

## NASA Earth Venture Suborbital 4 Program

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## Executive Summary

Agriculture is a pillar of the U.S. economy, yet it is also a major source of gaseous and particulate emissions that affect air quality, climate, ecosystems, and stratospheric ozone. FarmFlux is a NASA Earth Venture Suborbital mission designed to address major deficiencies in our understanding of the agriculture - atmosphere interface. FarmFlux aligns with NASA Atmospheric Composition and Carbon Cycle and Ecosystems focus areas and is ideally timed to support interpretation of new satellite observations. Science objectives center on agricultural emissions, atmospheric processes, and earth system impacts. The FarmFlux science team will be selected through a ROSES call in 2025 and will work together to address four related objectives.

**Objective 1.** Quantify the magnitude and near-source fate of emissions from animal feeding operations and characterize major human and environmental drivers.

**Objective 2.** Quantify the bidirectional exchange of gases over major crop systems and connect fluxes to surface and environmental controls.

**Objective 3.** Explain physical and chemical properties of particulate matter in agricultural regions.

**Objective 4.** Connect agricultural emissions to air quality impacts and advance new satellite data applications over agricultural areas.

These objectives call for sustained and coincident *in situ* observations of multiple atmospheric parameters across U.S. agricultural hotspots. FarmFlux will deploy two aircraft and leverage advanced airborne experiments to build an unprecedented dataset.

For Objective 1, a small aircraft (B200) will sample animal feeding operations in TX, CO, ID, IA, and CA during two deployments in 2026/27. Priority 1 measurements include  $\text{NH}_3$ ,  $\text{N}_2\text{O}$ ,  $\text{CH}_4$ ,  $\text{C}_2\text{H}_6$ , and aerosol size and composition. Flights will use pseudo-Lagrangian plume sampling with stacked vertical legs in the boundary layer for derivation of emission rates. Analysis will connect facility-level emissions to environmental (temperature, relative humidity) and management factors where possible.

For Objectives 2 and 3, a large aircraft (NASA P-3) will survey cropland in three intensives over a growing season (March - July 2027). Each deployment will consist of 3 weeks in the Midwest (corn/soy, wheat, cotton, rice, pasture) and 1 week in CA (rice, tree nuts, alfalfa, other specialty crops). Priority 1 measurements include gas concentrations ( $\text{NH}_3$ ,  $\text{NO}_x$ ,  $\text{N}_2\text{O}$ ,  $\text{CH}_4$ ,  $\text{CO}_2$ , VOC, and  $\text{O}_3$ ) with sufficient performance for eddy covariance. Priority 2 measurements include aerosol size, composition, and precursors ( $\text{SO}_2$ ,  $\text{HNO}_3$ ). Flights will combine stacked racetracks for eddy covariance to directly quantify net surface exchange, pseudo-Lagrangian sampling of urban outflow, vertical profiles in the lower troposphere, and opportunistic sampling of events (e.g., frontal passage). Analysis will connect emissions to surface drivers (soil moisture, fertilizer inputs, etc.) and probe aerosol formation and evolution.

Advanced modeling tools are central to all Objectives. Chemical transport and particle dispersion models will support flight planning, provide a platform for evaluation and improvement of emission inventories, and facilitate impact assessments (Objective 4). Biogeochemical soil and land surface models would also help connect soil emissions to nutrient cycling and provide a counterpoint to empirical emission parameterizations.

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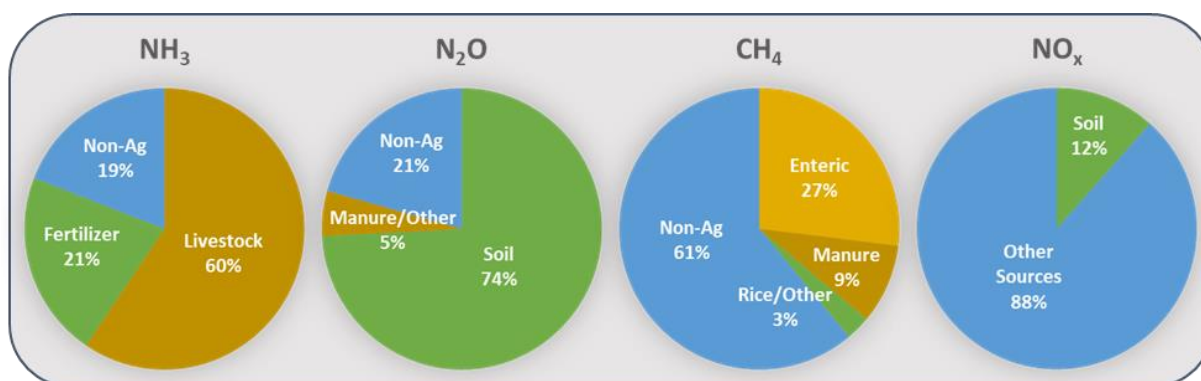
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*“The real wealth of a planet is in its landscape, how we take part in that basic source of civilization—agriculture.”*

*- Frank Herbert, Dune*

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**Figure 1. U.S. agriculture is a major source of reactive and greenhouse gases.** Total soil NO<sub>x</sub> is an upper limit for agricultural influence (neglecting farm machinery and combustion-related emissions). Data derived from EPA bottom-up inventories (US EPA, 2017, 2022a).

## Motivation

### Humans Shape Atmospheric Composition through Agriculture

Cropland and pasture comprise half of U.S. land cover (USDA ERS, 2024). Sustained intensification of U.S. agriculture has dramatically altered the soil, water, and air with sometimes profound consequences for human and ecosystem health (Erisman et al., 2008; S. L. Wang et al., 2015).

Crops and livestock are the largest sources of ammonia (NH<sub>3</sub>), nitrous oxide (N<sub>2</sub>O), and methane (CH<sub>4</sub>) in the U.S. (Fig. 1). Managed and natural soils contribute 12% to total nitrogen oxide (NO<sub>x</sub> = NO + NO<sub>2</sub>) emissions nationally but may be as much as 50% of total emissions in some regions (Almaraz et al., 2018; Oikawa et al., 2015). Agriculture also emits volatile organic compounds (VOCs) including small oxygenates, terpenes, amines, and pesticides (Kuhn et al., 2011; Loubet et al., 2022; Rappert & Müller, 2005; Socorro et al., 2016). Primary agricultural particulate matter (PM) emissions include soil dust, biological particles, and black carbon (Garcia et al., 2012; Lambert et al., 2020; Liu et al., 2021). Agricultural emissions occur throughout the U.S. and are most prominent in the Midwest and CA Central Valley (Fig. 2).

Agricultural emissions affect air quality, ecosystems, climate, and stratospheric ozone (O<sub>3</sub>). NH<sub>3</sub> and NO<sub>x</sub> are precursors to inorganic aerosol, which comprises roughly half of PM<sub>2.5</sub> (PM with diameter < 2.5 μm) (Mensah et al., 2012; Sorooshian et al., 2008; Young et al., 2016). PM<sub>2.5</sub> from agriculture causes ~15,000 U.S. deaths annually (Domingo et al., 2021; Lelieveld et al., 2015; Tschofen et al., 2019). NO<sub>x</sub> is often a limiting factor in tropospheric O<sub>3</sub> production, and reductions in combustion NO<sub>x</sub> have increased O<sub>3</sub> sensitivity to soil NO<sub>x</sub> (Geddes et al., 2022). O<sub>3</sub> damage reduces corn and soy yields by 5 – 10% in the U.S. Midwest, equivalent to economic losses of about \$9 billion per year (McGrath et al., 2015). Nitrogen deposition exacerbates terrestrial acidification, eutrophication, and loss of biodiversity (Clark et al., 2018). Agricultural CH<sub>4</sub> and N<sub>2</sub>O account for 9.8% of US CO<sub>2</sub>-equivalent greenhouse gas emissions (US EPA, 2022a). N<sub>2</sub>O is also currently the dominant stratospheric O<sub>3</sub>-depleting substance emitted by human activities (Ravishankara et al., 2009).

## Uncertainties in Emissions and Impacts

Uncertainties in the magnitude, variability, and fate of agricultural emissions blur connections between agricultural activities and impacts. Consider three key nitrogenous gases:

- **NH<sub>3</sub>**: Models under- or over-estimate NH<sub>3</sub> due to errors in emissions, deposition, or both, sometimes by factors of 3 or more (Kelly et al., 2018; Pleim et al., 2019). Models also misrepresent seasonal patterns (R. Wang et al., 2021) and are only beginning to represent bidirectional exchange (emission and deposition) in specialized applications (Pleim et al., 2019; L. Zhu et al., 2015). These issues complicate PM<sub>2.5</sub> control decisions and critical load exceedance attribution (Gu et al., 2021; Walker et al., 2019).
- **NO<sub>x</sub>**: Several recent studies argue that soil NO is 20 – 40% of California NO<sub>x</sub> emissions (Almaraz et al., 2018; Oikawa et al., 2015; Q. Zhu et al., 2023), versus < 4% in the state's official inventory and ~1% in a biogeochemical model (L. Guo et al., 2020). Enhanced soil NO emissions increase modeled surface O<sub>3</sub> by 23% (Sha et al., 2021) and are becoming relatively more important as fossil fuel NO<sub>x</sub> declines (Geddes et al., 2022). The functional representation of soil NO<sub>x</sub> emissions in models remains an open development (Huber et al., 2023; Y. Wang et al., 2021) and is based on limited observational constraints (Steinkamp & Lawrence, 2011).
- **N<sub>2</sub>O**: North American N<sub>2</sub>O emission estimates are uncertain by a factor of 3, with “top-down” emissions estimates 33% lower than “bottom-up” inventories on average (Xu et al., 2021). N<sub>2</sub>O emissions often occur in “hot moments,” where short, localized, strong emission events account for a substantial portion of total emissions (Anthony & Silver, 2021). Uncertainties impinge on climate mitigation strategies such as soil organic carbon storage (Guenet et al., 2021; Lawrence et al., 2021).

Across all these examples, models struggle with flux magnitude, sign, and variability. Empirical parameterizations often stem from limited ground-based observations that represent an incomplete subsample of a highly heterogeneous system, while our inherent understanding limits theory-based models. In some cases - such as the soil NO<sub>x</sub> discrepancies noted above - two models can produce very different conclusions despite both being validated against the same observations (Almaraz et al., 2018; L. Guo et al., 2020). Discrepancies between bottom-up and top-down budgets are partly related to vast differences in scale, with insufficient data to connect between local processes and regional atmospheric perturbations.

