emissions estimates may help to assess the efficacy of NH<sub>3</sub> abatement policies and provide quantitative support for future policy making.

## 1. Introduction

Atmospheric ammonia (NH<sub>3</sub>) has adverse effects on human health, ecosystem stability, and climate change via formation of fine particulate matter (PM<sub>2.5</sub>) and excessive deposition of reactive nitrogen (Nr) to bodies of water (Behera et al., 2013; J. W. Erisman et al., 2013; Krupa, 2003; Myhre et al., 2009; Nah et al., 2018; Sutton et al., 2020). Ammonia and ammonium (collectively, NH<sub>x</sub>) also modulate soil pH through deposition to surface soil (Galloway et al., 2003; Krupa, 2003). Ammonia is emitted mainly from agricultural activities (>80%) at national and global scales (Crippa et al., 2020; EEA, 2017; Huang et al., 2012; McDuffie et al., 2020; U.S. EPA, 2018) but can be dominated by non-agricultural emissions at local scales (Berner & Felix, 2020; Chang et al., 2016; Fenn et al., 2018). NH<sub>3</sub> emissions have been reported to pose severe air pollution problems and contribute to premature death across the world (Lelieveld et al., 2015). Surface measurements of ambient and precipitation concentrations across Europe and the United States also show that NH<sub>x</sub> is becoming the dominant contributor to Nr pollution given the substantial reduction of SO<sub>x</sub> and NO<sub>x</sub> emissions over the past decades (Du et al., 2014; Elguindi et al., 2020; Ellis et al., 2013; Li et al., 2016; Sutton et al., 2020; Tang et al., 2021). With sustained decreasing trends in SO<sub>x</sub> and NO<sub>x</sub> emissions projected alongside increasing trends in NH<sub>3</sub> emissions, NH<sub>x</sub> pollution is expected to become worse during the next few years. On top of that, it has been shown that there is a climate penalty on ammonia, resulting in increased emissions in a warmer future climate (Skj oth & Geels, 2013). Some studies have shown that reducing ammonia emissions is a cost-effective way to mitigate PM<sub>2.5</sub> pollution and nitrogen deposition (J. Erisman & Schaap, 2004; Paulot et al., 2014; X. Zhang et al., 2020). More specifically, recent studies show that reducing agricultural NH<sub>3</sub> emissions through changing livestock diets and improving animal housing as well as covering manure storage and fertilizer application are feasible and cost-effective ways to mitigate NH<sub>x</sub> air pollution in Europe, the United States, and China (Giannakis, Kushta, Giannadaki, et al., 2019; Goodkind et al., 2019; X. Zhang et al., 2020). Wetland restoration may also be a cost-effective way to reduce nitrogen pollution through biogeochemical process-based nutrient removal (Cheng et al., 2020). Reducing NH<sub>x</sub> pollution therefore has become an urgent need and an achievable goal for many countries, especially for some European countries facing the threat of a severe “nitrogen crisis” (Stokstad, 2019).

Since 1991, Europe has implemented a series of NH<sub>3</sub> abatement policies and achieved a 25% decrease in NH<sub>3</sub> emissions from 1990 to 2010 (EEA, 2017; Giannakis, Kushta, Bruggeman & Lelieveld, 2019; UNECE, 1999), primarily due to reductions in livestock emissions. However, more than 93% of NH<sub>3</sub> emissions over Europe in 2013 are still from agricultural sources (EEA, 2017). Therefore, additional efforts have been made to reduce NH<sub>3</sub> emissions over Europe during the past decade. For instance, a recent version of Gothenburg Protocol amended in 2012 has set a decreasing emission ceiling for European countries for 2005 to 2020, that aims to reduce NH<sub>3</sub> emissions from 3.854 Tg y<sup>-1</sup> in 2005 to 3.624 Tg y<sup>-1</sup> in 2020 (for EU28; EEA, 2020); however, bottom-up emission estimates still show a slight increase (0.6% y<sup>-1</sup>) from 2010 to 2018 (EEA, 2020; McDuffie et al., 2020), mostly due to increasing agricultural activities.

To better understand and mitigate the environmental effects of NH<sub>3</sub> and to examine the efficacy of NH<sub>3</sub> abatement policies as well as to facilitate future policy-making, long-term and up-to-date ammonia emission monitoring with high accuracy and fine resolution as well as great spatial coverage is required. Although bottom-up inventories are able to capture the general spatial pattern and trends in activity data to some degree, they typically have large uncertainties due to uncertain emission factors and missing potential sources over areas with limited statistics. Furthermore, they are unlikely to account for the climate-driven or meteorology-driven change (e.g., temperature and wind speed) in emission factors and activity increases in small-scale sources (Bash et al., 2013; Hoesly et al., 2018; McDuffie et al., 2020; Sommer et al., 2019; Sutton et al., 2013). Meanwhile, direct ammonia emission monitoring is usually expensive and thus is not feasible to be carried out at large scales. Instead, monitoring NH<sub>3</sub> concentrations and its downstream products (e.g., NH<sub>4</sub><sup>+</sup> and NH<sub>x</sub> wet deposition) at relatively lower cost can be used to investigate NH<sub>3</sub> emissions from local to national scales and to help assess the effectiveness of emission control policies (Nair & Yu, 2020; Sutton et al., 2003).

Previous studies have used ground-based measurements of NH<sub>x</sub> concentrations and NH<sub>x</sub> wet deposition to explore and constrain the seasonal cycle, interannual variability, and magnitude of ammonia emissions at local to regional

scales around the world (Gilliland et al., 2003; Henze et al., 2009; Kong et al., 2019; Lonati & Cernuschi, 2020; Paulot et al., 2014; Pinder et al., 2006; Sutton et al., 2003; Tang, Braban, et al., 2018; L. Zhang et al., 2012). The limitations of these surface measurement-based approaches lie in the scarcity of surface monitoring sites and uncertainty and biases in the instruments (von Bobruzki et al., 2010).

Alternatively, satellite  $\text{NH}_3$  observations can be used to monitor  $\text{NH}_3$  emissions. In terms of spatial coverage and long-term trends, satellite observations of  $\text{NH}_3$  offer distinct advantages over surface  $\text{NH}_x$  observations. Space-based observations of  $\text{NH}_3$  have thus been leveraged to study and constrain the spatiotemporal variation and magnitude of  $\text{NH}_3$  emissions and model simulations of  $\text{NH}_x$  during the past decade (Cao et al., 2020; Chen et al., 2021; Clarisse, Van Damme, Clerbaux, & Coheur, 2019; Clarisse, Van Damme, Gardner, et al., 2019; Dammers et al., 2019; Evangelio et al., 2021; Marais et al., 2021; Schiferl et al., 2016; Van Damme et al., 2020; Van Damme et al., 2018; R. Wang et al., 2021; Warner et al., 2016, 2017; L. Zhang et al., 2018; Zhu et al., 2013). Atmospheric  $\text{NH}_3$  concentrations can be retrieved from measured infrared radiance by remote sensing instruments onboard multiple satellites, such as Atmospheric Infrared Sounder (AIRS) onboard NASA's Aqua satellite (Warner et al., 2016), Tropospheric Emission Spectrometer (TES) onboard NASA's Aura satellite (Beer et al., 2008; Shephard et al., 2011), Infrared Atmospheric Sounding Interferometer (IASI) onboard European Space Agency's MetOp satellites (Clarisse et al., 2009; Van Damme et al., 2014), and Cross-track Infrared Sounder (CrIS) onboard NOAA's Suomi-NPP satellite (Shephard & Cady-Pereira, 2015; Shephard et al., 2020) and NOAA-20 satellite (Glumb et al., 2018). Schiferl et al. (2016) used summertime morning IASI  $\text{NH}_3$  column observations along with the GEOS-Chem model simulations and AMoN surface  $\text{NH}_3$  measurements to explore the drivers of annual variability of  $\text{NH}_3$  concentrations. Van Damme et al. (2018), Clarisse, VanDamme, Clerbaux, & Coheur (2019) and Dammers et al. (2019) used IASI-observed and CrIS-observed  $\text{NH}_3$  column concentrations to quantify  $\text{NH}_3$  emissions from large point sources through an oversampling approach. Warner et al. (2016) and Wang et al. (2021) analyzed spatial and intra-annual variability in AIRS and IASI observations at regional and global scales to identify major sources of  $\text{NH}_3$  in different regions during different seasons. Warner et al. (2017) and van Damme et al. (2020) explored the interannual variability in long-term global  $\text{NH}_3$  observations from AIRS and IASI instruments and found a general increasing trend in atmospheric  $\text{NH}_3$  over China, Europe, and the United States from 2002 to 2018. Along with chemical transport models and their adjoint models, Zhu et al. (2013), L. Zhang et al. (2018), Cao et al. (2020), and Chen et al. (2021) applied TES and CrIS  $\text{NH}_3$  profiles and IASI  $\text{NH}_3$  column concentrations for inverse modeling of  $\text{NH}_3$  emissions and generally found significant heterogeneous biases in anthropogenic  $\text{NH}_3$  inventories across the United States and China. Most recently, Marais et al. (2021) used the GEOS-Chem forward model and multiyear  $\text{NH}_3$  column concentrations from IASI (2008–2018) and CrIS (2013–2018) to constrain spatiotemporal variation and magnitude of  $\text{NH}_3$  emissions in the UK, and they found that bottom-up inventories were biased low by 27%–49% and miss the summer emissions peak compared to satellite-derived  $\text{NH}_3$  emissions.

Most previous inverse modeling studies (Cao et al., 2020; Chen et al., 2021; Henze et al., 2009; Paulot et al., 2014; L. Zhang et al., 2018; Zhu et al., 2013) using either satellite observations or surface observations have only used uni-directional (uni-di) dry deposition scheme (Wesely, 1989), which treats surface exchange of  $\text{NH}_3$  between the atmosphere and biosphere in a one-way manner (from air to surface) and ignores the impacts of change in environmental conditions (e.g., soil temperature, soil wetness, soil pH, fertilized condition and vegetation type) on  $\text{NH}_3$  emissions from fertilized soil and crops, which likely lead to high biases in top-down  $\text{NH}_3$  emission estimates. However, early studies have found that a process-based bi-directional (bi-di)  $\text{NH}_3$  flux scheme (Sutton et al., 1998) involving environmental conditions more realistically captures the dynamics in measured net  $\text{NH}_3$  fluxes in Europe and North America (Neiryck & Ceulemans, 2008; Nemitz et al., 2001; Pleim et al., 2013; Sutton et al., 1998). Later, application of bi-di  $\text{NH}_3$  flux schemes in regional and global chemical transport models generally enabled better model performance in representing ground-based and space-based measurements of  $\text{NH}_3$  surface and column concentrations and  $\text{NH}_x$  wet depositions over Europe and North America as well as East Asia (Bash et al., 2013; Pleim et al., 2019; Wichink Kruit et al., 2012; Zhu, Henze, Bash, Jeong, et al., 2015).

Therefore, to derive  $\text{NH}_3$  emissions from satellite observations while accounting for spatial and temporal changes in environmental conditions, use of a chemical transport model with a process-based bi-di  $\text{NH}_3$  flux scheme is preferable (Sutton et al., 2013). In addition, since Sun-synchronous satellites measure atmospheric  $\text{NH}_3$  concentrations only at certain time (e.g., the daytime and nighttime overpass of CrIS is around 13:30 local time (LT) and 01:30 LT, respectively), accurately simulating the diurnal variability of  $\text{NH}_3$  can increase the accuracy of

top-down emissions estimates (Zhu, Henze, Bash, Cady-Pereira, et al., 2015). Recently, van der Graaf et al. (2021) included a bi-di NH<sub>3</sub> flux scheme when assimilating CrIS-NH<sub>3</sub> observations to improve the spatiotemporal NH<sub>3</sub> distribution in Europe. Here we aim to conduct the first side-by-side comparison of an NH<sub>3</sub> inversion using both uni-directional and bi-di NH<sub>3</sub> flux schemes.

Based on a more complex bi-di NH<sub>3</sub> flux scheme in the CMAQ model (Bash et al., 2013), Zhu, Henze, Bash, Jeong, et al. (2015) implemented a simplified bi-di NH<sub>3</sub> flux scheme in the GEOS-Chem model involving soil temperature, soil pH, soil wetness, soil NH<sub>4</sub><sup>+</sup> concentrations and vegetation type and first developed the corresponding adjoint processes for this bi-di NH<sub>3</sub> flux scheme. With this updated GEOS-Chem forward and adjoint model, they first investigated the spatial and temporal sensitivity of simulated NH<sub>3</sub> concentration to fertilizer application rate and to soil pH at the global scale.