Model evaluation typically entails comparison against observed atmospheric state (e.g., gas concentrations), but models fundamentally represent processes like emissions, deposition, chemical transformation, and transport. The atmospheric concentration of any species represents the balance of multiple processes, and it is possible to incorrectly interpret a model-measurement difference when multiple processes are uncertain. Furthermore, available data in agricultural areas are often sub-optimal: ground networks are sparse and report few variables (Burns et al., 2023; Walker et al., 2019, 2020), airborne missions historically focus elsewhere (e.g., urban, forest, petrochemical), and satellite retrievals often lack sufficient spatiotemporal resolution and surface sensitivity. **Fundamentally, existing observations at the agriculture – atmosphere interface are insufficient to quantitatively test and improve model processes.**

## Imperative for New Observations

Despite myriad impacts on human health and the environment, U.S. agricultural emissions are historically under-regulated. For example, the U.S. Environmental Protection Agency (EPA) controls  $\text{NH}_3$  under several congressional acts, but agriculture – the dominant source – is mostly exempt (Lavaine et al., 2020; Ruhl, 2000). Atmospheric trends show declines in nearly all major pollutants in the twenty-first century except  $\text{NH}_3$  (US EPA, 2017).  $\text{CH}_4$  mitigation has received somewhat more attention (Hayek & Miller, 2021; US EPA, 2022b), but airborne research has historically focused on other  $\text{CH}_4$  emission sectors such as oil and natural gas. When regulations do target agriculture, “pollution swapping” can shift impacts from one area to another (Stevens & Quinton, 2009).  $\text{N}_2\text{O}$  is not controlled under the Montreal Protocol (Ravishankara et al., 2009).

Policy and practice are evolving in the agricultural and air quality sectors. Nascent initiatives advocate for increased scrutiny of agricultural emissions, such as greenhouse gas quantification via the Inflation Reduction Act (US EPA, 2022b) and the Justice40 initiative to aid disadvantaged communities including migrant farm workers (*Justice40 Initiative | Environmental Justice*, 2022). Precision agriculture is improving farm efficiency, with variable impacts on emissions (Balafoutis et al., 2017; Medel-Jiménez et al., 2022). With declining emissions from motor vehicles and energy production, air quality damages related to agriculture are now estimated to exceed those from utilities (Tschofen et al., 2019). **There is a need for data that quantifies current agricultural emissions and links atmospheric impacts to environmental and human controls.**

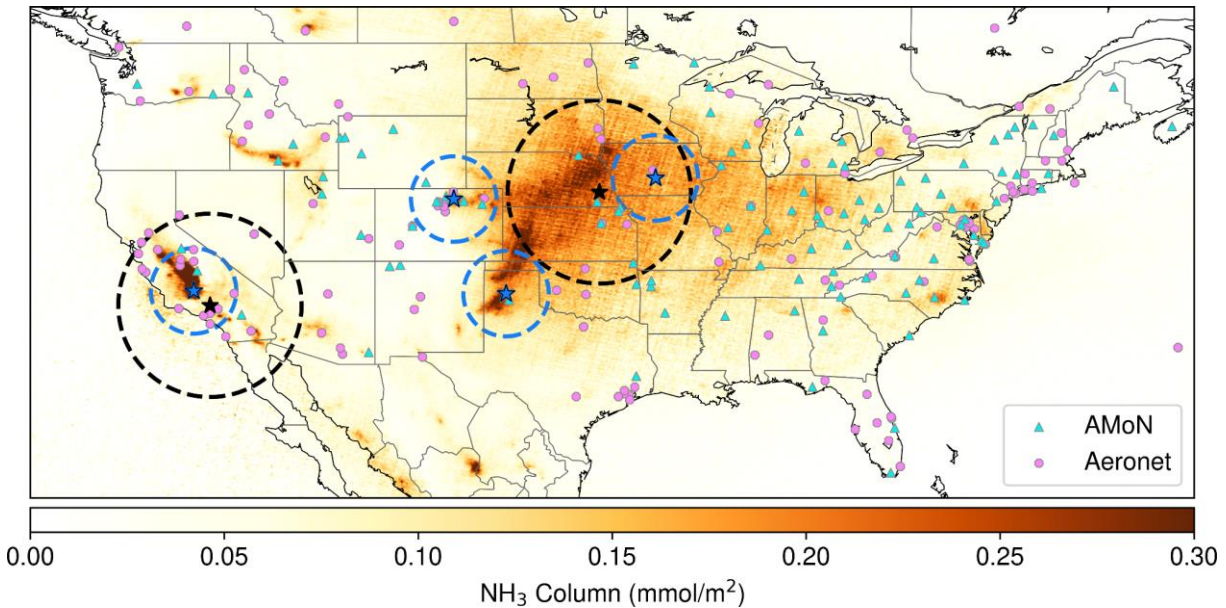
Current and upcoming satellite missions also need support for validation and applications. Satellite retrievals of  $\text{NH}_3$  are noisy even after over-sampling (Fig. 2), and resolving large emitters requires over-sampling with years of data (Van Damme et al., 2018).  $\text{NH}_3$  column retrievals and subsequent conversion to surface-level concentrations rely on model predictions of gas and aerosol vertical profiles, which are not well-constrained by observations (Shephard et al., 2020). The recently-launched geostationary TEMPO (Tropospheric Emissions: Monitoring of Pollution) instrument promises unparalleled spatial and temporal detail, but validation efforts to date have focused on urban areas. The TEMPO green paper proposes ambitious plans to investigate soil  $\text{NO}_x$  emissions,  $\text{O}_3$  and  $\text{NO}_2$  deposition, and plant physiology (*TEMPO Green Paper*, 2024). Without ground truth for near-surface process rates, these studies will face the same limitations and assumptions as their predecessors (H. Cao et al., 2020; Dang et al., 2022; Huber et al., 2020; Kharol et al., 2018; Van Damme et al., 2018). **To enable best use of satellite observations, we must expand “validation” to encompass constraints on relationships between atmospheric state and application-relevant processes, particularly in under-studied agricultural regions.**

Advances in instrumentation and methodology offer new opportunities to characterize atmospheric composition and net surface exchange. *In situ* instruments are now sufficiently compact, fast, and reliable that a single airborne payload can sample the full suite of trace gases emitted from agricultural activities (and nearby interfering sources). Such combined datasets are needed to untangle emission sources and their evolution within complex systems. In particular, recent work has demonstrated viable airborne observations of  $\text{NH}_3$ , a “sticky” gas that is notoriously difficult to measure at typical ambient levels (Pollack et al., 2019; Schobesberger et al., 2022). Airborne eddy covariance (AEC) has re-emerged in the last decade as a powerful tool for characterizing emissions and deposition, with wavelet transforms resolving spatial flux



variability over complex landscapes (Desjardins et al., 2018; Hannun et al., 2020; Hiller et al., 2014; Metzger et al., 2013; Misztal et al., 2014, 2016; Pfannerstill et al., 2023; Schobesberger et al., 2022; Wolfe et al., 2015, 2018; Q. Zhu et al., 2023). Many airborne instruments now meet the rigorous precision and frequency requirements for AEC.

Earth system simulations are also evolving rapidly. Finer resolution of atmospheric chemistry and land processes offers appealing opportunities to represent dynamic feedbacks between air quality and vegetation (Chang et al., 2020; Gao et al., 2023). Improving our understanding of the feedbacks between atmospheric chemistry and the biogeochemistry of managed ecosystems was identified as a priority research area in a recent National Academies report (*The Future of Atmospheric Chemistry Research*, 2016). Still, the representation of emissions (and deposition) of reactive trace gases and particulate matter from the terrestrial biosphere, and the response of these fluxes to environmental variables or anthropogenic land management, remains crude in most state-of-the-science Earth system and atmospheric chemistry models. While relevant model developments are ongoing, the dearth of *in-situ* atmospheric observations, especially across agricultural landscapes, prevents robust model evaluation. Current tactics to overcome this lack of data include comparisons with satellite-based retrievals of a limited number of relevant trace gases (H. Cao et al., 2020; Huber et al., 2020; Hudman et al., 2010; Van Damme et al., 2022; Vinken et al., 2014), but large uncertainties and systematic errors still exist in these products due to poorly constrained geophysical priors (Boersma et al., 2004, 2018; Van Damme et al., 2014).



**Figure 2. FarmFlux targets core U.S. agricultural emissions, including data-poor regions.** Background shows total  $\text{NH}_3$  columns from the Cross-track Infrared Sounder (CrIS) onboard the Suomi National Polar-orbiting Partnership (S-NPP) (Cady-Pereira, 2020) oversampled over April – August 2017 to  $0.05^\circ \times 0.05^\circ$  (K. Sun et al., 2018). Black/blue stars and circles show deployment locations and ranges (300 NM / 1 h and 140 NM / 0.5 h) for the large and small aircraft, respectively. Triangles and circles denote Ammonia Monitoring Network (AMoN) and Aerosol Robotic Network (AERONET) locations.



## FarmFlux Objectives

**FarmFlux is a NASA airborne mission to quantify gas and particle emissions from U.S. agriculture and characterize their impacts on air quality, climate, and ecosystems.** FarmFlux objectives target distinct aspects of the agriculture - atmosphere interface while embracing coupled system connections. Objectives 1 and 2 define threshold science requirements, while Objectives 3 and 4 define baseline requirements.

**Objective 1.** Quantify the magnitude and near-source fate of emissions from animal feeding operations and characterize major human and environmental controls.

**Objective 2.** Quantify the bidirectional exchange of gases over major crop systems and connect fluxes to surface and environmental controls.

**Objective 3.** Explain the physical and chemical properties of particulate matter in agricultural regions.

**Objective 4.** Connect agricultural emissions to air quality impacts and advance new satellite data applications over agricultural areas.

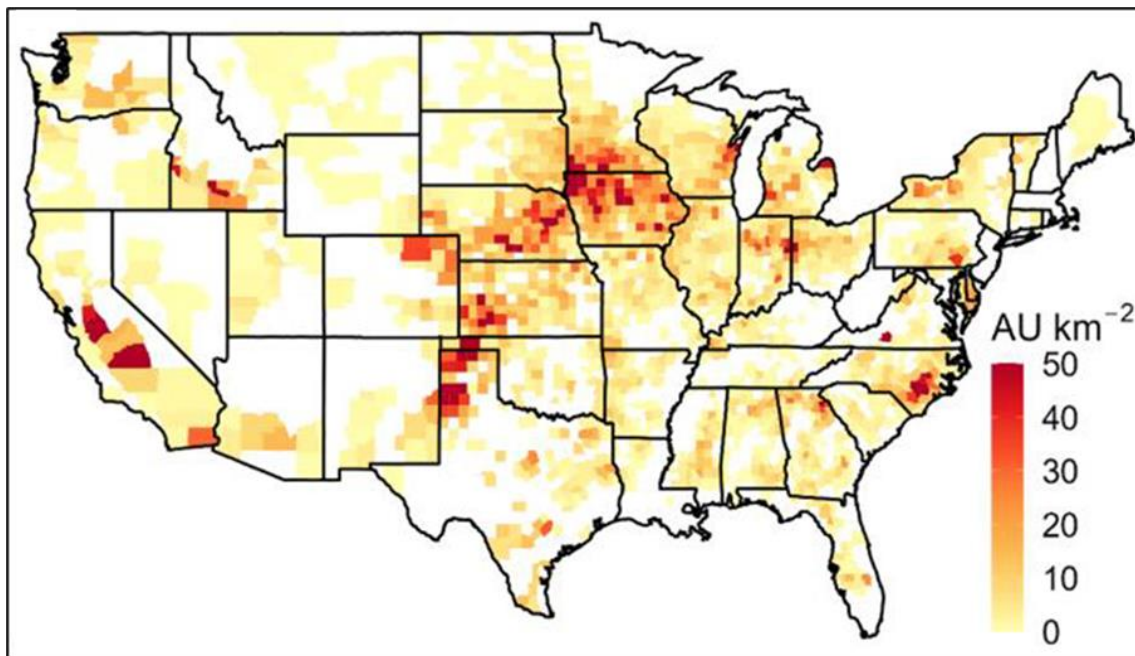
### Objective 1: Animal Feeding Emissions

Livestock are major sources of  $\text{NH}_3$ ,  $\text{N}_2\text{O}$ , and  $\text{CH}_4$  (Eilerman et al., 2016). Emissions of  $\text{NH}_3$  largely stem from manure and urine.  $\text{NH}_3$  is released during the breakdown of N-containing manure proteins, uric acid and urea. Thus  $\text{NH}_3$  emissions stem from the full chain of manure management activities, including from manure located in indoor facilities, open-air manure piles, lagoons, and applied to soil (Aguirre-Villegas et al., 2024; Waldrip et al., 2015). Manure, particularly from beef and dairy cattle, is also a major source of  $\text{N}_2\text{O}$ . It is assumed that  $\text{N}_2\text{O}$  is emitted during the nitrification (conversion of  $\text{NH}_3$  to nitrate) and denitrification (conversion of nitrate to gaseous N-containing species) of manure. Similar to cattle operations, slurry storage at hog operations is a source of  $\text{NH}_3$ ,  $\text{N}_2\text{O}$ ,  $\text{CH}_4$ , and  $\text{CO}_2$  (Kupper et al., 2020). The chemistry of manure management is complex because there is high spatiotemporal variability in manure piles, manure interacts with environmental conditions, and it is continuously subject to management practices (Brandani et al., 2023). 27% of total U.S.  $\text{CH}_4$  is produced from enteric fermentation by ruminants (Fig. 1), largely from cattle. On a per-animal basis, dairy cows emit more  $\text{CH}_4$  than beef cattle, and emissions can vary with species, diet, and genetic selection. Though existing data is more limited, livestock are also sources of  $\text{NO}_x$  (Kille et al., 2017) and VOCs (Yuan et al., 2017).

Concentrated animal feeding operations (CAFOs) are hotspots for livestock emissions. CAFOs exist throughout the U.S., with the highest concentrations of animals in CA, ID, the Midwest, and NC (Fig. 3). The pattern of animal unit (AU) density closely tracks satellite-observed  $\text{NH}_3$  (Fig. 2). Dominant animal types vary by location, with hog farms prevailing in IA and NC, chickens in the Southeast U.S., and cattle in most other regions. The AU density and number of CAFOs have increased in the last decade (Burns et al., 2023).

**FarmFlux will quantify the magnitude and near-source fate of emissions from animal feeding operations and connect emissions to major human and environmental controls.** Measurements will focus on  $\text{NH}_3$ ,  $\text{CH}_4$  and  $\text{N}_2\text{O}$ , and flights will be designed to quantify emission fluxes and emission ratios from individual facilities. FarmFlux will perform systematic sampling of select facilities in multiple locations (Fig. 2, small circles) and at different times to capture seasonal, meteorological, and facility-to-facility variability (Bunton et al., 2007; Golston et al., 2020). To the extent possible, FarmFlux will correlate emissions with facility characteristics (number of animals, area of manure ponds, management practices, etc.). The lifetime of  $\text{NH}_3$  is highly uncertain, especially immediately downwind of facilities where bidirectional surface exchange and gas-particle partitioning may change rapidly (Juncosa Calahorano et al., 2024b). For well-behaved plumes, FarmFlux will characterize the fate of  $\text{NH}_3$  through pseudo-Lagrangian experiments coupled with aerosol composition information and, possibly, eddy covariance. Measured emission rates and ratios will be compared to model parameterizations and bottom-up inventories, which will also contribute to Objective 3.

Beyond improved understanding of the magnitude, dependencies on temperature and relative humidity, and spatial distribution of these emissions, FarmFlux provides a unique opportunity to investigate model approximations of agricultural point sources. Instantaneous mixing of point sources into coarse grid boxes can lead to misrepresentation of non-linear chemistry (H. S. Kim et al., 2009; C. H. Song et al., 2003). This problem is amplified for agricultural point sources because emissions are typically aggregated to the county-scale (Schobesberger et al., 2022). With observations of multiple point source emissions and near-plume aging, FarmFlux will identify systematic errors arising from poor spatial representation and support case studies of “plume-in-grid” frameworks for CAFO emissions (Karamchandani et al., 2002; H. Sun et al., 2022).

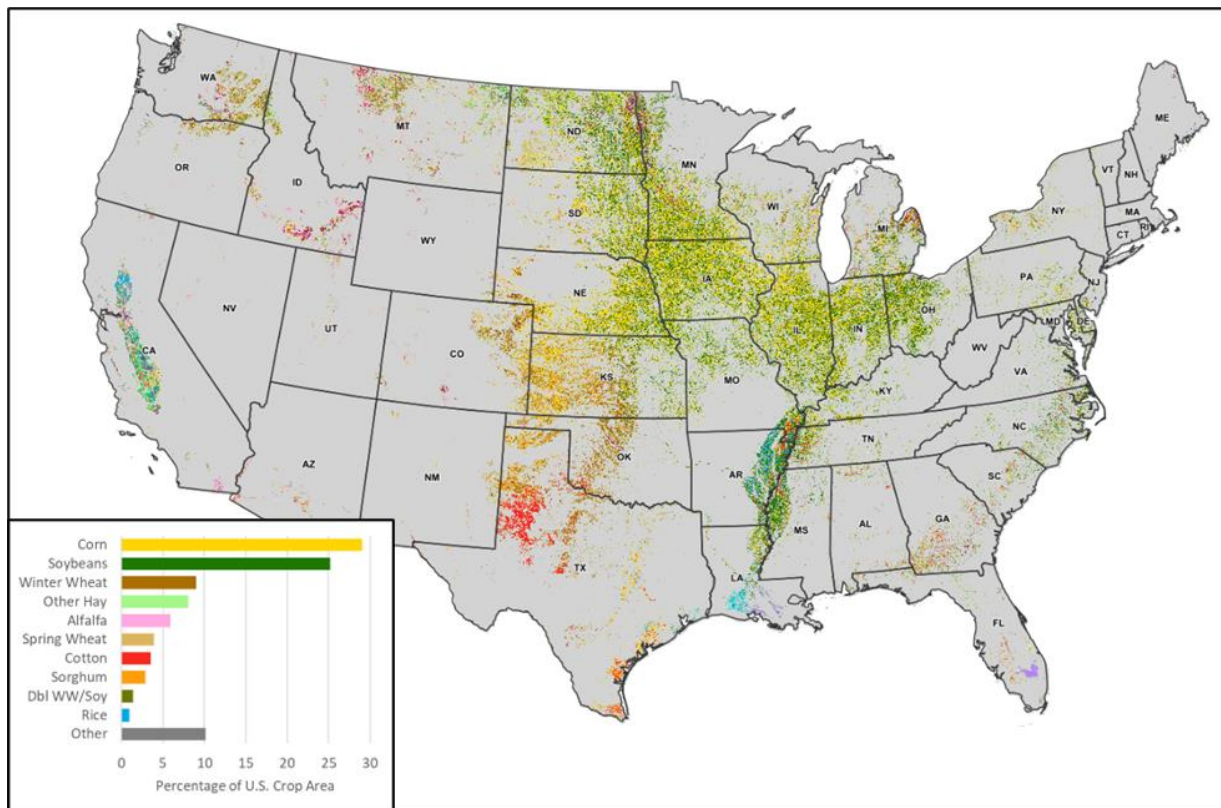


**Figure 3. 2017 county-level animal unit (AU) concentrations.** 1 AU = 1000 pounds live weight, or roughly 1 cattle, 2.5 swine, or 30 - 125 chickens. Adapted from Burns et al. (2023).

## Objective 2: Cropland Emissions and Deposition

U.S. cropland is diverse. Major crops include corn and soy in the Midwest and Mississippi River Valley, grains in the plains, cotton in northern TX, rice in the Mississippi River Valley and northern CA, and numerous specialty crops (grapes, citrus, avocados, nuts, alfalfa, etc.) in central and south CA (Fig. 4). The top 10 crop categories by area comprise 90% of total U.S. crop coverage (Fig. 4 inset). Patterns of fertilizer use broadly follow the crop distribution, with the highest per-area use for corn and rice and largest fertilizer applications in the spring (P. Cao et al., 2018). Roughly 25% of harvested U.S. cropland is irrigated, with the highest shares of irrigation in NE and CA (USDA, 2024a; USDA-ERS, 2023).