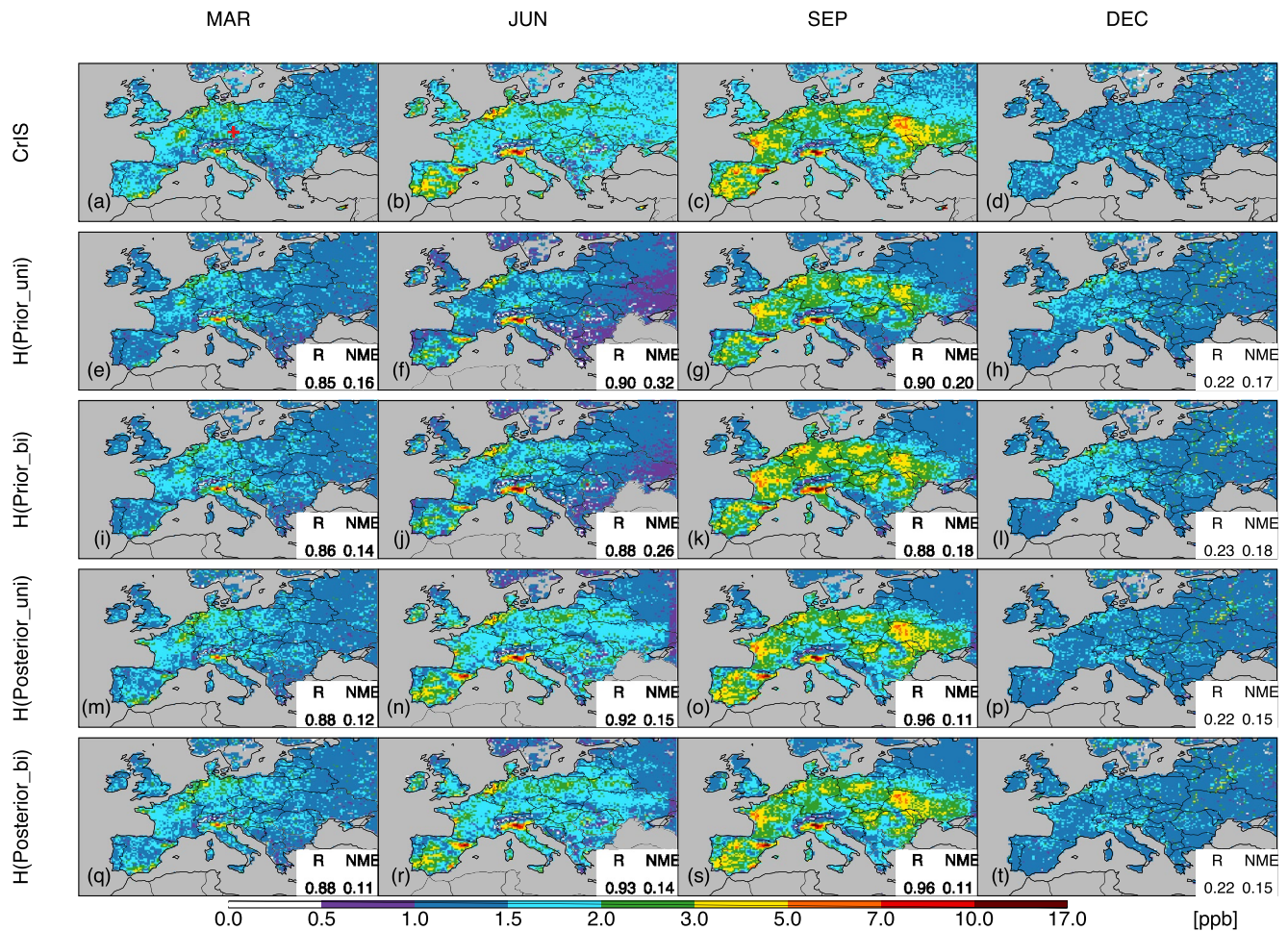
Here we incorporate the bi-di forward and bi-di adjoint processes developed by Zhu, Henze, Bash, Jeong, et al. (2015) into a more recent GEOS-Chem adjoint model version (v35m) coupled with the CrIS NH<sub>3</sub> observation operator (Cao et al., 2020) and apply this updated GEOS-Chem adjoint model to constraining NH<sub>3</sub> emissions using CrIS daytime NH<sub>3</sub> profile observations in 2016 using the four dimensional variational (4D-Var) approach. To more completely understand the implications of neglecting the bi-di exchange of NH<sub>3</sub> (as all previous top-down studies have done), we also conduct a 4D-Var inversion using uni-di NH<sub>3</sub> emissions and compare our posterior NH<sub>3</sub> emissions from these two inversions, presenting the first side-by-side study to explore the uncertainty in top-down NH<sub>3</sub> emissions estimates arising from the NH<sub>3</sub> flux scheme. We use CrIS NH<sub>3</sub> because (a) it provides vertical profiles and averaging kernels (essential for data assimilation), both which are absent from IASI retrievals, and (b) it combines extensive spatial coverage, low noise, and fine spatial resolution (Shephard & Cady-Pereira, 2015), and (c) it has greater spatial coverage than TES, with global coverage similar to IASI and AIRS, and lower signal noise compared to other sensors (Zavalyov et al., 2013), which improves sensitivity in the boundary layer. We further evaluate our CrIS-derived NH<sub>3</sub> emission estimates using independent measurements of surface NH<sub>3</sub> and bulk wet NH<sub>x</sub> deposition from domain-wide monitoring sites over Europe in 2016.

## 2. Data

### 2.1. CrIS NH<sub>3</sub> Observations

CrIS is an infrared sounder on board the sun-synchronous satellite Suomi National Polar-orbiting Partnership (SNPP, used here; Tobin, 2012) launched in October 2011 and the NOAA-20 (JPSS-1) launched in November 2017 (Glumb et al., 2018). CrIS has a cross-track scanning swath width of 2200 km and a nadir spatial resolution of 14 km, which enable CrIS to achieve global coverage twice a day with daytime and nighttime overpasses at 13:30 LT and 01:30 LT, respectively. NH<sub>3</sub> profile and column observations are retrieved through the CrIS Fast Physical Retrieval algorithm (CFPR), which minimizes the difference between measured and simulated spectral radiance in the NH<sub>3</sub> spectral feature around 967 cm<sup>-1</sup> (Shephard & Cady-Pereira, 2015). Pixel-specific a priori profiles and averaging kernels comprise the observation operator ( $\mathbf{H}$ ), which is essential for comparison between satellite retrievals and model simulations. The CFPR algorithm uses three a priori NH<sub>3</sub> profiles, representative of polluted, moderately polluted, and clear conditions. For each NH<sub>3</sub> retrieval, one a priori profile is selected based on an estimated NH<sub>3</sub> signal (Shephard & Cady-Pereira, 2015). We used high-quality daytime CrIS v1.5 NH<sub>3</sub> observations (QF ≥ 3; Shephard et al., 2020) over the Europe domain [15°W–40°E, 32°–62°N] in 2016. Daytime CrIS NH<sub>3</sub> observations have been validated by and generally show good agreement with ground-based and aircraft observations in select regions (Dammers et al., 2017; Shephard & Cady-Pereira, 2015).

We derived linearized averaging kernels  $\left(\frac{\partial(\mathbf{x}_{\text{retrieval}})}{\partial(\mathbf{x}_{\text{true}})}\right)$  from the original logarithmic averaging kernels  $\left(\frac{\partial(\ln(\mathbf{x}_{\text{retrieval}}))}{\partial(\ln(\mathbf{x}_{\text{true}}))}\right)$  following L. Zhang et al. (2010) and Cao et al. (2020) to avoid (a) unrealistic small model column concentrations with the application of logarithmic averaging kernels and (b) numerically large gradient of the cost function with respect to simulated NH<sub>3</sub> concentrations in our 4D-Var inversion.  $\mathbf{x}_{\text{retrieval}}$  and  $\mathbf{x}_{\text{true}}$  are CrIS NH<sub>3</sub> profile retrieval and the true state of atmospheric NH<sub>3</sub> profile, respectively. During the linearization of the averaging kernels (L. Zhang et al., 2010), we also limited the ratio of  $\frac{x_a(i)}{x_a(j)}$  to be in the range of 0–3 in order to avoid unrealistically large values of averaging kernels at higher levels.  $x_a(i)$  and  $x_a(j)$  are CrIS NH<sub>3</sub> a priori values at level  $i$  and  $j$ , respectively.



**Figure 1.** Monthly mean surface  $\text{NH}_3$  concentrations from CrIS ((a)–(d)), simulations driven by prior emissions with uni-di ((e)–(h)) and bi-di ((i)–(l)), simulations driven by posterior emissions derived through uni-di ((m)–(p)) and bi-di ((q)–(t)), respectively, in March, June, September, and December in 2016.  $R$  is the spatial correlation coefficient between  $\text{NH}_3$  simulation and CrIS surface  $\text{NH}_3$ ; NME is the normalized mean error of  $\text{NH}_3$  simulation relative to CrIS surface  $\text{NH}_3$ . The red cross in panel (a) indicates the location of the background site in Germany in Figure 2.

Figures 1a–1d show the spatial and seasonal variability of CrIS  $\text{NH}_3$  mixing ratios at surface level over Europe for March, June, September, and December 2016. Higher  $\text{NH}_3$  concentrations are generally found during warm months over northern Germany, the Netherlands, western France, Northern Italy, South UK, and Ireland as well as southern and northeastern Spain, where there are intense agricultural activities. Unlike the United States (Cao et al., 2020), Europe saw higher CrIS  $\text{NH}_3$  concentrations in September than in June, which is consistent with the September/June contrast in independent surface and IASI-based measurements of  $\text{NH}_3$  averaged across the European domain (Figure 10a and Figure S3 in Supporting Information S1). This September/June contrast in both space-based and ground-based surface  $\text{NH}_3$  observations is most likely caused by larger  $\text{NH}_x$  wet deposition in June than in September (Figure 11a), but this might not represent the typical condition of a normal year since 2016 was exceptionally warm across Europe (<https://www.knmi.nl/nederland-nu/klimatologie/maand-en-seizoensoverzichten/2016/jaar>).

## 2.2. Surface Observations

We evaluate CrIS-derived  $\text{NH}_3$  emissions using extensive independent measurements of surface  $\text{NH}_3$  and bulk  $\text{NH}_x$  wet deposition in 2016 collected from the European Monitoring and Evaluation Program (EMEP; Tørseth et al., 2012), the UK Eutrophying and Acidifying Atmospheric Pollutants (UKEAP) networks: National Ammonia Monitoring Network (NAMN, <https://uk-air.defra.gov.uk/interactive-map?network=namn>; Tang, Stephens, et al., 2018), the Measuring Ammonia in Nature (MAN) network (Lolkema et al., 2015) and the Dutch Monitor-

ing Air Quality Network (LML; Landelijk Meetnet Luchtkwaliteit; van Zanten et al., 2017) in the Netherlands, a nation-wide ammonia monitoring network in Switzerland (Seitler & Meier, 2021), the German Länder networks and the German Environment Agency (<https://www.umweltbundesamt.de>), the Danish Background Air Quality Monitoring Program (Ellermann et al., 2018; Geels et al., 2012), as well as some short-term field campaign sites and long-term monitoring sites distributed in France (Flecharde et al., 2011), Germany (Wintjen et al., 2020; Zöll et al., 2016, 2019), and UK (Twiggy et al., 2015; H. L. Walker et al., 2019).

### 3. Methods

#### 3.1. Uni-Di and Bi-Di NH<sub>3</sub> Flux Schemes

Both uni-di and bi-di NH<sub>3</sub> flux schemes are treated like an electrical resistance model, wherein the flux between the atmosphere and biosphere is analogous to electrical current and the difference between the air and surface concentrations is analogous to electrical voltage (Wesely, 1989). While the uni-di scheme assumes the surface concentration to be zero and thus the air-surface exchange is only downward deposition from the atmosphere to the biosphere (Wesely, 1989), the bi-di scheme more realistically accounts for both air-to-surface deposition and surface-to-air diffusion by introducing a canopy compensation point. This approach, while recognized for some time, has been increasingly implemented in regional and global CTMs in recent years (Bash et al., 2013; Nemitz et al., 2001; Pleim et al., 2013, 2019; Sutton et al., 1998; J. T. Walker et al., 2013; Wichink Kruit et al., 2012; Zhu, Henze, Bash, Jeong, et al., 2015). A key aspect of the bi-di scheme is the calculation of the canopy compensation point ( $C_c$ ), which involves the resistances in the quasi-laminar boundary layers of leaf surface and ground surface, resistances in the leaf stomatal and cuticle and soil, and NH<sub>3</sub> emission potential in the soil and stomatal, as well as soil temperature and leaf surface temperature (Zhu, Henze, Bash, Jeong, et al., 2015). The direction of bi-di NH<sub>3</sub> flux is determined by the sign of the difference between the canopy compensation point and ambient NH<sub>3</sub> concentration ( $C_c - C_a$ ). NH<sub>3</sub> emission potential in the soil is calculated as the ratio of soil NH<sub>4</sub><sup>+</sup> concentration to soil H<sup>+</sup> concentration. The sources of soil NH<sub>4</sub><sup>+</sup> include fertilizer application and wet and dry deposition. Only 60% of the deposited NH<sub>4</sub><sup>+</sup> is assumed to enter the soil, while the rest is assumed to be lost due to run-off into waterways (Hudman et al., 2012). The major sink of soil NH<sub>4</sub><sup>+</sup> is nitrification with a lifetime of 15 days (Zhu, Henze, Bash, Jeong, et al., 2015).

#### 3.2. GEOS-Chem and Its Adjoint Model

We use GEOS-Chem v9-02 with a bi-di NH<sub>3</sub> flux scheme (Zhu, Henze, Bash, Jeong, et al., 2015) to relate NH<sub>3</sub> emissions to NH<sub>3</sub> concentrations in the atmosphere. The corresponding adjoint model (v35m; Henze et al., 2007) is used to derive the gradient of the cost function with respect to NH<sub>3</sub> emissions and fertilizer rates in our 4D-Var inversion. Our GEOS-Chem nested simulations were driven by Goddard Earth Observing System (GEOS-FP) assimilated meteorological fields with a horizontal resolution of 0.25° latitude × 0.3125° longitude and 47 vertical levels up to 0.01 hPa over the Europe domain (15°W–40°E, 32°–62°N). The boundary conditions from global simulations with a horizontal resolution of 2° latitude × 2.5° longitude were supplied to our nested simulations every 3 hr.

In order to reduce computation cost, we use an offline NH<sub>x</sub> simulation in our 4D-Var inversion following previous studies (Cao et al., 2020; Paulot et al., 2014; L. Zhang et al., 2018). We only simulate NH<sub>3</sub> emissions, wet and dry deposition (Amos et al., 2012; H. Liu et al., 2001; Q. Wang et al., 2011; Y. Wang et al., 1998; Wesely, 1989; L. Zhang et al., 2001), transport of NH<sub>x</sub>, and NH<sub>x</sub> partitioning (Binkowski & Roselle, 2003; Park et al., 2004) in our offline simulations. The NH<sub>x</sub> partitioning is driven by archived hourly SO<sub>4</sub><sup>2-</sup>, HNO<sub>3</sub>, and NO<sub>3</sub><sup>-</sup> concentrations from the standard O<sub>3</sub>-NO<sub>x</sub>-VOC-aerosol simulation (Mao et al., 2010; Park et al., 2004). The high-biased GEOS-Chem-simulated HNO<sub>3</sub> (Heald et al., 2012; L. Zhang et al., 2012) was reduced by 15% at each time step (10 min) before the NH<sub>3</sub> – NH<sub>4</sub><sup>+</sup> partitioning in the aerosol thermodynamics following Heald et al. (2012).

Changes in emissions of SO<sub>x</sub> and NO<sub>x</sub> can modulate the lifetime of NH<sub>3</sub> in the atmosphere (M. Liu et al., 2018; Yu et al., 2018). Here we drive our standard simulations, which were used to output hourly SO<sub>4</sub><sup>2-</sup>, NO<sub>3</sub><sup>-</sup>, and HNO<sub>3</sub> at 0.3125° longitude × 0.25° latitude for the year 2016, using rescaled SO<sub>x</sub> and NO<sub>x</sub> emissions from HTAP v2 (originally for 2010) by emission ratios between 2016 and 2010 taken from satellite-derived SO<sub>2</sub> and NO<sub>x</sub> emissions (Miyazaki et al., 2019, 2020). To explore the impacts of this emission rescaling and the abundance of acidic aerosol on our inversion results, we performed monthly sensitivity simulations driven by the original HTAP v2

NO<sub>x</sub> and SO<sub>2</sub> emissions. We found that the monthly cost functions at the first iteration differ by 0.0%–5.5% with and without emission rescaling for uni-di simulations, and by 0.0%–4.0% for bi-di simulations. This indicates that the changes from 2010 to 2016 in SO<sub>2</sub> and NO<sub>x</sub> emissions have small impacts on our inversion results.

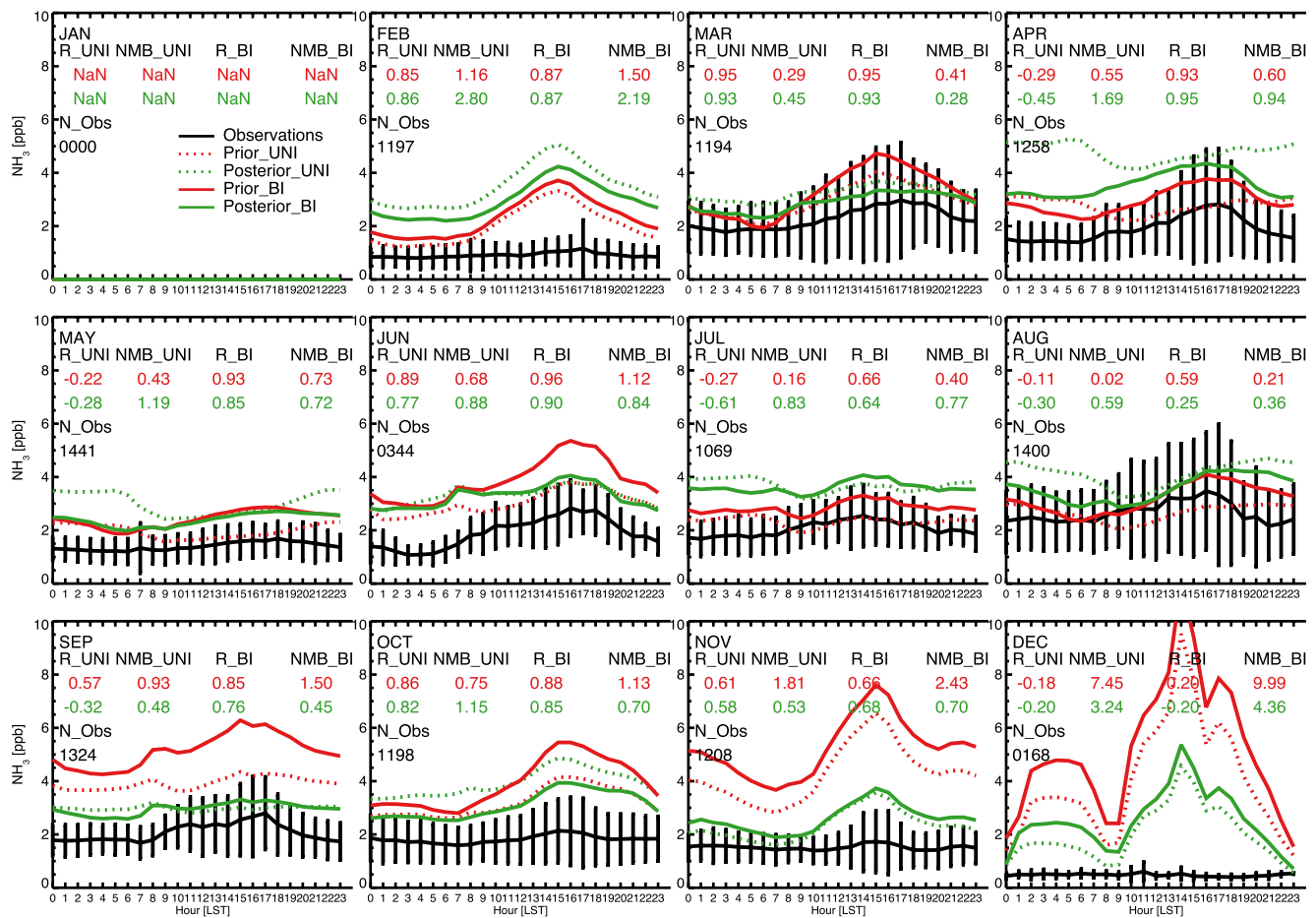
Our prior NH<sub>3</sub> emissions consist of livestock emissions from HTAP v2 (Janssens-Maenhout et al., 2015), emissions originating from fertilizer application (Lu & Tian, 2017), and biomass burning emissions from GFED3 (van der Werf et al., 2010). We scaled the original total anthropogenic NH<sub>3</sub> emissions from HTAP v2 using the MASAGE monthly livestock/agriculture emission ratio (Figure S1 in Supporting Information S1, originally for the year 2006 with a resolution at 2.0° latitude × 2.5° longitude; Paulot et al., 2014) as our prior livestock NH<sub>3</sub> emissions, with diurnal variability of livestock NH<sub>3</sub> emissions calculated following Zhu, Henze, Bash, Jeong, et al. (2015). For the initial guess of fertilizer application rate, we used an annual fertilizer application rate for 2013 from Lu et al. (2017), which is the most up-to-date gridded data. Only a negligible increase (<4.0%) was found in total N-fertilizer consumption over western and central Europe from 2013 to 2016 (<https://www.ifastat.org/databases/plant-nutrition>), with a small shift from 21.4% to 24.4% found in the portion of urea which has a relatively high NH<sub>3</sub> emission factor compared to other N fertilizers (EEA, 2016). This annual fertilizer application rate was further scaled to daily values using day-to-day variation derived from MODIS Enhanced Vegetation Index (EVI) product (Hudman et al., 2012; Zhu, Henze, Bash, Jeong, et al., 2015). To compare with those from uni-di, NH<sub>3</sub> emissions ( $F_{emis}$ ) and deposition ( $F_{dep}$ ) from bi-di were calculated using Equation 1 and Equation 2, respectively, following Zhu, Henze, Bash, Jeong, et al. (2015) and Bash et al. (2013):

$$F_{emis} = \frac{C_c}{R_a + 0.5R_{inc}} \Big|_{C_a=0}, \quad (1)$$

$$F_{dep} = \frac{C_c - C_a}{R_a + 0.5R_{inc}} \Big|_{C_{st}=0, C_g=0}, \quad (2)$$

where  $C_a$ ,  $C_g$ ,  $C_{st}$  are GEOS-Chem-simulated NH<sub>3</sub> concentrations in the air (at surface level), soil, and leaf stomata, respectively.  $C_c$  is the canopy compensation point.  $R_a$  and  $R_{inc}$  are the aerodynamic resistance and the in-canopy aerodynamic resistance, respectively.  $F_{emis}$  represents surface-to-air flux in the bi-di scheme when the air concentration is assumed to be zero;  $F_{dep}$  is the air-to-surface flux when the soil concentration is assumed to be zero.  $F_{emis} + F_{dep}$  is the net flux from bi-di. By splitting the net flux into  $F_{emis}$  and  $F_{dep}$ , we can compare bi-di emissions and deposition with those from uni-di in a comparable manner. To drive uni-di simulations with the same prior monthly emissions from bi-di, we first ran bi-di simulations without optimization, saved the monthly NH<sub>3</sub> emissions, and then used these NH<sub>3</sub> emissions as the prior NH<sub>3</sub> emissions for uni-di simulations.

The bi-di NH<sub>3</sub> flux scheme (Zhu, Henze, Bash, Jeong, et al., 2015) is explicitly applied to fertilizer application. We calculated the NH<sub>3</sub> emission potential in fertilized soil using soil pH and soil NH<sub>4</sub><sup>+</sup> concentration. We updated the soil pH from an older version of the World Soil Information dataset used in Zhu, Henze, Bash, Jeong, et al. (2015) to a more recent dataset (Hengl et al., 2017), which has been constrained using long-term soil profile measurements (Batjes et al., 2020). In contrast, livestock NH<sub>3</sub> emissions are implicitly involved in the bi-di process via their impact on simulated surface NH<sub>3</sub> concentrations and deposition to soil, with the latter serving as a NH<sub>4</sub><sup>+</sup> reservoir for bi-di NH<sub>3</sub> flux (Zhu, Henze, Bash, Jeong, et al., 2015). Previous studies (Denmead & Freney, 1992; Larsen et al., 2001; Liss & Galloway, 1993; Quinn et al., 1996) have shown similar bi-di NH<sub>3</sub> exchange between the atmosphere and surface water. Although the air-water exchange of NH<sub>3</sub> is based on Henry's Law, it is also determined by the difference between the atmospheric concentration and the “effective” concentration in the surface water, whereby the NH<sub>3</sub> flux can be upward emission and downward deposition and thus is similar to our bi-di scheme here. Therefore, we also apply the compensation point-based bi-di scheme to water grid cells in our model following a previous study (Wichink Kruit et al., 2012). In general, the resulting NH<sub>3</sub> emissions from water grid cells are negligible except some coastal grid cells (Figures 4 and 6) and the spatial distribution of NH<sub>3</sub> emissions from coastal grids to remote ocean grids is also consistent with those of simulated and observed NH<sub>3</sub> emission potential ( $\Gamma$ ) in the water in Wichink Kruit et al. (2012). Overall, this bi-di NH<sub>3</sub> flux scheme generally increases the effective lifetime of atmospheric NH<sub>3</sub> and early afternoon concentrations (Figures 3i–3l), and thus it is expected to lead to lower top-down NH<sub>3</sub> emissions estimates compared to those derived using uni-di NH<sub>3</sub> emissions. Here we roughly estimate the relative difference in the lifetime of NH<sub>3</sub> within the EU domain using the relative difference in GC surface NH<sub>3</sub> concentrations (without application of the CrIS observation operator) given that the prior emissions are the same between these two simulations. We found that NH<sub>3</sub> lifetime in the bi-di



**Figure 2.** Monthly mean hourly surface  $\text{NH}_3$  concentrations at a background site (Bavarian Forest National Park) [48°56'N, 13°25'E, 807 m a.s.l., marked by the red cross in Figure 1(a)] in Germany observed via a quantum cascade laser (QCL) spectrometer (black) and simulated by GC driven by prior (red) and posterior (green) emissions through uni-di (dotted) and bi-di (solid) schemes for 11 months in 2016.  $R_{\text{UNI}}$  is the correlation coefficient between measured hourly surface  $\text{NH}_3$  and uni-di  $\text{NH}_3$  simulations. The same for  $R_{\text{BI}}$ , but between  $\text{NH}_3$  measurements and bi-di  $\text{NH}_3$  simulations.  $\text{NMB}_{\text{UNI}}$  is the NMB in uni-di  $\text{NH}_3$  simulations relative to  $\text{NH}_3$  measurements. The same for  $\text{NMB}_{\text{BI}}$ , but for bi-di  $\text{NH}_3$  simulations. We use NMB here to show the sign of the difference between simulations and in-situ measurements to indicate the overestimation or underestimation of  $\text{NH}_3$  in model simulations.

simulation is longer than that in the uni-di simulations by 21.3% (February) to 40.5% (May), with generally larger differences found in warm months (>30% from April to September).