Soil microbes generate N-containing gases naturally as metabolic byproducts, but animal-based and synthetic fertilizers amplify these processes. Soil emissions account for a significant portion of U.S.  $\text{NH}_3$ ,  $\text{N}_2\text{O}$ , and  $\text{NO}$  emissions (Fig. 1). Soil  $\text{NH}_3$  emission rates depend on fertilizer application methods, meteorology, soil properties, and vegetation (Wyer et al., 2022).  $\text{N}_2\text{O}$  emissions are particularly sensitive to soil water content and temperature and are highly episodic and localized, with “hot spots” and “hot moments” comprising a large fraction of total emissions (Butterbach-Bahl et al., 2013). Freeze-thaw cycles may also be under-represented in bottom-up estimates (Wagner-Riddle et al., 2017). Such heterogeneity is difficult to capture with typical chamber and tower-based measurements. Soil  $\text{NO}$  emissions depend on similar factors, but the



**Figure 4. 2023 U.S. crop distribution.** Inset shows land cover of top 10 crops in 2023, with colors corresponding to those in the map (USDA, 2024b).

functional relationships of NO and N<sub>2</sub>O emissions differ (Hall et al., 2018). NO emissions can also spike following wetting of dried soils (Eberwein et al., 2020). Fertilized soils may also emit nitrous acid (HONO) (Y. Song et al., 2023; Xue et al., 2021), which photolyzes to OH and NO with a lifetime of ~10 minutes.

Croplands are also regionally important sources of CH<sub>4</sub> and other VOC. Anaerobic conditions - typically related to surface inundation - promote CH<sub>4</sub> production (Oertel et al., 2016). Rice paddies and drained peatlands account for 3% of U.S. CH<sub>4</sub> emissions (Fig. 1), and CH<sub>4</sub> emissions can occur in hot moments similar to N<sub>2</sub>O (Anthony & Silver, 2021). VOC emissions include ethene, small oxygenates (methanol, ethanol, acetaldehyde, acetone, acetic acid), terpenoids and benzenoids. Emission factors vary by crop and location (Bachy et al., 2016). Several studies have proposed using VOC as markers for plant phenotyping, growth stage, or stress (Karl et al., 2008; Niederbacher et al., 2015).

Trace gases also deposit to plant and soil surfaces. Dry deposition lifetimes range from hours to days and vary with surface and gas properties. Uptake through plant stomata primarily depends on water, light, and CO<sub>2</sub> (Franks et al., 2018) and is a conduit for both nutrients (NH<sub>3</sub>, CO<sub>2</sub>) and hazardous gases (O<sub>3</sub>). Deposition to other surfaces such as leaf cuticles, plant stems, soil, and water can also remove gases, with controlling factors including soil pH, leaf area, surface wetness/temperature, and gas volatility/reactivity (Zhang et al., 2003). Deposited N may be re-emitted as HONO or N<sub>2</sub>O (Yang et al., 2021; Ye et al., 2017). NH<sub>3</sub> dry deposition occurs in tandem with emission, and the net flux can change signs over a short period (Pleim et al., 2013).

**FarmFlux will quantify the bidirectional exchange of gases over major crop systems.** Target species include all those listed above: NH<sub>3</sub>, N<sub>2</sub>O, NO<sub>x</sub>, CH<sub>4</sub>, VOCs, O<sub>3</sub>, CO<sub>2</sub>, and H<sub>2</sub>O. Eddy covariance measurements of net fluxes provide a starting point for quantifying individual processes (emissions and deposition). Coincident multi-species flux and concentration measurements create unique data analysis opportunities via complementary information on multiple processes (Wolfe et al., 2015).

**FarmFlux will also connect fluxes to surface and environmental controls.** Major drivers include:

- Crop type and growth stage
- Fertilization amount, type, and application method (e.g., broadcast vs injection)
- Surface water content and application method (e.g., rainfed vs irrigated)
- Local meteorology (temperature, freeze/thaw status, precipitation history)

Surface fluxes respond to different combinations of these drivers and with different functional relationships. Also, some surface properties will covary (e.g., fertilizer application is highest for corn). Measurements will focus first on major crops (corn, soy, grasses, cotton, and rice) and second on the diverse cropland of central and south CA, where the air quality impact of agriculture remains uncertain (Almaraz et al., 2018; L. Guo et al., 2020). Investigation design will exploit management-related gradients in surface drivers and revisit the same location in different seasons and after events (e.g., major precipitation).

Advanced statistical techniques are available to link fluxes and surface properties. Methods such as environmental response functions (Metzger et al., 2013) combine fluxes, footprint analysis, and machine learning to extract empirical relationships that facilitate model evaluation and flux upscaling. Surface information can be the same as that used for flight planning, supplemented with model output and satellite products. Simpler analyses such as

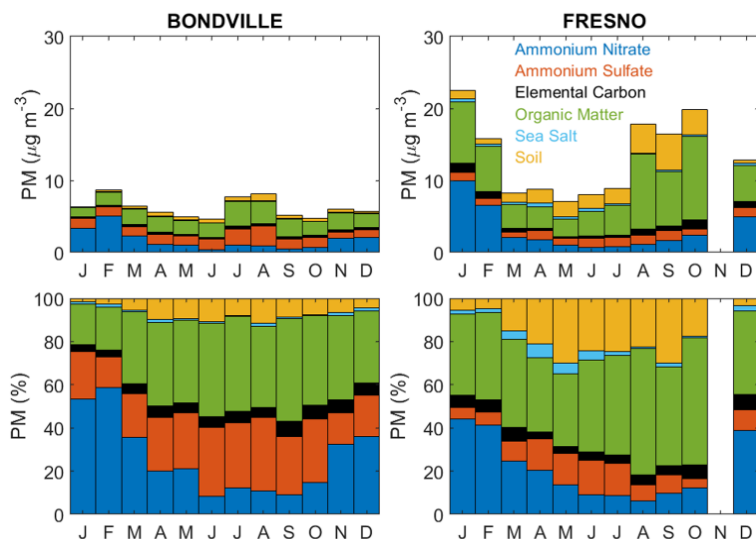
tracer correlations (McCabe et al., 2023) will help segregate crop emissions from other sources (e.g., animals or petrochemical extraction). FarmFlux will also employ concentration-based methods such as boundary layer budgets (Herrera et al., 2021) or inversions (Del Grosso et al., 2022) to quantify regional emissions where appropriate.

Application of AEC at this scale is unprecedented and will transform the atmospheric chemistry community's approach to model evaluation. FarmFlux will evaluate model predictions of soil and crop flux magnitudes, variability, and environmental responses. Multi-species flux observations will enable detailed comparisons of empirical and process-based emission estimates, bridging gaps between atmospheric and biogeochemical disciplines (Beaudor et al., 2023; Del Grosso et al., 2008; L. Guo et al., 2020; Rasool et al., 2016). Where appropriate, deposition fluxes and velocities will be evaluated within the canonical resistance framework (Wesely, 1989; Zhang et al., 2003). Fluxes of CO<sub>2</sub> and H<sub>2</sub>O will help constrain stomatal uptake, improving assessment of individual deposition pathways (Clifton et al., 2017; Wong et al., 2022). Vertical and horizontal gradients of gas concentrations will also aid model evaluation via more traditional approaches.

### Objective 3: Particulate Matter

Figure 5 compares near-surface PM speciation for locations in the Midwest and CA. Multiple patterns are evident: ambient temperature influences the relative contributions of ammonium nitrate and organics; sulfate is prominent in the Midwest; soil dust is more abundant in the dry CA Central Valley summer and fall. Variation among and within these classes influences gas-phase composition, air quality, and solar radiation. Meanwhile, the size distribution is fundamental to cloud formation, particle lifetime, direct radiative forcing, and human health effects (J. Li et al., 2022; Seinfeld et al., 2016; Shiraiwa et al., 2017).

Each PM component has unique sources, impacts, and relationships with other classes. VOC speciation, atmospheric oxidative capacity, and temperature influence secondary organic aerosol (SOA) formation. OA speciation informs understanding of aerosol sources (Young et al., 2016) and new particle formation (NPF) (Kiendler-scharr et al., 2009). Reactive N uptake may link



**Figure 5. PM varies across seasons and locations.** 2021 seasonal PM<sub>2.5</sub> mass (top) and percentage (bottom) for Bondville, IL (left) and Fresno, CA (right) from the IMPROVE (Interagency Monitoring of Protected Visual Environments) network (Malm et al., 1994). Fresno is an agriculturally impacted urban area.



organic and inorganic aerosol (Montoya-Aguilera et al., 2018) and serve as an important sink of  $\text{NO}_x$  and  $\text{NH}_3$  emitted by agricultural operations (Nenes et al., 2021). Acid availability can limit inorganic PM in  $\text{NH}_3$ -saturated conditions (Chen et al., 2020), but the relative importance of sulfate and nitrate varies by location. Inorganics are central to NPF, a source of cloud condensation nuclei (CCN) (Gordon et al., 2017; M. Wang et al., 2020). Dust is a major component of coarse PM lofted via wind and mechanical disturbance (e.g., tilling and harvesting). Dust transports nutrients, pesticides, and microorganisms and acts as a sink for nitrate (Brahney et al., 2015; Karydis et al., 2016; Maltz et al., 2022; Zaady et al., 2022). Agricultural expansion and drought have doubled coarse mode aerosol optical depth (AOD) in the Great Plains over the last two decades (Lambert et al., 2020). Black carbon is produced from farm machinery and field burning (Liu et al., 2021).

**FarmFlux will explain the physical and chemical properties of particulate matter in agricultural regions.** Understanding aerosol origins and evolution requires coordinated measurements of aerosol size distributions, and organic and inorganic composition, and gas-phase precursors. Agricultural emissions, local meteorology, and urban influence likely modulate seasonal and spatial variability in PM. Objective 2 entails sampling across relevant rural gradients. Objective 3 calls for additional sampling downwind of urban areas, behind frontal systems, and vertically into the lower free troposphere. Such experiments will capture changes related to aging, temperature, aerosol surface area, and other variables.

Analysis will explore processes controlling agricultural PM. Thermodynamic equilibrium (Y. Kim et al., 2022) and volatility basis set (Donahue et al., 2011) models are required to probe inorganic and organic aerosol chemistry, respectively. Thermodynamic models rarely have all constraints needed to assess gas-particle partitioning, which depends on precursor gas concentrations (i.e.,  $\text{NH}_3$ ,  $\text{HNO}_3$ ,  $\text{H}_2\text{SO}_4$ , VOC), T, RH, and other aerosol constituents (H. Guo et al., 2016). FarmFlux will not include observations of low-volatility organic precursors; however, positive matrix factorization and other tools may elucidate aerosol sources and organic/inorganic interactions. Evaluation of CTMs against observations of aerosol composition and size will support continued improvement of models. This work also ties to aspects of Objectives 1 and 2; for example, poor representation of  $\text{NH}_3$  emissions propagates to poor predictions of aerosol nitrate (Vira et al., 2022).