Figure 2 shows that the application of bi-di (red solid line) in GEOS-Chem improved the simulated diurnal cycle during most of the year (especially from April to September) compared to uni-di (red dotted line) when evaluated against surface  $\text{NH}_3$  measurements at a background site [48°56'N, 13°25'E, 807 m a.s.l.] in Germany. The correlation coefficient ( $R$ ) between monthly mean hourly  $\text{NH}_3$  measurements and our prior bi-di simulation ranges from 0.59 to 0.96 from February to November, compared to our prior uni-di  $R$  ranging from -0.29 to 0.95. The improved simulated diurnal variation of  $\text{NH}_3$  is very important for the assimilation of sun-synchronous satellite measurements as satellite data is used only once or twice per day; hence, the model's native diurnal variability has to be assumed to be correct. The prior bi-di simulation also shows a better performance in reproducing domain and nation average monthly means of surface  $\text{NH}_3$  measurements and of  $\text{NH}_x$  wet deposition measurements for most of Europe in 2016 with reduced normalized mean error (NME) and similar correlation coefficient compared to the prior uni-di simulation (see Figures 10 and 11).

We correspondingly updated the GEOS-Chem adjoint model for the bi-di scheme. Additionally, we constructed the adjoint of run-off into waterways of deposited  $\text{NH}_4^+$  before it entered the soil as well as the deposition-associated source and the nitrification-associated sink of  $\text{NH}_4^+$  in the soil. We propagated these adjoint gradients back to the wet and dry deposition adjoint modules, all of which were absent from the original bi-di adjoint code (Zhu,



**Table 1**  
Setup for Inversion Experiments

Inversion experiments	Dry deposition scheme	Posterior emissions
IE_bi	bi-directional	Posterior_bi
IE_uni	uni-directional	Posterior_uni

Henze, Bash, Jeong, et al., 2015). We calculated the gradients of simulated  $\text{NH}_3$  to fertilizer application rates and soil pH in addition to the gradients with respect to anthropogenic emissions (excluding fertilizer application), biomass burning emissions, and natural emissions. We validated our bi-di adjoint gradients with respect to fertilizer application rate and pH scale factors as well as to livestock emission scale factor for the Europe domain at  $0.3125^\circ \times 0.25^\circ$  using finite difference gradients (Figure S2 in Supporting Information S1), which were found to be in adequate agreement ( $R^2 \geq 0.99$ , slope  $\approx 1.00$ ).

### 3.3. Design of Inversion Experiments

We applied the updated GEOS-Chem model and its adjoint to conduct a 4D-Var inversion using CrIS  $\text{NH}_3$  profile measurements in 2016 following Cao et al. (2020). In our 4D-Var inversion using bi-di, we optimized scale factors of gridded  $\text{NH}_3$  emissions from non-fertilizer sources and that of gridded fertilizer application rate ( $\text{ng N m}^{-2} \text{ day}^{-1}$ ) but not soil pH, as the latter has already been directly constrained using soil pH measurements (Hengl et al., 2017). The regularization parameter  $\gamma$ , which is introduced to balance the observation and penalty terms in our 4D-Var inversion, was calculated via multiplying the  $\gamma$  in Cao et al. (2020) by the cost function ratio at the first iteration  $\left(\frac{J^1_{\text{this study}}}{J^1_{\text{Cao et al. 2020}}}\right)$ . We used the sum of smoothing and measurement error from the CrIS v1.5 retrieval product as the observation error covariance matrix ( $S_o$ ). Due to lack of quantitative knowledge of our prior emission uncertainties, the diagonal elements of our prior emission error covariance matrix ( $S_a$ ) are assumed to be 100% and the correlation length is assumed to be 100 km in latitudinal and longitudinal directions. For more details about the 4D-Var inversion, please refer to Cao et al. (2020).

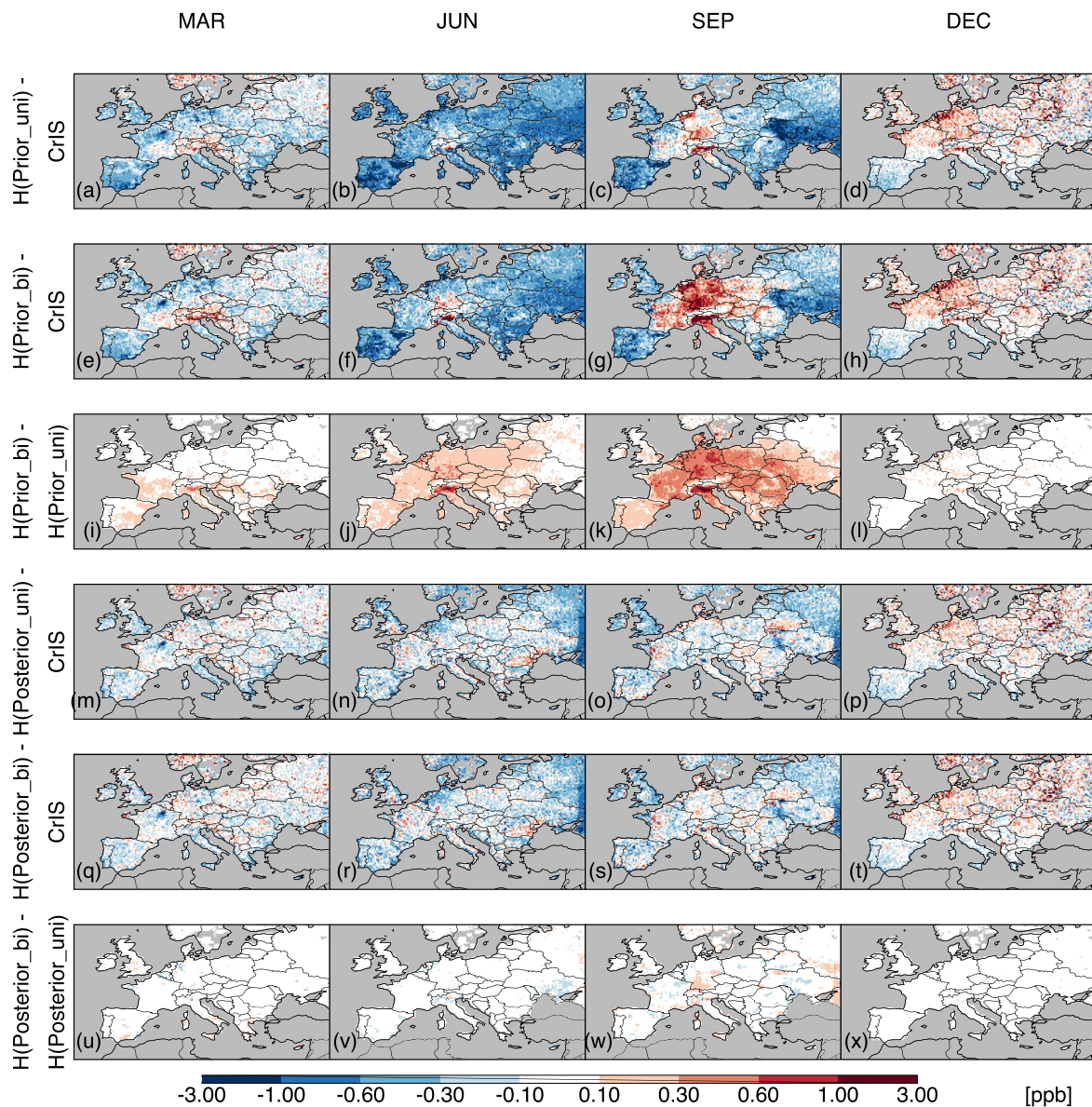
To explore the impacts of different dry deposition schemes on posterior  $\text{NH}_3$  emissions, we conducted two inversion experiments as shown in Table 1. IE\_uni utilized uni-di, while IE\_bi deployed bi-di. In the 4D-Var inversion using uni-di, we optimized scale factors of gridded  $\text{NH}_3$  emissions from different sources. For both inversions, the same input parameters (including prior emissions,  $\gamma$ ,  $S_a$ , and  $S_o$ ) were used.

## 4. Results

### 4.1. Prior and Posterior $\text{NH}_3$ Simulations Compared to CrIS Observations

We start the analysis of our results by comparing the prior  $\text{NH}_3$  simulations to CrIS observations. Figures 1e–1l show prior uni-di and bi-di simulations of monthly mean surface  $\text{NH}_3$  concentrations averaged from 13:00–14:00 LT during March, June, September, and December 2016, respectively. Both of our prior simulations using the uni-di scheme (hereafter H(Prior\_uni)) and the bi-di scheme (hereafter H(Prior\_bi)) generally capture CrIS-observed seasonality and spatial variability ( $R$  ranging from 0.85 to 0.90 during warm months), with higher  $\text{NH}_3$  concentrations found during warm months (especially in September) over agricultural areas. However, Figures 3a–3h show that our prior simulations failed to reproduce CrIS surface  $\text{NH}_3$  concentration magnitudes, with substantial overestimation over central Europe year round and underestimation over Northern and Southern Europe during warm months. H(Prior\_bi) is generally higher than H(Prior\_uni) over most of Europe throughout the year (Figures 3i–3l) due to the increased  $\text{NH}_3$  lifetime in the bi-di simulation, with better agreement (NME ranging from 0.14 to 0.26) with CrIS  $\text{NH}_3$  during warm months compared to H(Prior\_uni) (NME ranging from 0.16 to 0.32). Here we use changes in NME instead of normalized mean bias (NMB) to show the improvement in simulations because in our 4D-Var inversion we minimize the error-weighted squared difference between simulation and satellite measurements.

The discrepancies between simulated  $\text{NH}_3$  and CrIS observations as mentioned above were generally reduced after emission optimization. Figures 1m–1t show monthly mean surface  $\text{NH}_3$  simulations driven by posterior  $\text{NH}_3$  emissions derived from CrIS  $\text{NH}_3$  profiles from inversion experiments IE\_uni and IE\_bi. The posterior uni-di  $\text{NH}_3$  simulation (H(Posterior\_uni)) was simulated using the uni-di scheme and was driven by posterior  $\text{NH}_3$  emissions derived using the uni-di scheme. Correspondingly, our posterior bi-di  $\text{NH}_3$  simulation (H(Posterior\_bi)) was simulated using the bi-di scheme and was driven by posterior  $\text{NH}_3$  emissions derived using the bi-di scheme.

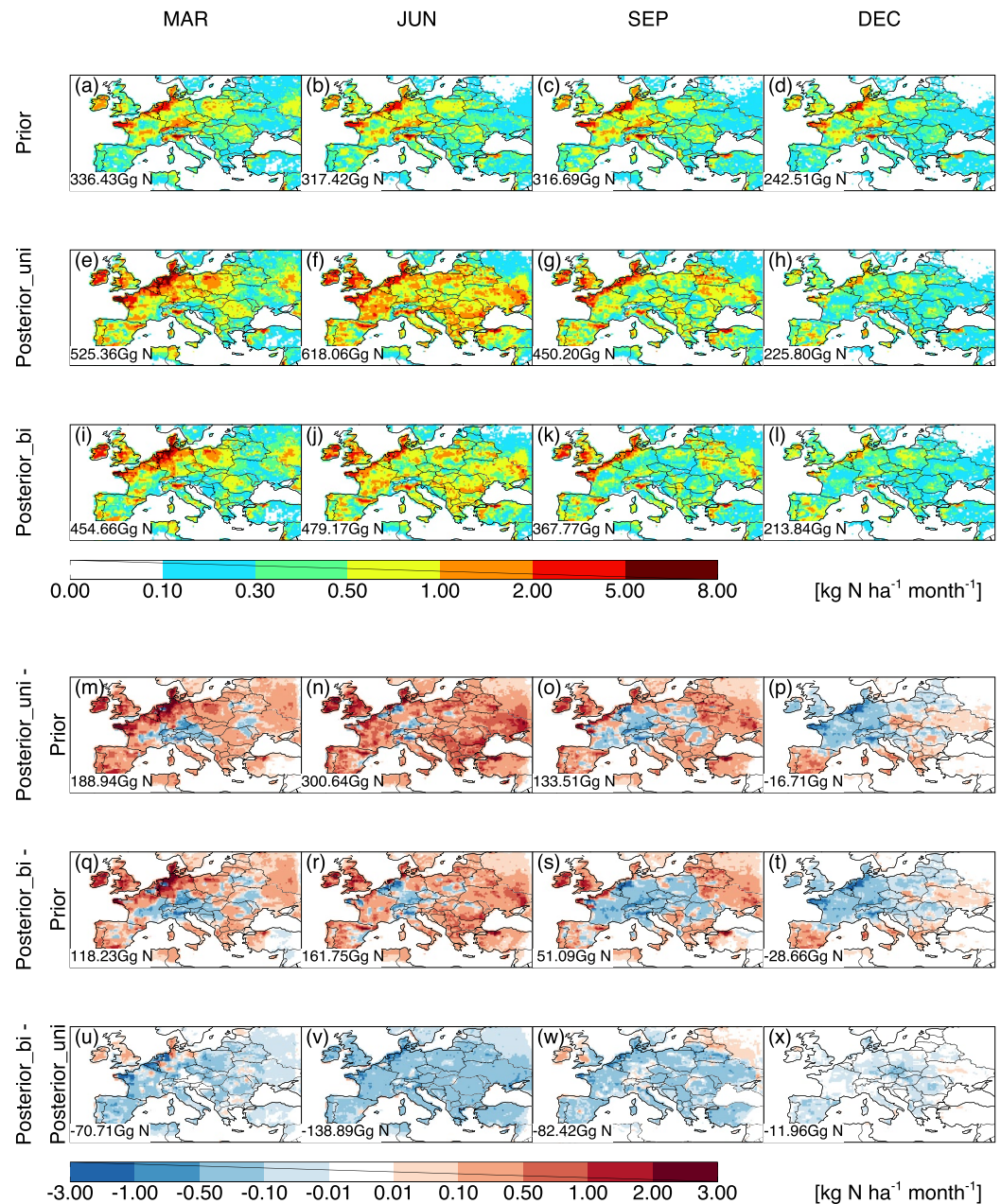


**Figure 3.** Difference between monthly mean CrIS surface  $\text{NH}_3$  concentrations and prior and posterior simulations with uni-di and bi-di, respectively, in March, June, September, and December in 2016.

Compared to  $H(\text{Prior\_uni})$  and  $H(\text{Prior\_bi})$ ,  $H(\text{Posterior\_uni})$  and  $H(\text{Posterior\_bi})$  better reproduced CrIS-observed  $\text{NH}_3$  with slightly increased  $R$  (0.88–0.96 during warm months) and significantly decreased NME (ranging from 0.11 to 0.15) throughout the year with the exception of December. Figures 3m–3t show improvement in posterior  $\text{NH}_3$  simulations across most of the European domain during most of the year, especially over areas with intense agricultural practices during warm months. Significant differences remained on the eastern edge of the domain for the posterior simulations (Figure 3), which is a consequence of the boundary condition from the coarse simulation ( $2^\circ \times 2.5^\circ$ ) being held constant.

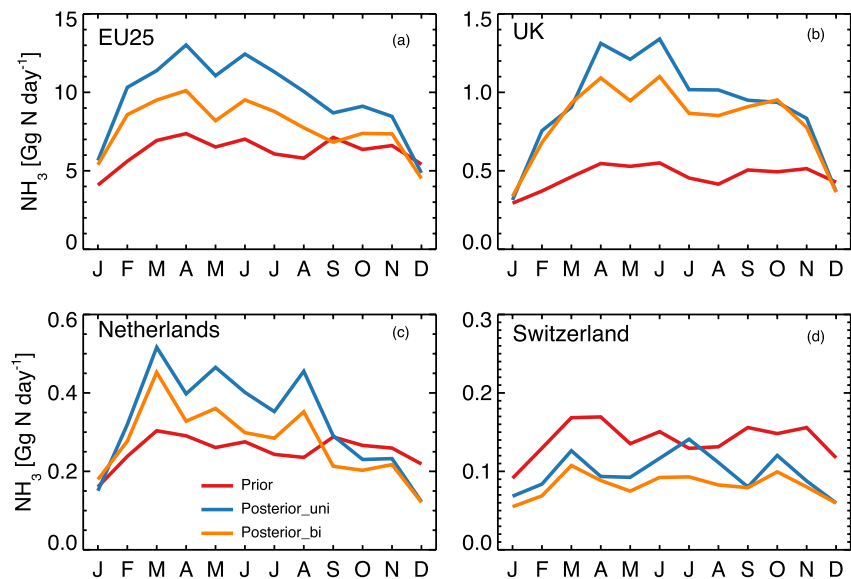
#### 4.2. Posterior $\text{NH}_3$ Emissions

In this section we evaluate the similarity and difference between the posterior and the prior anthropogenic  $\text{NH}_3$  emissions, and those between the posterior emissions derived using uni-di and bi-di schemes, in terms of spatial distribution, seasonal variation, and emission magnitude.



**Figure 4.** Spatial distribution of prior (first row), posterior (second and third row derived through uni-di and bi-di, respectively) monthly anthropogenic  $\text{NH}_3$  emissions for March, June, September, and December 2016 over Europe; difference (fourth and fifth row for uni-di and bi-di, respectively) between posterior and prior monthly anthropogenic  $\text{NH}_3$  emissions; difference (sixth row) between posterior monthly anthropogenic  $\text{NH}_3$  emissions derived through uni-di and bi-di schemes.

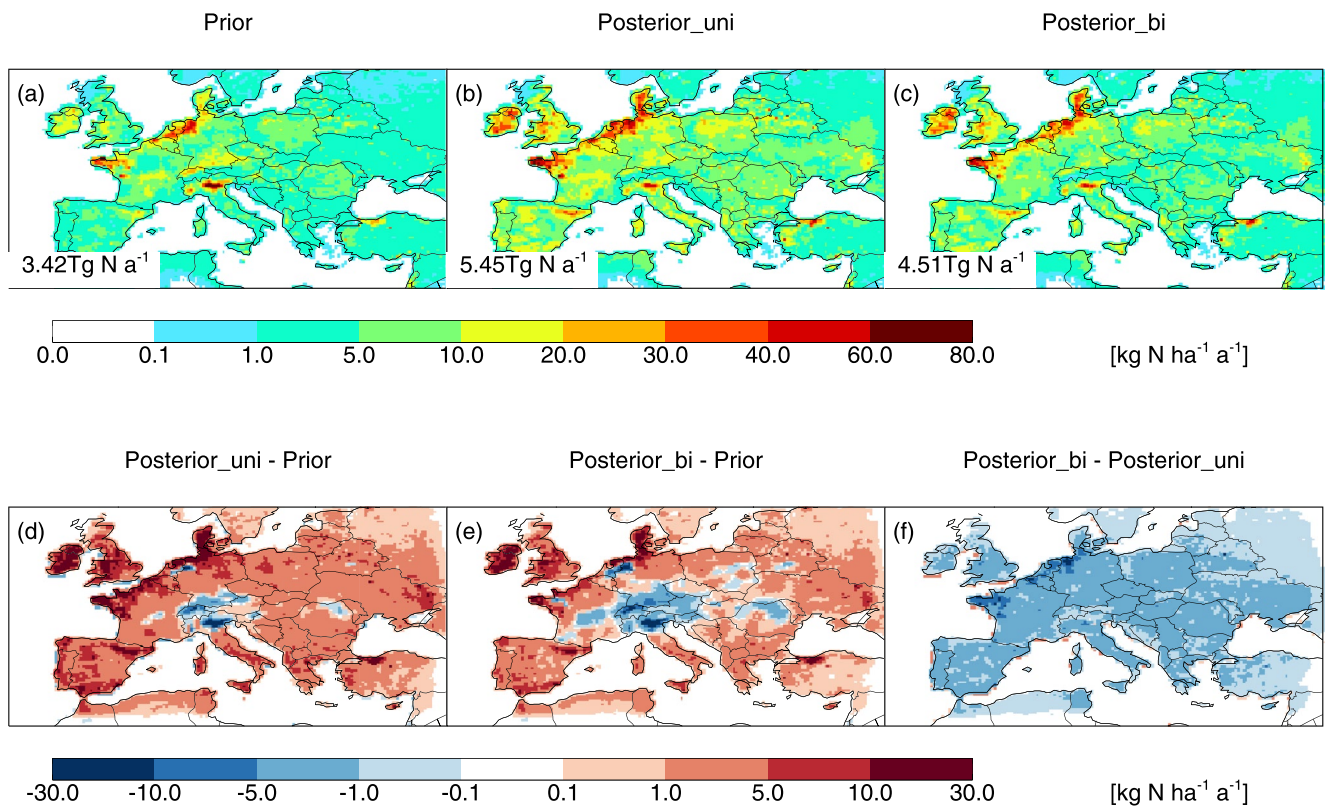
Figures 4a–4l compare the posterior monthly anthropogenic  $\text{NH}_3$  emissions from our inversion experiments (IE\_uni and IE\_bi) to the prior emissions during March, June, September, and December 2016. Posterior  $\text{NH}_3$  emissions derived using both uni-di (Posterior\_uni) and bi-di (Posterior\_bi) schemes have similar spatial distribution as the prior emissions throughout the year, with generally larger emissions ( $>2 \text{ kg N ha}^{-1} \text{ month}^{-1}$ ) over Germany, western France, North Italy, the Netherlands, Ireland, and the UK. However, Figures 4m–4t show that heterogeneous emission adjustments occurred across the European domain year round in both the Posterior\_uni and Posterior\_bi emissions, with decreases of  $-10\%$  to  $-50\%$  found over central Europe and increases of  $10\%$ – $400\%$  found over most of the rest of Europe during warm months. In December, much of Europe witnessed a decrease between  $-10\%$  and  $-50\%$ .



**Figure 5.** Regional/national monthly anthropogenic  $\text{NH}_3$  emission estimates from prior inventory (red), and those derived from CrIS  $\text{NH}_3$  with uni-directional scheme (blue) and with bi-directional scheme (orange), respectively. EU25 consists of Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain.

Also shown in Figure 4, is the difference between monthly Posterior\_bi and Posterior\_uni anthropogenic  $\text{NH}_3$  emissions over Europe for March, June, September, and December 2016. The Posterior\_bi emissions are generally smaller than the Posterior\_uni emissions by a factor of 1.1–2.0 over most of the domain throughout the year owing to increased lifetime of  $\text{NH}_3$  in the bi-di simulations, while some exceptions (higher by a factor of 1.1–1.3) occurred at small scales (e.g., Ireland and Denmark) during March and September likely because the global convergence was reached earlier than local convergence during the course of our 4D-Var inversion, which means that the sum of the error-weighted residuals across the European domain significantly reduced while some local residuals may have not been completely reduced yet.

Europe not only incurred spatially-varying adjustments in emissions but also temporally-varying adjustments. Figure 5 compares the posterior monthly anthropogenic  $\text{NH}_3$  emissions from inversion experiments IE\_uni and IE\_bi to the prior monthly estimates for EU25, UK, the Netherlands, and Switzerland at regional and national scales in 2016. EU25 consists of 25 European Union member countries (see caption of Figure 5 for details). Both the Posterior\_uni and Posterior\_bi emissions generally have similar seasonality as the prior monthly emissions, with larger emissions found in warm months and smaller emissions found in cold months, except that the posterior emissions identified an enhanced springtime peak, which is most likely related to substantial fertilizer use and manure application during the crop-growing season. The general seasonal patterns of our posterior emissions are more consistent with those of agricultural  $\text{NH}_3$  emissions over some European countries developed by the Netherlands Organisation for Applied Scientific Research (TNO) and described by Copernicus Atmosphere Monitoring Service TEMPORal profiles and Generation of European Emission Data for Episodes project (Denier van der Gon et al., 2011; Friedrich, 2000; Guevara et al., 2021; Marais et al., 2021) and those constrained by satellite  $\text{NH}_3$  observations (Marais et al., 2021). In the meantime, the seasonal variabilities of our posterior emissions are less consistent with that in the bottom-up  $\text{NH}_3$  emissions from Backes et al. (2016) which shows a second sharp peak in September with similar magnitude as that in the spring. However, their evaluation against surface  $\text{NH}_3$  concentrations at five sites suggests that Backes et al. (2016) tends to significantly overestimate  $\text{NH}_3$  emissions in the peaks, whereas our evaluation against domain-averaged measurements shows that our monthly posterior  $\text{NH}_3$  emissions generally enable the model to capture the seasonal cycle and magnitude of observed surface  $\text{NH}_3$  and  $\text{NH}_x$  wet deposition (Figures 10a and 10b and Figures 11a and 11b). In this study the posterior emissions are generally larger than the prior emissions by a factor of 1.1–2.4 over EU25, the UK, and the Netherlands during most of the year, especially in spring and summer, while they are consistently lower than

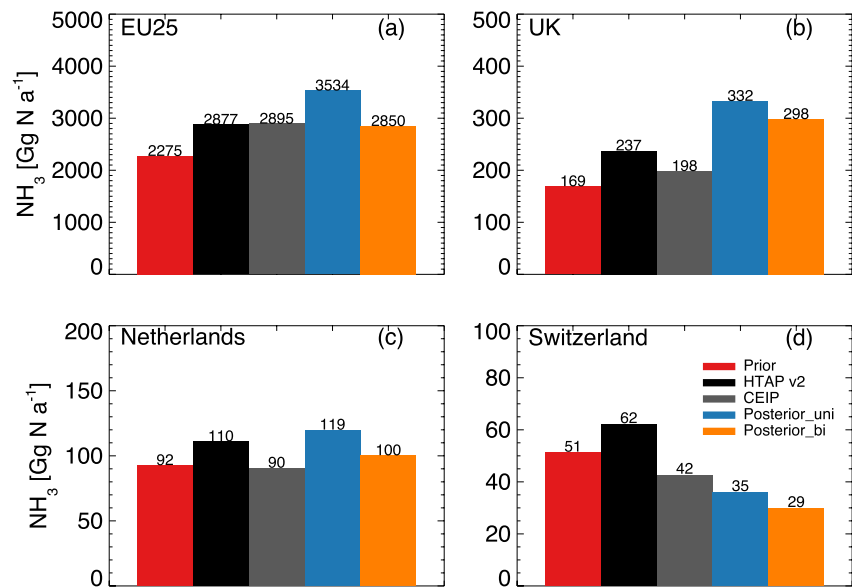


**Figure 6.** Spatial distribution of prior (a), posterior ((b) and (c) derived through uni-di and bi-di, respectively) annual anthropogenic  $\text{NH}_3$  emissions over Europe in 2016; difference ((d) and (e) for uni-di and bi-di, respectively) between posterior and prior annual anthropogenic  $\text{NH}_3$  emissions; difference (f) between posterior annual anthropogenic  $\text{NH}_3$  emissions derived through uni-di and bi-di schemes.

the prior emissions by 15%–49% over Switzerland year round except Posterior\_uni in July. The Posterior\_bi emissions for EU25, UK, the Netherlands, and Switzerland are generally smaller than the Posterior\_uni emissions by a factor of 1.01–1.52 throughout the year except those for the UK in March and October and those for the Netherlands in January, which was likely caused by the difference in global and local convergence in our emission optimization as mentioned above.