#### Objective 4: Air Quality and Satellite Applications

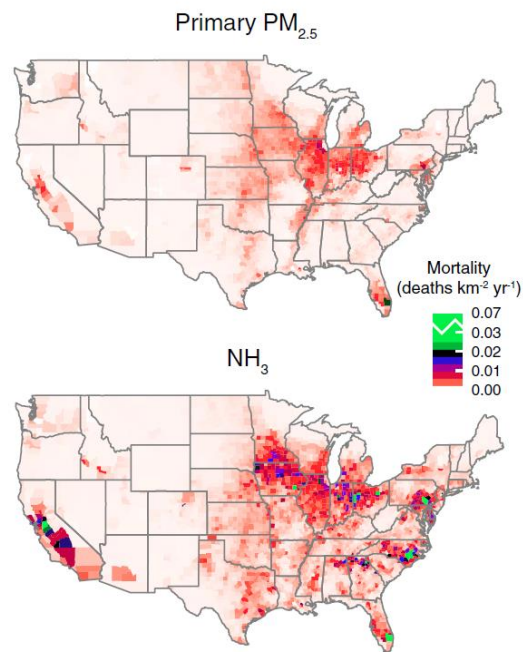
Recent studies attribute \$100 - \$200 billion in economic damages and 10 – 20 thousand premature deaths, annually, to U.S. agriculture through air pollution (Domingo et al., 2021; Goodkind et al., 2019; Luo et al., 2022; Tschofen et al., 2019). These same studies highlight a lack of experimental constraints on emissions as a major limitation. Model chemistry errors also affect such estimates, due partly to the wide range of spatial scales involved (from point source to downwind regional transport). The spatial disparity between satellite observed  $\text{NH}_3$  (Fig. 2) and deaths estimated from agricultural emissions (Fig. 6) highlights the varied roles of emissions, chemistry, and transport.



**FarmFlux will connect agricultural emissions to air quality impacts.** Refinements to model representations of agricultural emissions and chemistry resulting from Objectives 1 - 3 will enhance the accuracy and spatial resolution of health assessments beyond the current state-of-the-art. Investigations may leverage CTMs and integrated assessment models (Tessum et al., 2017) to evaluate ambient exposures from agriculturally-derived air pollution, particularly primary and secondary PM and ozone. Exposure metrics may also account for differences in particle toxicity (Park et al., 2018). Disadvantaged rural populations are of special interest (*Justice40 Initiative | Environmental Justice*, 2022), although this may be challenging for poorly-documented groups like migrant farm workers. Ambient exposure estimates in areas with dense aircraft sampling and ground network support may be specific enough to attribute impacts to distinct agricultural sectors (*e.g.*, different crop systems and animal operations). High-resolution information is especially important for large point sources, where nonlinear chemistry and coarse representation of emissions may mask true disparities in air pollutant exposure. For example,  $\text{NH}_3$  emissions are aggregated to the county level ( $\sim 1000 \text{ km}^2$  in Iowa) whereas regional air quality models run at a resolution of 1 - 10 km.

Satellites offer the potential to quantify emissions and deposition at global scales over long intervals. Satellite  $\text{NH}_3$  columns suggest that inventories underestimate  $\text{NH}_3$  point source emissions by orders of magnitude; however, order-of-magnitude uncertainties in  $\text{NH}_3$  lifetimes limit the accuracy of such estimates (Van Damme et al., 2018). Inversions indicate both high and low bias in model emissions depending on region and season, but these calculations likely also suffer from undiagnosed errors in gas-particle partitioning and deposition (H. Cao et al., 2020). Soil  $\text{NO}_x$  emissions may have a discernible influence on tropospheric  $\text{NO}_2$  columns (Huber et al., 2023), but other sources of “background”  $\text{NO}_2$  variability such as fires, aircraft emissions, and lightning (Dang et al., 2022) may wash out the agricultural signature. Deposition estimates rely on poorly-constrained model deposition velocities and cannot capture all important forms of N (Kharol et al., 2018).

**FarmFlux will advance new satellite data applications over agricultural areas.** Point source  $\text{NH}_3$  emission rates acquired via Objective 1 provide indirect constraints on satellite-based estimates (which require months or years of oversampling), which may identify biases in the latter. Regional fluxes of  $\text{NH}_3$ ,  $\text{NO}_x$ , and other gases can serve as ground truth for inversions. Furthermore, FarmFlux may discover relationships between key emissions that can be exploited to generate satellite-based proxies for gases not easily observed from space (*e.g.*,



**Figure 6. Agriculture costs lives.** Mortality attributed to primary  $\text{PM}_{2.5}$  (top) and secondary  $\text{PM}_{2.5}$  from  $\text{NH}_3$  (bottom). Maps show where the impact originates, not necessarily where it is experienced (Domingo et al., 2021).

linking surface N<sub>2</sub>O with NO<sub>2</sub> and NH<sub>3</sub>). Although retrieval validation is not within FarmFlux's scope, concentration measurements will help link column and surface concentrations, which is a critical aspect of satellite applications. FarmFlux observations will be most useful in combination with NH<sub>3</sub> products from infrared sounders (CrIS, IASI, AIRS) and NO<sub>2</sub>, HCHO, and O<sub>3</sub> products from UV-Vis spectrometers (TEMPO, TROPOMI). FarmFlux data may also complement ongoing NASA missions to study aerosol (EMIT, MAIA), carbon (OCO2/3, MethaneSAT), and land surface processes (ECOSTRESS).

2026										2027															
AUG				SEPT				OCT	MAR		APRIL				MAY				JUNE				JULY		
1 2 3 4				1 2 3 4				1	3 4		1 2 3 4				1 2 3 4				1 2 3 4				1 2		
CROPS										MidW	CA					MidW	CA					MidW	CA		
ANIMALS					Texas		Colorado				Iowa	CO + ID		CA											

**Figure 7. Notional FarmFlux deployment schedule.**

## Measurement Strategy

FarmFlux will leverage recent advances in observational capabilities to quantify agricultural emissions and their atmospheric evolution. Airborne in situ instrumentation can provide fast (~1 Hz or better) and precise measurements of key agricultural emissions. The recent Transport and Transformation of Ammonia (TRANS<sup>2</sup>Am) study applied a proven methodology for quantifying emissions from cattle and dairy operations, and FarmFlux will adopt the same techniques to address Objective 1. Quantifying wide-area fluxes per Objective 2 requires AEC at an unprecedented scale. Objective 3 requires coincident determination of multiple aerosol properties and gas-phase precursors.

Airborne data acquisition is necessary to meet FarmFlux objectives, which span a wide geographic area and multiple seasons. Two aircraft will conduct *in situ* sampling of gas and aerosol properties in the U.S. Midwest, Mississippi River valley, Mountain West, and California Central and Imperial Valleys. A small aircraft with a payload tailored towards reactive nitrogen and greenhouse gases will assess animal feeding operations. A large aircraft with a comprehensive payload will perform extensive crop surveys, profiling of the lower troposphere, and sampling of events (dust storms, post-frontal cleanout). Sampling will occur in several deployments over a single year (Figure 7).

### Small Aircraft

A King Air B200 will provide the maneuverability and low floor (500') needed to sample point source emissions from CAFOs for Objective 1. Typical flight duration is 4 h.

### Payload

Table 1 lists the ideal payload for CAFO sampling. Priority 1 measurements are required to complete threshold science (Objective 1), Priority 2 measurements are required for baseline

**Table 1. Small aircraft payload.** *P is Priority (1 = required for threshold science, 2 = required for baseline science, 3 = desired and/or useful).*

Measurement	P	Precision @ 1Hz	Accuracy	Rate	Objective
3-D winds, P, T	1	0.1 m/s, 0.1 K, 1 mb	5%	1 Hz	1,2
NH <sub>3</sub>	1	60 pptv	15%	1 Hz	1
N <sub>2</sub> O	1	30 ppt	10%	1 Hz	1
CH <sub>4</sub>	1	2 ppbv	10%	1 Hz	1
ethane	1	90 pptv	10%	1 Hz	1
Aerosol size distribution	1	NA	15%	1 Hz	1,3
Aerosol composition	1	NA	10%	1-2 min	1,3
HNO <sub>3</sub>	2	200 pptv	20%	1 min	3
NO, NO <sub>2</sub>	2	0.5 ppbv	10%	1 Hz	1
CO	3	30 ppbv	10%	1 Hz	1
Speciated VOC	3	1 – 100 pptv	15%	1 Hz	1

science (Objectives 3 and 4), and Priority 3 measurements add value beyond baseline objectives. A King Air B200 can accommodate all Priority 1 and some Priority 2/3 measurements, particularly if instruments can quantify multiple species simultaneously or share sampling infrastructure (e.g., pumps, chillers, inlets).

**Priority 1:** Fast state parameters (1 Hz temperature, pressure, and 3-D wind velocity) are required for mass flux calculations (C-MAPEX, 2012; Hacker et al., 2016; Staebler et al., 2009). Animal feeding operations are large sources of NH<sub>3</sub>, N<sub>2</sub>O, and CH<sub>4</sub> (Miller et al., 2015; Nowak et al., 2012). CH<sub>4</sub> is also a conserved tracer for plumes (Juncosa Calahorano et al., 2023, 2024a). Prior work has proposed and attempted to use the ratio of NH<sub>3</sub> to CH<sub>4</sub> to constrain NH<sub>3</sub> deposition downwind of feedlots (Juncosa Calahorano et al., 2024b). Texas, Colorado, and California all have large animal feeding operations interspersed with oil and gas operations. Ethane (C<sub>2</sub>H<sub>6</sub>) is needed to partition observed CH<sub>4</sub> between feedlot and oil and gas sources (McCabe et al., 2023). NH<sub>3</sub> reacts rapidly with sulfuric and nitric acids to form fine PM. Thus, a full understanding of NH<sub>3</sub> emissions necessitates sampling of NH<sub>x</sub> (NH<sub>3</sub> + NH<sub>4</sub><sup>+</sup>), and Priority 1 instrumentation includes aerosol composition and size.

**Priority 2/3:** Depending on community interest and instrument configurations, the B200 could support different combinations of Priority 2/3 instruments. High emissions of NH<sub>3</sub> likely contribute to significant fine particulate matter formation (Benedict et al., 2013; E. Li et al., 2024; Nowak et al., 2012; Schiferl et al., 2014). HNO<sub>3</sub> measurements would help constrain thermodynamic modeling of ammonium nitrate formation. NO<sub>x</sub> emissions have also been observed from CAFOs, likely from soil microbial activity (Kille et al., 2017). CO is a valuable tracer of combustion emissions, which are a potentially confounding source of Priority 1 species. CAFOs

also emit VOCs, and different sources within CAFOs (e.g., animal exhalation, animal waste, feed storage and handling) have different VOC emission profiles (Yuan et al., 2017), making VOC potentially valuable tracers for fine-scale source attribution.