Finally, a comparison between the posterior and the prior anthropogenic emissions at an annual scale is displayed in Figure 6. The Posterior\_uni and Posterior\_bi anthropogenic  $\text{NH}_3$  emissions have similar spatial patterns as the prior emissions, but are generally lower by 10%–50% over central Europe (e.g., North Italy) and higher by a factor of 1.1–3.0 over most of the rest of Europe, especially over Ireland, UK, Denmark, North Germany, and western France. The Posterior\_bi annual emissions are generally smaller than the Posterior\_uni emissions across most of the domain by 10%–40% except some coastal grids due to bi-di emissions from water bodies near high-emission land cells. These high bi-di emissions over coastal grids are similar to those reported at the Chesapeake Bay (the largest estuary in the United States; Larsen et al., 2001) and are also consistent with the higher simulated  $\text{NH}_3$  concentrations with bi-di compared to those without bi-di in the coastal area of the North Sea (Wichink Kruit et al., 2012).

Overall, these emission adjustments led to smaller gaps between simulated  $\text{NH}_3$  and CrIS observations for both uni-di and bi-di models and thus better consistency (Figures 3u–3x) between early afternoon  $\text{NH}_3$  simulations using uni-di and bi-di. Figures 1e–1t and Figures 3a–3x show that  $H(\text{Posterior\_uni})$  and  $H(\text{Posterior\_bi})$  had similar agreement with CrIS  $\text{NH}_3$  observations after assimilation of CrIS  $\text{NH}_3$  despite  $H(\text{Prior\_uni})$  and  $H(\text{Prior\_bi})$  having significantly different mismatches with CrIS  $\text{NH}_3$  during warm months, especially during September (Figures 3c and 3g). Meanwhile, significant differences were found between the Posterior\_uni and Posterior\_bi monthly emissions (Figure 4) and between the simulated hourly surface  $\text{NH}_3$  concentrations driven by Posterior\_uni and Posterior\_bi emissions (Figure 2). This contrast demonstrates the extent to which data assimilation



**Figure 7.** Regional/national total annual anthropogenic  $\text{NH}_3$  emission estimates from prior inventory (red), HTAP v2 inventory (black, for 2010), CEIP inventory (gray, for 2016), and those derived from CrIS  $\text{NH}_3$  through uni-di scheme (blue) and bi-di scheme (orange), respectively.

can correct model simulated concentrations while also revealing how it may compensate for mechanistic biases in the model, such as the omission of  $\text{NH}_3$  bi-di exchange. The amount by which the posterior monthly emissions at regional and national scales (Figure 5) differ in this case provides a means of quantifying the uncertainty in previous top-down studies that did not include bi-di, which we find to be [+22%, +26%] for EU25, [+4%, +22%] for the UK, [+18%, +27%] for the Netherlands, [+1%, +34%] for Switzerland during warm months (from April to September) when the bi-di scheme is expected to averagely have larger and more frequent upward flux due to higher temperature and more fertilizer and manure application across most of the Europe. Also, these differences in posterior emissions between bi-di and uni-di can be interpreted as the differences between the effective lifetimes of  $\text{NH}_3$  in uni-di and bi-di schemes since the posterior  $\text{NH}_3$  columns concentrations from these two simulations are generally close to each other across most of the domain throughout the year (Figures 3u–3x).

### 4.3. Comparison With Previous Anthropogenic $\text{NH}_3$ Emission Estimates

Figure 7 compares the posterior annual total anthropogenic emission estimates from the inversion experiments IE\_uni and IE\_bi with previous emission estimates for EU25, UK, the Netherlands, and Switzerland. The Posterior\_uni estimates of annual total anthropogenic emissions from EU25, the UK, and the Netherlands are 3534  $\text{Gg N a}^{-1}$ , 332  $\text{Gg N a}^{-1}$ , and 119  $\text{Gg N a}^{-1}$ , respectively, generally larger than our prior estimates and the estimates from HTAP v2 and EMEP Centre on Emission Inventories and Projections (CEIP) by a factor of 1.1–2.0, while the Posterior\_uni estimate for Switzerland is significantly smaller than these bottom-up estimates by a factor of 1.2–1.8. In contrast, the Posterior\_uni estimates of EU25 and the Netherlands are 2850  $\text{Gg N a}^{-1}$  and 100  $\text{Gg N a}^{-1}$ , respectively, much closer (<2% difference for EU25, 10% difference for the Netherlands) to the HTAP v2 and CEIP estimates and a recent improved dynamic agricultural emission estimate (95  $\text{Gg N a}^{-1}$  for the Netherlands) from Ge et al. (2020). While the Posterior\_bi emission estimate for the UK is significantly larger than these bottom-up estimates by a factor of 1.3–1.8, the Posterior\_bi emission estimate for Switzerland is consistently smaller than these bottom-up estimates by a factor of 1.4–2.1. The differences between our posterior emissions estimates and these bottom-up emissions estimates are unlikely caused by the choice of year for this study (2016) because the annual average of CrIS  $\text{NH}_3$  columns over Europe in 2016 is similar to the multi-year average of CrIS  $\text{NH}_3$  columns over Europe from 2014 to 2018. The Posterior\_bi annual total anthropogenic emissions are smaller than the Posterior\_uni estimates over EU25, the UK, the Netherlands, and Switzerland by 10%–20%.

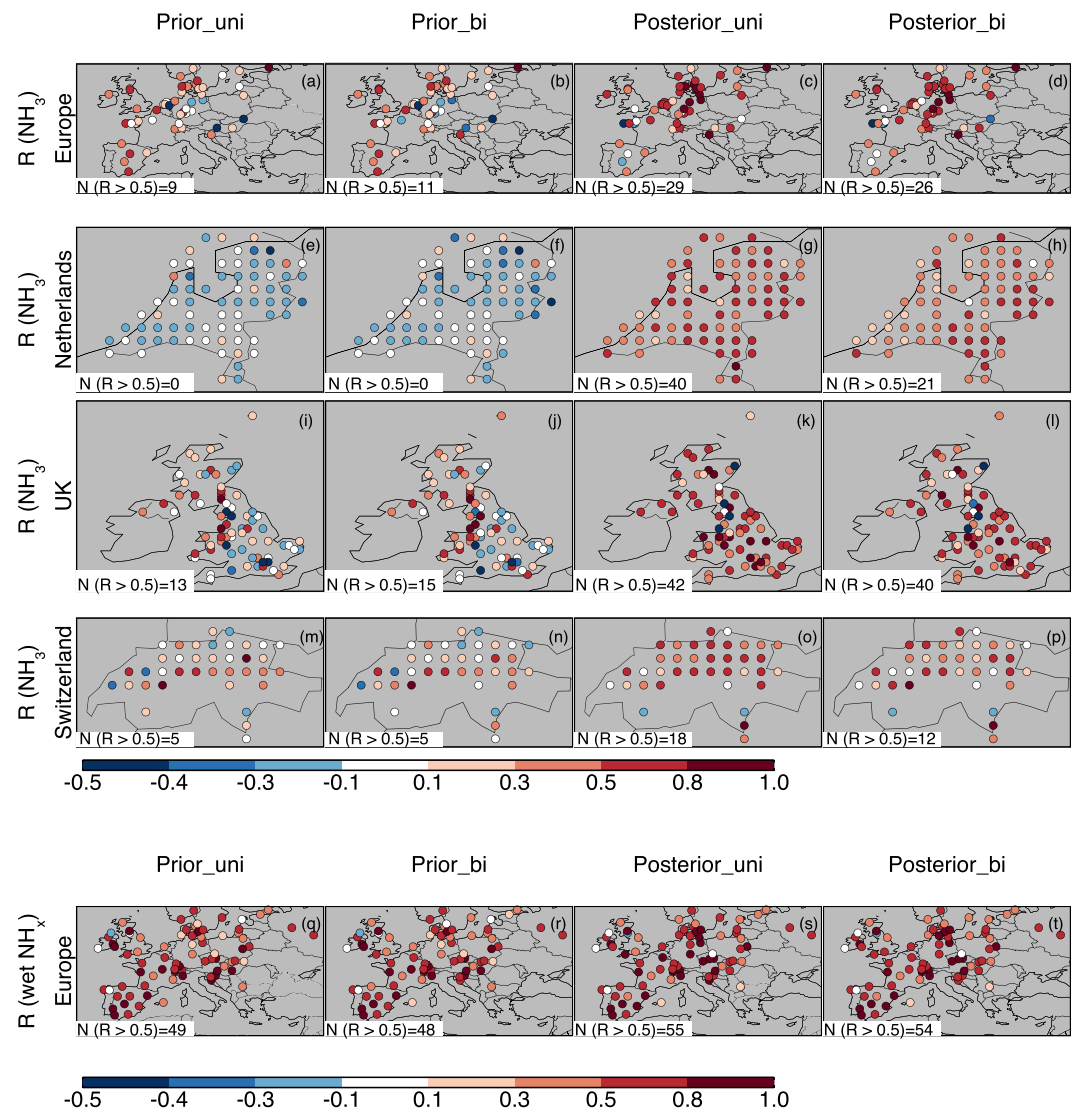
Our Posterior\_uni (332 Gg N a<sup>-1</sup>) and Posterior\_bi (298 Gg N a<sup>-1</sup>) estimates for the UK are at the lower end of the recent satellite-derived anthropogenic NH<sub>3</sub> emission estimate range between 315 (IASI) and 516 (CrIS v1.6) Gg N a<sup>-1</sup> by Marais et al. (2021). The large difference between our CrIS-derived estimates and the CrIS-based estimate from Marais et al. (2021) is most likely caused by the different methods to calculate the top-down emissions: we used a Bayesian inversion in which the prior information imposes a penalty term on the emission optimization, whereas Marais et al. (2021) directly rescale emissions using the column ratio between CrIS NH<sub>3</sub> and GC NH<sub>3</sub>. And the fact that the top-down annual emissions in Marais et al. (2021) was scaled from satellite-derived monthly emissions from March to September using uncertain seasonal scaling factors might also contribute to the difference with our CrIS-derived emission estimates.

#### 4.4. Cross-Validation Using Surface NH<sub>3</sub> and NH<sub>x</sub> Wet Deposition Measurements

We evaluate the posterior NH<sub>3</sub> emissions by comparing the prior and posterior simulations against measurements of surface NH<sub>3</sub> and NH<sub>x</sub> wet deposition in 2016 from sites across Europe including the EMEP monitoring network, the LML and MAN networks in the Netherlands, the NAMN network in the UK, the Switzerland national monitoring network, the Danish Background Air Quality Monitoring Program, and some short-term campaign sites and long-term monitoring sites in France, the UK, and Germany. We first filtered out sites with monthly mean values beyond the monthly domain average by three times the standard deviation in order to reduce impacts from outliers. Then we averaged multiple sites within one model grid before comparing between simulations and measurements. In the comparison against NH<sub>x</sub> wet deposition measurements, simulated NH<sub>x</sub> wet deposition consists of wet deposition of aerosol-phase NH<sub>4</sub><sup>+</sup> and gas-phase NH<sub>3</sub>. To remove the bias caused by the difference between measured and simulated precipitation, we scaled the measured NH<sub>x</sub> wet deposition by the ratio of modeled to measured precipitation,  $\left(\frac{P_{model}}{P_{measurement}}\right)^{0.6}$ , following Paulot et al. (2014). We compared simulated NH<sub>x</sub> wet deposition to measurements with  $\frac{P_{model}}{P_{measurement}}$  between 0.25 and 4.0 (Paulot et al., 2014) for EMEP sites.

In general, the posterior NH<sub>3</sub> emissions improve the model's ability to present observed seasonality in surface NH<sub>3</sub> concentrations and NH<sub>x</sub> wet deposition throughout the European domain. Figure 8 shows the correlation coefficient between monthly mean simulations and measurements of surface NH<sub>3</sub> and NH<sub>x</sub> wet deposition for each site. The first two columns of Figure 8 show that our prior uni-di simulation and prior bi-di simulation well reproduce the seasonal variability of NH<sub>x</sub> wet deposition measurements across Europe, but poorly capture the seasonality of surface NH<sub>3</sub> observations across Europe, especially in the Netherlands, where none of the 70+ sites have a correlation coefficient (*R*) exceeding 0.5. The third and fourth columns of Figure 8 show that the emission optimization in our inversion experiments enables both our uni-di model and bi-di model to better reproduce the observed monthly variability of surface NH<sub>3</sub> for most sites across the domain, especially those located in the Netherlands and the UK. The number of sites with *R* for surface NH<sub>3</sub> measurements exceeding 0.5 increased from about 10 to approximately 30 over Europe (Figures 8a–8d), from 0 to 21–40 over the Netherlands (Figures 8e–8h), from 13–15 to 40–42 over the UK (Figures 8i–8l), and from 5 to 12–18 over Switzerland (Figures 8m–8p). In comparison, the improvement in simulating the seasonality of NH<sub>x</sub> wet deposition (Figures 8q–8t) is moderate, with the number of sites with *R* exceeding 0.5 increased by less than 10 for Europe. This is likely due to the prior simulations capturing the seasonality of NH<sub>x</sub> wet deposition well.

Figure 9 shows NMB of the annual mean of the prior and posterior monthly simulations relative to the annual mean of the monthly measurements of surface NH<sub>3</sub> and NH<sub>x</sub> wet deposition, respectively, for each site across Europe. The first two columns of Figure 9 show that our prior uni-di and bi-di simulations generally have variable bias compared to the annual mean surface NH<sub>3</sub> measurements across most of Europe, except that a nation-wide negative bias is identified in the Netherlands. Our prior uni-di and bi-di NH<sub>x</sub> wet deposition is generally lower than NH<sub>x</sub> wet deposition measurements at most of the European sites. The third and fourth columns of Figure 9 show that slight to significant improvements are found in posterior uni-di and bi-di simulations of surface NH<sub>3</sub> and NH<sub>x</sub> wet deposition across most of the domain, especially in the Netherlands, although Switzerland witnessed a slightly worse performance in posterior surface NH<sub>3</sub> likely due to the difficulty in both the model and remote sensing data presented by complex topography. The number of sites with absolute NMB exceeding 0.5 is reduced by a factor of 1.1–3.2 in the posterior surface NH<sub>3</sub> simulations over the Netherlands and the UK and in posterior NH<sub>x</sub> wet deposition simulations across the whole Europe. The negative biases at most of the densely-distributed national monitoring sites across the Switzerland and the Netherlands in the posterior NH<sub>3</sub> simulations (Figures 9g,

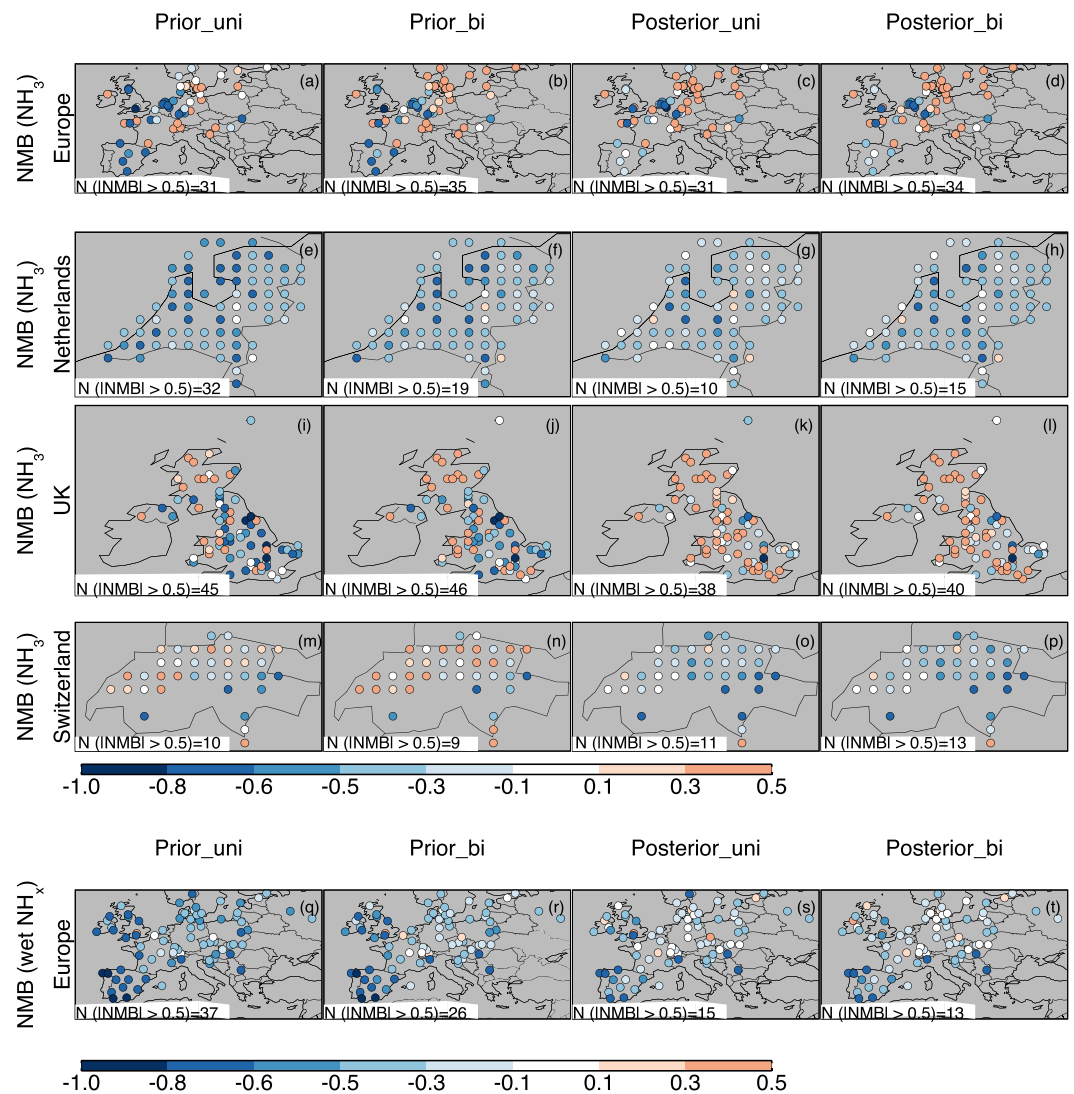


**Figure 8.**  $R$  between monthly mean surface  $\text{NH}_3$  observations from European sites in 2016 (over Europe (a–d), Netherlands (e–h), UK (i–l), and Switzerland (m–p)) and simulations driven by prior and posterior emissions derived through uni-di and bi-di schemes, respectively, with linear averaging kernel.  $R$  between monthly mean  $\text{NH}_x$  wet deposition measurements and simulations over Europe (q–t) in 2016.

9h, 9o and 9p) are also potentially partly owing to the fact that some of those national sites are located near animal housing or farm land (Sutton et al., 2015) and our model resolution of about  $25 \text{ km}^2$  is unable to capture the local sharp gradients of  $\text{NH}_3$  concentrations. On the other hand, the high bias across most of the UK sites and EMEP sites in the posterior  $\text{NH}_3$  simulations (Figures 9k, 9l, 9c and 9d) is likely caused by the fact that the CrIS v1.5 retrieval used in this study did not include non-detect pixels and is thus biased high over background areas and cloudy areas (good-weather bias), such as the UK. An updated CrIS v1.6 retrieval including the non-detects has been used to constrain the UK emissions in a recent study (Marais et al., 2021) and was found to reduce the high bias to some extent. While we do recommend using CrIS v1.6 for future studies, we were not able to use the v1.6 product for this study as it was not publicly available at the time our calculations were conducted. The inclusion of non-detects will unlikely significantly impact the uncertainty associated with the  $\text{NH}_3$  flux scheme in our top-down emissions as we use the same satellite data for both uni-di and bi-di inversions.

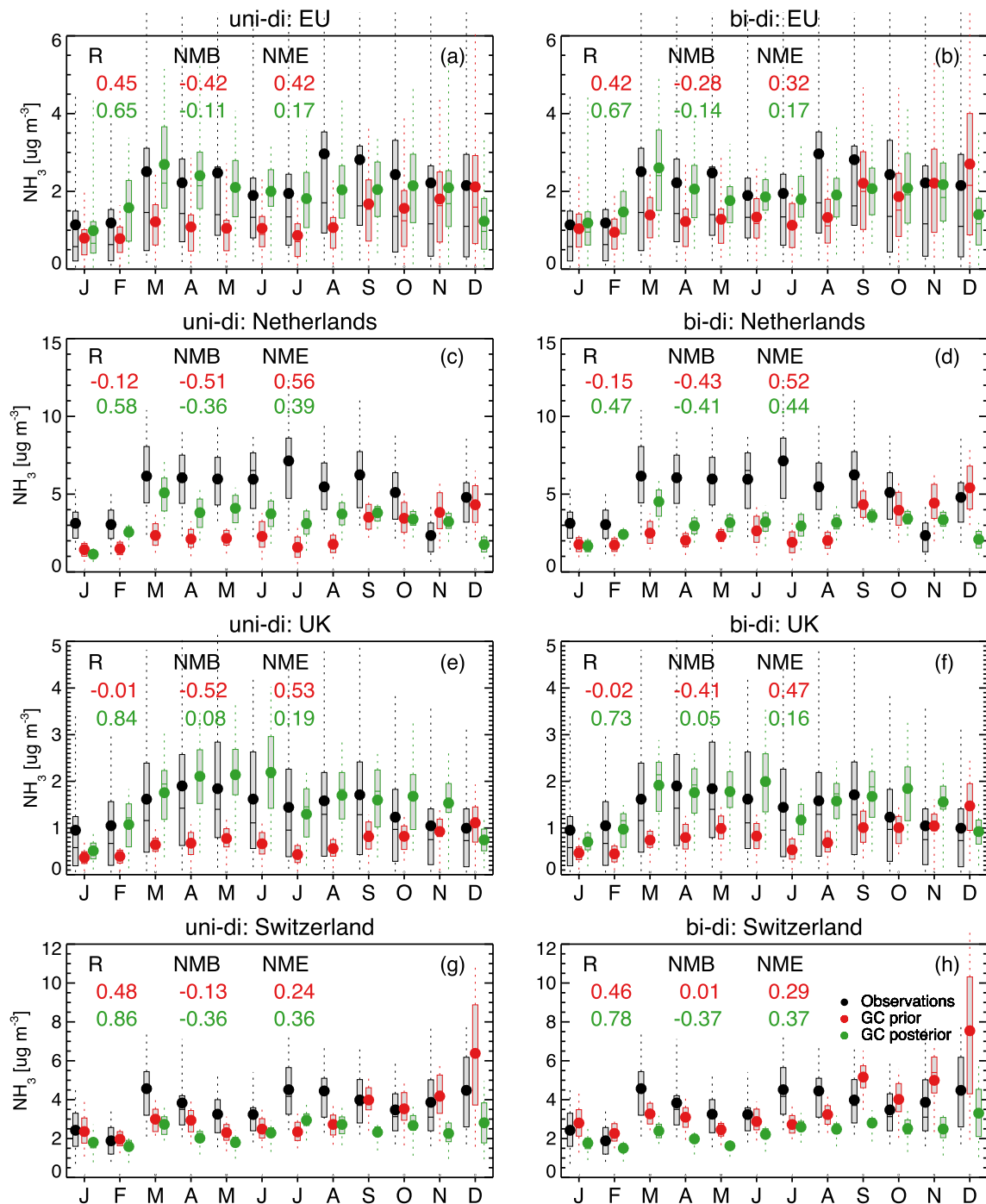
Further comparison between the prior and posterior simulations of surface  $\text{NH}_3$  and monthly mean measurements at regional and national scales is shown in Figure 10. Figures 10a and 10b show that monthly mean domain average of surface  $\text{NH}_3$  measurements over the EU are generally larger in warm months and lower in cold months,





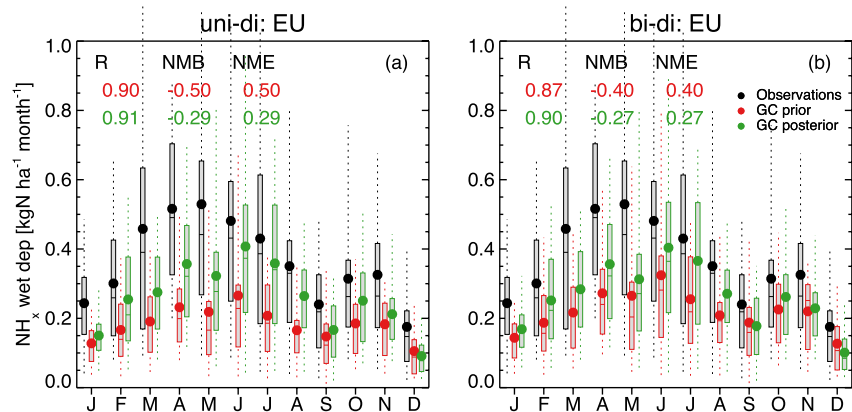
**Figure 9.** Annual NMB of monthly surface  $\text{NH}_3$  simulations driven by prior and posterior emissions relative to monthly mean surface  $\text{NH}_3$  observations from many sites in 2016 over Europe (a–d), Netherlands (e–h), UK (i–l), and Switzerland (m–p). Annual NMB of monthly  $\text{NH}_x$  wet deposition simulations relative to monthly mean  $\text{NH}_x$  wet deposition measurements over Europe (q–t) in 2016.

which is consistent with CrIS surface  $\text{NH}_3$  observations (Figures 1a–1d) and suggests larger  $\text{NH}_3$  emissions in warm months and smaller emissions in cold months in a general sense. Moreover, the unusual September/June contrast in surface  $\text{NH}_3$  observations (Figures 10a and 10b) is also consistent with that in CrIS surface  $\text{NH}_3$  observations (Figures 1b and 1c), which, however, cannot be explained by the September/June contrast in posterior emissions (Figure 5) but is most likely caused by the significantly larger  $\text{NH}_x$  wet deposition in June than in September (Figures 11a and 11b) in 2016. Both our prior uni-di and bi-di models show poor to fair skill in reproducing the monthly variation of surface  $\text{NH}_3$  measurements at regional and national scales, with  $R$  between 0.42 and 0.48 for EU and Switzerland and  $R$  below zero over the Netherlands and the UK. Prior uni-di and bi-di monthly simulations are significantly lower than monthly mean regional and national averages throughout most of the year except cold months, resulting in annual regional and national NMB values ranging from  $-0.13$  to  $-0.52$  in uni-di simulations and from  $0.01$  to  $-0.43$  in bi-di simulations. Generally, the emission optimization enabled better uni-di and bi-di simulations of surface  $\text{NH}_3$  with a substantially increased correlation coefficient between monthly simulations and monthly mean spatial averages of surface  $\text{NH}_3$  measurements and significantly reduced NME over most of the European countries except Switzerland, which experienced a slight increase in the annual NME.