### Locations and Timing

The small aircraft will target five regions with high CAFO density. Figure 2 shows 140 NM ranges for the 4 base locations, representing 30 minutes of one-way travel. The small plane schedule (Fig. 7) considers the frequency of winds > 4 m/s needed for horizontal flux calculations. It is also designed to reduce the likelihood of encountering the most extreme heat in Texas, avoid frequent precipitation, and create opportunities for coordination with the large aircraft.

1. **Bakersfield, CA.** Flights from Bakersfield will target cattle/dairy operations in the Central Valley. Recent measurements in this region suggest that dairies account for > 50% of CH<sub>4</sub> emissions in the southern San Joaquin Valley, but meteorological influence is not well represented in current inventories (Schulze et al., 2023).
2. **Amarillo, TX.** Flights from Amarillo will sample large cattle feeding operations in TX, OK and NM, which collectively account for >25% of U.S. beef production.
3. **Greeley, CO.** Spring and fall sampling of dairies and cattle feedlots in northeastern CO under cool and wet conditions will provide contrast with prior warm season studies (Eilerman et al., 2016; Y. Li et al., 2017). Emissions from large animal husbandry facilities in this region were sampled during summer 2021/22 under hot and dry conditions (Juncosa Calahorano et al., 2023, 2024a, 2024b; E. Li et al., 2024; McCabe et al., 2023). Aerosol partitioning is likely to be substantially different during other seasons (E. Li et al., 2024). A small number of these facilities were also sampled during November 2019 (Pollack et al., 2022), but no aerosol phase data were collected at that time.
4. **Twin Falls, ID.** Colorado operations will also include one or more “suitcase” flights to Idaho to sample dairies in the Magic Valley in coordination with ground-based USDA efforts (Leytem et al., 2009, 2018).
5. **Des Moines, IA.** Deployment near Des Moines will focus on hog operations. Approximately one third of hogs in the U.S. are raised in IA.



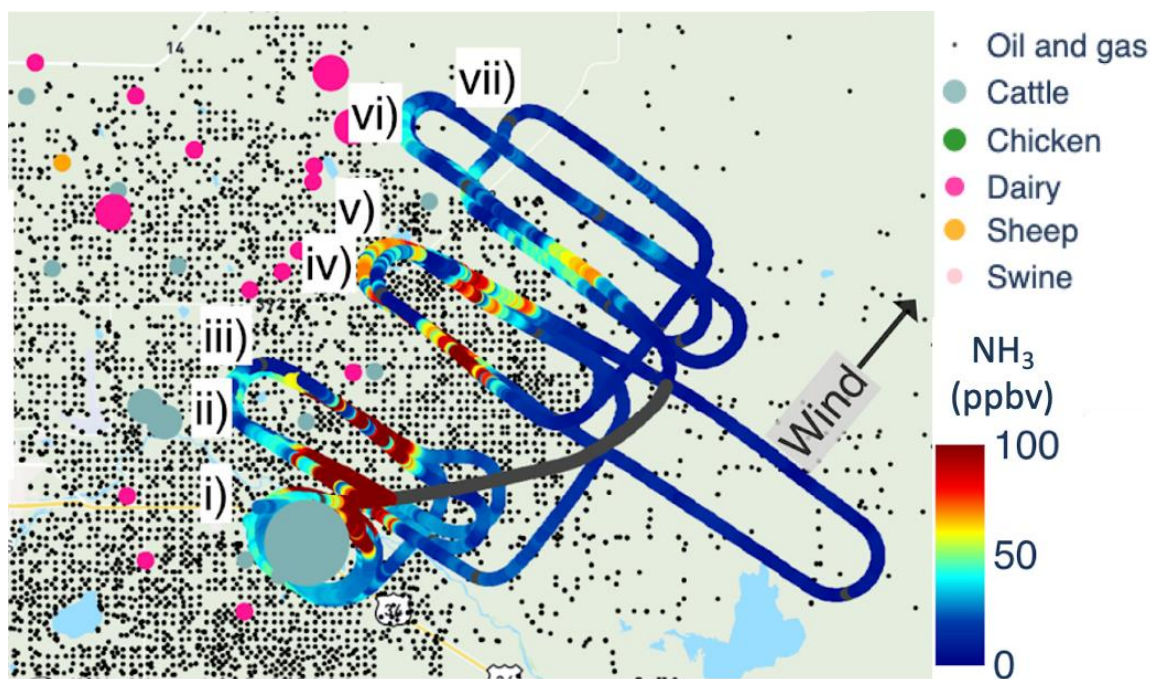
Figure 8. Example CAFO operations for cattle (left) and swine (right).



### Flight Planning

FarmFlux will identify and prioritize facilities using a combination of oversampled CrIS  $\text{NH}_3$  observations and satellite imagery (Fig. 8), possibly assisted by AI (Handan-Nader & Ho, 2019). Isolated facilities that can be sampled repeatedly under a variety of wind directions and environmental conditions without interference from other plumes are preferable. FarmFlux will also prioritize facilities with active coincident ground sampling and locations where information is available on management practices and animal numbers. Flights will focus on CAFOs, with selective sampling of fertilizer production facilities or other sources identified in satellite data and emission inventories.

Plume sampling will utilize methods developed during TRANS<sup>2</sup>Am (Fig. 9). First, the aircraft approaches a target facility from the top of the boundary layer. Once the pilot visually identifies the target facility, the aircraft circles at 1000' AGL to identify obstacles and determine plume outflow direction. If safe, the aircraft performs an additional circle at 500' AGL. During these maneuvers, the aircraft remains 3000' from the edge of each facility to limit animal noise exposure. The aircraft then completes a set of stacked boxes crossing the plume downwind at different vertical levels. Altitudes are chosen to optimize sampling throughout the boundary layer, with a nominal vertical separation of 500'. The closest and farthest legs of the boxes are



**Figure 9. Small aircraft can densely sample agricultural point sources.** Example flight pattern for the small aircraft based on observations collected in the Colorado Front Range in August 2021. (Juncosa Calahorano et al., 2023). The flight track is colored by observed  $\text{NH}_3$ . Colored and sized dots represent CAFOs housing different animals. Black dots signify oil and gas operations. Letters (i–vii) refer to different “vertical walls” that can be used for emission rate calculations and cover the length of the plume to document evolution. The distance from the cattle facility to the furthest plume transects in this case is ~19 km.

located 5 and 10 km downwind and can be shifted as needed for obstacles or other aircraft. When plumes are clearly detected 10 km downwind (as is the case in the example shown in Fig. 9), another set of stacked boxes can be completed further downwind. Integration of the box “curtains” provides multiple independent flux estimates per facility (Hacker et al., 2016).

True Lagrangian plume sampling is challenging from a practical standpoint.  $\text{NH}_3$  emissions change dramatically with temperature, particularly in the morning to early afternoon period (Juncosa Calahorano et al., 2024b). The small aircraft will frequently return to re-circle each facility to document changes in  $\text{NH}_3$  relative to  $\text{CH}_4$  and other tracers throughout a flight. This combined approach (i.e., downwind boxes with repeated near-source circles) will capture the diurnal cycle of emissions, provide multiple opportunities for flux calculations, and support analyses to constrain the evolution of plumes in the nearfield.

### Large Aircraft

The NASA P-3 Orion will provide the payload and range to address Objectives 2 and 3. This platform will also assist with long-range aspects of Objective 1, but it is not well-suited for close sampling of point sources. Typical flight duration is 6 hours. The P-3 has a nominal floor of 1000' above ground level (AGL) over unpopulated land, introducing some challenges with AEC applications. Careful flight planning and footprint analysis can mitigate these issues.

### Payload

Table 2 lists the ideal large aircraft payload. The P-3 can accommodate all Priority 1 and some Priority 2/3 measurements. Space will be available for additional instruments beyond those directly supported by FarmFlux, providing opportunities for collaboration.

**Priority 1:** Fast meteorology (10 Hz temperature, pressure, and 3-D wind velocity) is required for eddy covariance flux calculations. Fast water vapor supports calculation of latent heat fluxes, which relate to evapotranspiration and stomatal activity. High-quality latent and sensible heat fluxes also provide a time response standard for corrections to other fluxes based on spectral similarity (ref. Wolfe 2018). The desired response time for other flux-capable measurements is 5 Hz, sufficient to capture dominant eddy scales in the lower mixed layer, although measurements as slow as 1 Hz can be used (ref. Wolfe 2015). N-containing gases ( $\text{NO}_x$ ,  $\text{NH}_3$ , and  $\text{N}_2\text{O}$ ) are major emissions over fertilized lands.  $\text{CH}_4$  is emitted from rice patties and other inundated areas.  $\text{CO}_2$  fluxes are a direct measure of net ecosystem exchange (NEE). Ethene, oxygenated VOCs and terpenes are emitted directly from crops and may serve as markers for vegetation stress or influence from non-agricultural sources.  $\text{O}_3$  and CO are fundamental tracers for anthropogenic influence.  $\text{O}_3$  deposition fluxes are also of interest for vegetation health. Recent work has demonstrated AEC applications for  $\text{NH}_3$  (Schobesberger et al., 2022),  $\text{NO}_x$  (Q. Zhu et al., 2023),  $\text{N}_2\text{O}$  (Wilkerson et al., 2019), VOCs (Pfannerstill et al., 2023; Wolfe et al., 2015),  $\text{O}_3$  (Conley et al., 2011), and  $\text{CO}_2/\text{CH}_4$  (Desjardins et al., 2018; Hannun et al., 2020; Wolfe et al., 2018).

**Priority 2:** Size measurements from 3 nm to 50  $\mu\text{m}$  will span ultrafine, accumulation, and coarse-mode aerosol to constrain new particle formation (NPF), direct emission (dust/combustion), and



**Table 2. Large aircraft payload.** Measurements with flux capability are italicized. P is Priority (1 = threshold, 2 = baseline, 3 = desired and/or useful).