**Figure 10.** Comparison between domain-averaged monthly mean surface  $\text{NH}_3$  observations (black) from European sites in 2016 and simulations driven by prior (red) and posterior (green) emissions derived through uni-di and bi-di schemes, respectively. Lower and upper box boundaries represent the 25th and 75th percentiles, respectively; the line in the box is the median and the filled circle is the monthly mean domain average. The range of the dashed line is that of the monthly mean measurements at those sites. NME and NMB were calculated using the monthly mean domain average.

Improvements in the posterior simulations are found in comparison with spatially averaged monthly mean  $\text{NH}_x$  wet deposition measurements over Europe as shown in Figure 11, similar to ambient  $\text{NH}_3$  results. Domain average monthly mean  $\text{NH}_x$  wet deposition measurements over Europe is higher in warm months and shows a larger peak in the spring and a smaller peak in late autumn, likely due to the combined impacts of the seasonality of agricultural emissions and precipitation. Both our prior uni-di and bi-di monthly simulations can capture the



**Figure 11.** Comparison between domain-averaged monthly mean  $\text{NH}_x$  wet deposition observations (black) from European (EMEP) sites in 2016 and simulations driven by prior (red) and posterior (green) emissions derived through uni-di and bi-di schemes, respectively. The definition of the box plot and the calculation of NMB and NME are the same as those in Figure 10.

observed seasonal variation of  $\text{NH}_x$  wet deposition measurements at regional and national scales with  $R$  ranging between 0.87 and 0.90 but are significantly lower than the measurements during most of the year (especially in warm months) with annual NMB ranging between  $-0.40$  and  $-0.50$ . Our posterior  $\text{NH}_3$  emissions improve the overall ability of the model to reproduce  $\text{NH}_x$  wet deposition measurements at regional and national scales with significantly reduced NMB ( $-0.27$  to  $-0.29$ ) and similar high  $R$  (0.90–0.91) as that of prior simulations, although our posterior simulations still show low bias compared to the  $\text{NH}_x$  wet deposition measurements, especially from March to May (Figure 11). The underestimation in posterior  $\text{NH}_x$  wet deposition simulations can be caused by (a) potential underestimation in  $\text{NH}_3$  emissions, (b) measurement error of  $\text{NH}_x$  wet deposition, and (c) that the precipitation correction method which was originally based on simulations and measurements of  $\text{NH}_4$  wet deposition and precipitation in the United States (Paulot et al., 2014) is not well tuned for the  $\text{NH}_x$  wet deposition comparison over Europe. The last two factors might also potentially contribute to the inconsistency between  $\text{NH}_x$  wet deposition comparison (Figure 11) and surface  $\text{NH}_3$  comparison (Figure 10). Meanwhile, the differences in site locations and in the number of valid sites (Figures 9d and 9t) and the  $\text{NH}_3$  measurement errors likely also contribute to this inconsistency.

Finally, another evaluation using hourly measurements of surface  $\text{NH}_3$  at a background site (Bavarian Forest National Park) in Germany (Wintjen et al., 2020) is displayed in Figure 2. As mentioned in Section 4.1, the prior bi-di model better reproduces the observed diurnal variability of surface  $\text{NH}_3$  throughout most of the year, especially during warm months, compared to the prior uni-di model. Both the prior uni-di and bi-di models overestimate the monthly mean hourly surface  $\text{NH}_3$  measurements year round by a factor of 1.02–10.99. While generally having a similar diurnal cycle as the prior simulations, the posterior bi-di simulation better reproduces the magnitude of monthly-averaged hourly surface  $\text{NH}_3$  measurements in most of the year, reducing the monthly NMB to between 0.28 and 4.36. In contrast, the Posterior\_uni emissions generally degrade the uni-di model's performance in reproducing the magnitude of surface  $\text{NH}_3$  observations at a monthly scale, increasing the monthly NMB by a factor of 1.3–29.5 during most of the year except September, November, and December. Although our optimizations reduced the monthly NMB in December by more than a factor of 2 for both inversions, large NMB values were still found in the posterior simulations, which is likely owing to (a) the poor temporal coverage of in-situ measurements during December and (b) the high bias in CrIS v1.5 over background (low-concentration) areas (especially in winter months) due to exclusion of non-detects as mentioned above.

## 5. Summary and Conclusions

This study presents the first 4D-Var inversion of  $\text{NH}_3$  sources using a bi-di  $\text{NH}_3$  flux scheme and CrIS  $\text{NH}_3$  measurements. The posterior annual anthropogenic  $\text{NH}_3$  emissions have a similar spatial distribution as the prior emissions, but are generally smaller over central Europe and larger over most of the rest of Europe compared to the prior emissions. The posterior monthly emissions generally have a more pronounced springtime peak than

the prior. The Posterior\_bi regional and national total anthropogenic NH<sub>3</sub> emissions are generally less than the Posterior\_uni emissions by 10%–20% for EU25, the UK, the Netherlands, and Switzerland at an annual scale, while up to –34% difference is found at a monthly scale. These differences can provide a rough estimate of the uncertainty associated with NH<sub>3</sub> flux estimates in previous inverse modeling studies using uni-di only.

The Posterior\_bi annual regional total anthropogenic NH<sub>3</sub> emissions are generally within the bottom-up estimate ranges over EU25 (2275–2895 Gg N a<sup>-1</sup>) and the Netherlands (90–110 Gg N a<sup>-1</sup>), while the Posterior\_uni estimates are greater than the upper range by 8% over the Netherlands and by 22% over the EU25. Our posterior estimates of national total anthropogenic NH<sub>3</sub> emissions are greater than the upper range of bottom-up estimates (169–237 Gg N a<sup>-1</sup>) by 26%–40% in the UK. On the other hand, our posterior estimates of national total anthropogenic NH<sub>3</sub> emissions are less than the lower end of bottom-up estimates (42–62 Gg N a<sup>-1</sup>) by 17%–31% in Switzerland, which likely has large uncertainty due to the difficulty in both the model and remote sensing data presented by the complex topography there.

Cross-validation by measurements of surface NH<sub>3</sub> and NH<sub>x</sub> wet deposition from extensive sites across Europe show that our posterior emissions from inversions enable our uni-di model and bi-di model to better reproduce monthly mean measurements of NH<sub>3</sub> and NH<sub>x</sub> wet deposition increasing the *R* between simulated and observed monthly mean regional and national averages from between –0.15 and 0.90 to between 0.47 and 0.91 and reducing the NME by a factor of 1.2–2.9 (except Switzerland).

While evaluation against monthly mean surface measurements of NH<sub>3</sub> and NH<sub>x</sub> wet deposition show similar improvements in both bi-di and uni-di simulations after data assimilation, another evaluation (Figure 2) against hourly measurements of surface NH<sub>3</sub> at a background site in Germany suggests bi-di better reproduces the observed diurnal variability of surface NH<sub>3</sub>. The coexistence of this difference in hourly simulations of surface NH<sub>3</sub> (Figure 2) using bi-di and uni-di and the difference between Posterior\_bi and Posterior\_uni monthly emissions (Figures 4 and 5) and the consistency in early afternoon NH<sub>3</sub> simulations using these two schemes (Figures 3u–3x) demonstrate the importance of accurately simulating diurnal cycle of NH<sub>3</sub> in the assimilation of the Sun-synchronous satellite observations, and calls for highly temporally resolved constraints from geostationary satellites.

While the bi-di scheme seems to better capture the diurnal variability at the background site in Germany, such improvements may not be ubiquitous. For comparison, different diurnal cycles were identified at urban and suburban sites at Beijing in Lan et al. (2021), where generally higher concentrations of ammonia during the daytime and low concentrations during the nighttime were observed at a suburban site during most of the year except autumn, while the opposite condition was found at an urban site during non-spring seasons. As discussed therein, the complexity and variability of NH<sub>3</sub> diurnal cycles is owing to multiple competing factors including sources, chemical sinks, vertical mixing, horizontal transport, temperature, relative humidity, and other meteorological impacts; improvements made owing to bi-di alone may not lead to improved simulated diurnal variability in all conditions.

It may be hard to disentangle this multitude of effects due to the sparsity of hourly in-situ measurements of NH<sub>3</sub>. In addition, some urban sources (e.g., vehicular emissions) lead to more variable diurnal cycles in NH<sub>3</sub> concentrations (Whitehead et al., 2007) and the underestimate of such vehicular sources in current bottom-up inventories (Sun et al., 2017) could introduce additional uncertainty in simulating NH<sub>3</sub> diurnal cycles in urban area. Overall, estimating and constraining NH<sub>3</sub> emissions would greatly benefit from additional widespread hourly measurements that could be provided by geostationary satellite observations (Clarisse et al., 2021).

Given the critical role of NH<sub>3</sub> in PM<sub>2.5</sub> formation and excessive deposition of Nr and the severe nitrogen crisis some European countries are facing (Stokstad, 2019) as well as the current and projected decrease of SO<sub>x</sub> and NO<sub>x</sub> emission trends and increasing NH<sub>3</sub> emission trend in Europe, measures to be taken to reduce NH<sub>3</sub> emissions in Europe such as the amended National Emission Ceiling Directive (NEC) (EC, 2016) targeting reducing NH<sub>3</sub> emissions between 2020 and 2030 are increasingly valuable. In the meantime, spatially and temporally resolved monitoring of NH<sub>3</sub> emissions at a large scale is needed for assessing the effectiveness of NH<sub>3</sub> abatement policies across Europe. Our 4D-Var inversion system implemented with bi-di and uni-di NH<sub>3</sub> flux schemes and coupled with CrIS NH<sub>3</sub> observations can provide comprehensive and up-to-date spatially resolved evaluation of NH<sub>3</sub> emissions. Moreover, up-to-date posterior NH<sub>3</sub> emissions can improve air quality forecasts and thus have the potential to help guide strategies for reducing PM<sub>2.5</sub> exposure. Operational near-real-time observations of

NH<sub>3</sub> using satellite instruments could also be used to explore regional and global NH<sub>3</sub> emissions trends (Glumb et al., 2018; Shephard & Cady-Pereira, 2015; Shephard et al., 2020), which may support broader adoption of environmental policy regarding Nr.

## Data Availability Statement

The surface NH<sub>3</sub> measurements and NH<sub>x</sub> wet deposition measurements used in this study are available at <https://ebas.wp2.nilu.no/data-access/> [Dataset], <https://uk-air.defra.gov.uk/> [Dataset], <https://zenodo.org/record/4513855#.YRt41edBpHE> [Dataset], <https://data.rivm.nl/data/luchtmeetnet/> [Dataset], <https://man.rivm.nl/> [Dataset], <https://www.bafu.admin.ch/bafu/en/home/topics/air/publications-studies/studies.html> [Dataset], and <https://ebas.wp2.nilu.no/data-access/> [Dataset]. The CrIS CPFV Version 1.5 ammonia data is publicly available at [https://hpfx.collab.science.gc.ca/~mas001/satellite\\_ext/cris/snpp/nh3/](https://hpfx.collab.science.gc.ca/~mas001/satellite_ext/cris/snpp/nh3/) [Dataset]. GEOS-Chem adjoint v35m source code is available online ([http://wiki.seas.harvard.edu/geos-chem/index.php/GEOS-Chem\\_Adjoint](http://wiki.seas.harvard.edu/geos-chem/index.php/GEOS-Chem_Adjoint)) [Software].

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