Measurement	P	Precision @ 1Hz	Accuracy	Rate	Objective
<i>Temperature, Pressure</i>	1	0.05 K, 0.003 mb	0.3 K, 0.3 mb	10 Hz	2,3
<i>Horizontal, vertical winds</i>	1	0.1, 0.05 m s <sup>-1</sup>	1, 0.3 m s <sup>-1</sup>	10 Hz	2,3
<i>water vapor</i>	1	100 ppmv	5%	10 Hz	2,3
<i>NH<sub>3</sub></i>	1	20 pptv	15%	5 Hz	2,3
<i>NO, NO<sub>2</sub></i>	1	1, 10 pptv	10%	5 Hz	2,3
<i>CO<sub>2</sub>, CH<sub>4</sub>, N<sub>2</sub>O</i>	1	200, 3, 0.4 ppbv	1%	5 Hz	2
<i>VOC (C<sub>1</sub>-C<sub>2</sub> alcohols, aldehydes, acids; acetone; terpenes)</i>	1	1 – 100 pptv (varies by species)	15%	5 Hz	2,3
<i>Ozone</i>	1	0.1 ppbv	5%	5 Hz	2
<i>CO</i>	1	1 ppbv	2%	1 Hz	2
Aerosol size distributions (3 nm – 50 µm)	2	NA	15%	0.1 Hz	3
Speciated inorganic, organic aerosol mass (< 1 µm)	2	100 ng m <sup>-3</sup>	35%	1 Hz	3
SO <sub>2</sub>	2	50 pptv	15%	1 Hz	3
HNO <sub>3</sub>	2	50 pptv	30%	1 Hz	2,3
f(RH)	3	NA	NA	0.1 Hz	3
aerosol scattering, extinction	3	1 Mm <sup>-1</sup>	20%	1 Hz	3
aerosol absorption	3	0.2 Mm <sup>-1</sup>	20%	0.1 Hz	3
Black carbon	3	50 ng m <sup>-3</sup>	25%	1 Hz	3
single particle composition	3	100 ng m <sup>-3</sup>	50%	Variable	3
Bioaerosol content	3	NA	20%	1 Hz	3
CCN	3	NA	20%	1 Hz	3
<i>organic nitrates</i>	3	10 pptv	30%	5 Hz	2
Amines	3	10 pptv	20%	1 Hz	2,3
<i>HONO</i>	3	5 pptv	15%	5 Hz	2
<i>Total oxidized nitrogen (NO<sub>y</sub>)</i>	3	20 pptv	15%	5 Hz	2
<sup>15</sup> NO	3	1 pptv	10%	0.1 Hz	2
Ethane	3	0.2 ppbv	10%	1 Hz	2
UV spectral actinic flux	3	80° SZA equivalent	10%	1 Hz	2

secondary production. Speciation of inorganic PM (primarily nitrate, sulfate and ammonium), as well as organic components, is necessary for probing aerosol chemistry and evolution. Measurements of gas-phase inorganic aerosol precursors, including  $\text{SO}_2$  and  $\text{HNO}_3$ , are also needed to constrain thermodynamic aerosol models. Hygroscopicity ( $f(\text{RH})$ ) will help connect other aerosol properties to cloud formation, aqueous processing, and wet scavenging.

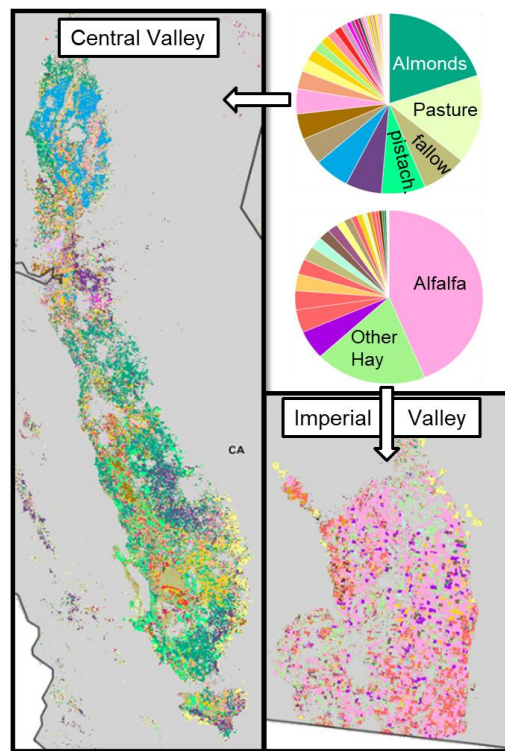
**Priority 3:** Additional aerosol properties, including black carbon mass, single-particle composition, bioaerosol content, optical properties, and cloud condensation nuclei (CCN), would provide additional insights into air mass history, novel processes, and connections to clouds and radiation. Observations of organic nitrates (peroxyacyl nitrates (PANs) and alkyl nitrates), HONO, and total oxidized nitrogen ( $\text{NO}_y$ ) would allow a more complete accounting of the sources and fate of reactive nitrogen. Amines are emitted from herbicide salts (Sharkey et al., 2022) and manure (Ge et al., 2011).  $^{15}\text{NO}$ , a stable isotope of nitric oxide, would facilitate discrimination of  $\text{NO}_x$  sources in complex regions like the CA Central Valley (Su et al., 2020). Ethane is a tracer for petrochemical influence. Photolysis frequencies derived from spectral actinic flux are useful for assessing the photochemical fate of agricultural emissions.

#### Locations and Timing

Factors influencing agricultural emissions vary by location and season. In the Midwest, planting follows the last frost, which changes with latitude from early March in Texas to late May in North Dakota. Spring thaw is also associated with spikes in  $\text{N}_2\text{O}$  emissions (Wagner-Riddle et al., 2017). Fertilizer application begins in April and continues throughout the growing season. Gross primary productivity and rainfall peak in June/July. In CA, fertilizer is applied throughout the spring and summer and weather is hotter and drier.

The large aircraft will conduct three 4-week intensives over a single year (Fig. 7). Each deployment consists of 3 weeks in the Midwest and 1 week in CA. This schedule balances the desire to span a full growing season with budget considerations and requires a single integration period prior to the first deployment. Figure 2 shows 300 NM range rings for Lincoln, NE and Ontario, CA, representing 1-way travel of 1 h.

Primary targets in the Midwest are corn/soy, sorghum/wheat, cotton, and rice monocultures (Fig. 4). Predominance of individual crops in different regions aids flight planning, as we can isolate a single crop type or combination over a large area and probe gradients in management strategies (irrigation, fertilization). The Midwest also features moderately-



**Figure 10. 2023 CA crop distribution in the Central Valley (left and top pie chart) and Imperial Valley (right and bottom pie chart) for 2023 (USDA, 2024b).**

sized, somewhat isolated cities for semi-Lagrangian experiments on agriculturally-impacted urban air, which provides a natural perturbation experiment with sharp contrast in chemical conditions ( $\text{NO}_x$ , oxidants, aerosol surface area).

California grows a variety of specialty crops. In the Central Valley, 50% of cropland consists of almonds, grass/pasture, pistachios, grapes, and rice (Fig. 10). Crop cover is mixed, but there are somewhat uniform patches of almonds (to the south), corn and citrus, grapes, and rice. The Imperial Valley (south of the Salton Sea) primarily grows alfalfa and other hay, with sugar beets, carrots, and other crops dispersed throughout. This patchiness will reduce our ability to ascribe emissions to crop types or farm practices, although recent observations of VOC fluxes in the lower Central Valley have demonstrated success with flux disaggregation (Pfannerstill et al., 2023).

### Flight Planning

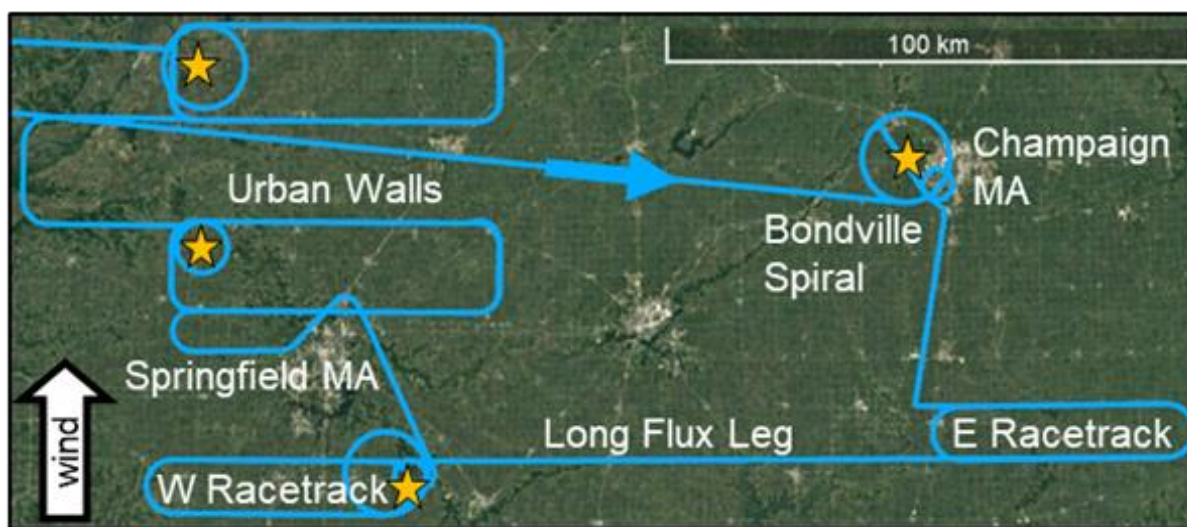
Flight plan development will require detailed surface information, including crop cover, fertilizer inputs, planting stage, soil pH, soil moisture, irrigation status, CAFO density, and precipitation history. For some parameters this information is available in near-real time, such as soil moisture from NASA's Short-term Prediction and Transition Center Land Information system (SPoRT-LIS) (*NASA SPoRT-LIS Soil Moisture Products*, 2024) and meteorological variables from data assimilation systems. Crop cover for prior years is available on CropScape (USDA, 2024b). Other parameters such as historical average irrigation, fertilizer inputs, and CAFO density are contained in the USDA Census of Agriculture, which is published on a five-year cycle and aggregates most data to county or state-level (USDA, 2024a). High-resolution information on fertilizer inputs is especially challenging to obtain (Xia et al., 2021). FarmFlux will collaborate with farm management experts to help guide flight planning, acquire high-resolution surface information where available, and improve communication with local and regional stakeholders. Model predictions of emissions, as well as the parameters underlying such models (Cooter et al., 2012), will also inform flight planning.

**Table 3. Possible crop survey experiments.**

Location	Crop Focus	Experiment notes
North Dakota	Corn/soy, spring wheat	Late thaw, low livestock density
Nebraska	Corn/soy	East-West gradient in rain-fed and irrigated crops
Illinois/Indiana	Corn/soy	Significant difference in fertilizer between IL and IN
Kansas	Sorghum, winter wheat, pasture	East-west gradients in fertilization and irrigation
North Texas	Cotton	North-south differences in CAFO density
Arkansas	Soy, rice, corn, cotton	High-moisture soil
Central Valley N	Rice	Significant drought impacts
Central Valley S	Tree nuts, citrus	Soil vs combustion $\text{NO}_x$
Imperial Valley	Alfalfa	Water management; $\text{NO}_2$ hotspot in TEMPO

Flight plans will target specific crops and sample across gradients in management, meteorology, and chemical regimes. Table 3 lists nine target areas where surface variability provides for “natural” experiments. Co-sampling of CAFOs and grazing areas is unavoidable, but judicious selection of locations (e.g., avoiding northern IA) can minimize this influence. Moreover, pasture qualifies as managed land and should not be overlooked. Proposed flight experiments will be refined following community and science team input. FarmFlux envisions 4 optimized flight plans for the Midwest and 2 plans for CA that will be repeated on each of the 3 deployments. Meteorological and chemical forecasting will be crucial for flight decisions and taking advantage of novel events, such as flying the same area before and after a storm to capture soil emission pulses.

Specific flight plans will combine modules to address multiple objectives and accommodate variable meteorology (especially wind direction). Figure 11 illustrates an example flight profile in central IL that assumes southerly flow. Major features include 1) vertical profiles in the vicinity of the ground-based AERONET and Pandora remote sensors, 2) stacked racetracks and a long flux leg in the rural boundary layer, 3) wall patterns downwind of an urban center, and 4) missed approaches to sample near-surface air. Stacked racetracks and walls constrain vertical flux divergence and sample variability in aerosol thermodynamics. As drawn, this flight plan is 6.7 hours with the P-3 and yields 500 km of surface flux data.



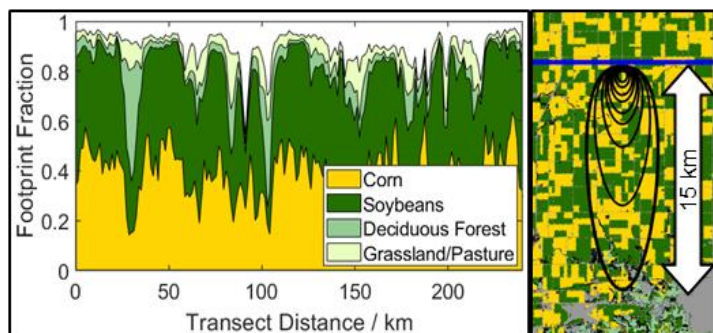
**Figure 11. The large aircraft simultaneously addresses multiple FarmFlux objectives. Example flight plan for central IL. Blue arrow: flight direction. MA: missed approach. Stars: vertical profiles. Racetracks and urban walls consist of 3 sets of stacked legs at altitudes of 1000' - 3000' AGL. Corn and soy farms dominate land cover.**

#### Eddy Covariance Analysis

AEC offers unique advantages and challenges. Whereas ground-based eddy covariance measures long-term, localized (10 - 100 m) fluxes, AEC acquires a snapshot of fluxes over a wide spatial domain (100's of km). Wavelet transforms resolve fluxes at horizontal scales of ~1 km along the flight track (Karl et al., 2009). Flux footprints, which statistically represent surface contributions

to vertical fluxes, extend 2 – 10 km upwind. Figure 12 shows the contributions of different crop classes within a hypothetical footprint for the “long flux leg” from Fig. 10, revealing the dominance of corn and soy with smaller contributions from forest, pasture, and other land types. Fluxes also change with altitude. Accounting for vertical flux divergence entails measuring fluxes at multiple altitudes in the boundary layer and/or flying “racetracks” or other patterns to constrain advection and chemistry. AEC-based studies on the NASA DC-8 have exploited flux divergence to simultaneously constrain emission/deposition and *in situ* chemistry (Novak et al., 2021; Wolfe et al., 2015).

Eddy covariance calculations will follow well-established methods for quality control, bias rectification, divergence corrections, and uncertainty quantification (Wolfe et al., 2018). Footprints are readily derived from meteorological observations (Kljun et al., 2015) and can be combined with flux disaggregation (Hannun et al., 2020; Hutjes et al., 2010) or machine learning techniques (Metzger et al., 2013) to disentangle multi-dimensional relationships with surface drivers. The science team will share code and work collaboratively to improve existing methodology and develop flux data products for wider community use.



**Figure 12. AEC footprints capture heterogeneity in surface fluxes.** (Left) Estimated fractional land cover contributions to flux footprint for the “long flux leg” (Fig. 11) based on 2022 CropScape data (USDA, 2024b). (Right) Example 2-D footprint. Contours represent 10-percentile contributions in 10% increments from 10% to 90%.

## Aircraft Coordination

For the most part, the small and large aircraft will operate asynchronously. Some overlap is built into the schedule to permit measurement inter-comparison and some coordinated sampling. For large CAFOs with well-behaved plumes, the small aircraft can sample near the source while the large aircraft follows the plume over longer timescales (physical ages of 1 - 6 hours, depending on dilution) to document aerosol evolution and  $\text{NH}_3$  fate. The two aircraft will also develop coordinated flight plans that produce flux estimates for large facilities using both mass balance (small aircraft) and AEC (large aircraft) approaches. AEC is not traditionally employed for point-source emission quantification, making this effort experimental. The large aircraft will inevitably sample livestock emissions during large-area surveys, and co-flying with the small aircraft will provide insights on how to best utilize this data.

## Modeling Tools

Improving predictions of agricultural impacts on air quality will require multi-scale models that range from site-level process-based agricultural and biogeochemical land models to regional and



continental-scale CTMs (Table 4). Footprint modeling that estimates surface areal contributions to vertical fluxes will be key to connecting the measurements to specific surface characteristics (crop type, soil moisture, animal density). A regional CTM (e.g., WRF-CMAQ or WRF-Chem) is needed to simulate chemistry and surface exchange at spatial scales of 1 - 12 km, linking the measurements in Objectives 1 and 2 to the modeling components of Objective 4. New developments to continental-scale CTM simulations (on spatial scales of 12 - 25 km) with state-of-the-art chemical mechanisms and interoperable aerosol schemes (e.g. GEOS-Chem) would best advance Objectives 3 and 4. Advances to modeling of point-scale agricultural plumes (e.g., plume-in-grid parameterizations), higher fidelity soil emissions, and better constrained reactive nitrogen emissions should be transferable across model platforms. Chemical (e.g. WRF-Chem or GEOS-CF) and weather forecasting (e.g. WRF) will also be required for flight planning.

Biogeochemical models of agricultural soils can also calculate emissions of  $N_2O$ ,  $NH_3$ , and  $NO$  (e.g., DNDC, DayCent, ORCHIDEE), and mechanistic cropping system models can be well-parameterized and constrained for our systems of interest. FarmFlux presents new opportunities to compare nitrogen emissions simulated by these process-based approaches with the empirical parameterizations and static inventories that currently support CTMs. Comparisons will be directed towards improving atmospheric chemistry modeling and air quality forecasts in agricultural regions. Efforts may also advance integrated Earth system models (e.g., CESM).

**Table 4. FarmFlux modeling capabilities.** *P is Priority (1 = threshold, 2 = baseline, 3 = desired and/or useful).*

Modeling Capability	P	Characteristics	Objective
Continental-Scale Chemical Transport Model	1	Regional (continental) scale processes and impacts at ~25 km spatial resolution. Online empirical parameterization of soil $NO_x$ emissions. Resistance-based (or other) online dry deposition scheme. Simple and volatility basis set organic aerosol schemes.	All
High Resolution Chemical Transport Model	1	High spatial resolution (1 to 12 km) chemistry. Different soil N emission parameterizations. Chemical forecasts.	All
flux footprints, machine learning algorithms	1	2-D flux footprint estimation. Ability to ingest multiple surface properties to generate flux predictions and relationships.	1,2
Aerosol thermodynamics	2	Explicit representation of inorganic aerosol equilibria	3
Land Surface Model	2	Dynamic land cover representation. Process-based soil biogeochemistry and reactive nitrogen cycling/emissions.	2
Cropping systems model	3	Crop-specific growth, responses to water and nutrients, daily time step.	2
Plume-in-grid	3	Treatment of dispersion and effects of turbulence for sub-grid scale effects.	1
Lagrangian particle dispersion model	3	Simulation of forward and backward trajectories for regional emissions estimation.	All
Integrated Assessment Model	3	Compatibility with CTM outputs, community-level health impact characterization	4



## Science Questions

FarmFlux deliverables include 1) gas emission ratios and fluxes from CAFOs spanning diverse environmental conditions, 2) a database of surface-atmosphere fluxes over U.S. cropland, including footprint-integrated surface characteristics, and 3) simultaneous observations of gas and aerosol properties throughout under-sampled regions of the U.S. The prospect of such a dataset gives rise to myriad science questions. The list provided below is not exhaustive and is a starting point for discussion and future thought.

### Objective 1: Livestock

- What are the magnitudes of the emission fluxes of  $\text{NH}_3$ ,  $\text{N}_2\text{O}$ ,  $\text{CH}_4$  and other trace gases from cattle, dairy and hog operations? How do emissions vary with time of day, season, environmental conditions, and management practices?
- What is the lifetime of  $\text{NH}_3$  emitted from cattle, dairy and hog operations? How does this vary in relation to season, time of day, and underlying surface conditions?
- What is the spatiotemporal contribution of concentrated cattle, dairy and hog operations to nitrogen deposition?
- Should animal feeding operations be treated as point or area sources in atmospheric chemistry models to best predict air quality impacts?
- How do fixed N emissions from concentrated cattle, dairy and hog operations impact emissions from soils in surrounding areas?

### Objective 2: Crops

- What are the magnitudes and signs of fluxes of N-containing gases ( $\text{NH}_3$ ,  $\text{N}_2\text{O}$ ,  $\text{NO}_x$ )? How do fluxes vary with soil state, fertilizer inputs, meteorology, and crop type?
- What is the spatial and temporal extent of pulse emissions of  $\text{NO}_x$  and  $\text{N}_2\text{O}$ ?
- What are the dominant VOCs emitted by different crops in terms of mass and reactivity?
- What is the magnitude and variability of ozone deposition across cropland, and do crop damage estimates capture this accurately?
- What is the net  $\text{CO}_2$ -equivalent greenhouse gas exchange rate for different crops?
- How well do empirical and biogeochemical parameterizations of soil/crop fluxes match observations? Where, when, and why do model predictions diverge?

### Objective 3: Particulate Matter

- How do meteorology and agricultural activity drive PM composition through influences on emissions, secondary formation, evolution, and loss mechanisms?
- What are the relative contributions of CAFO and cropland emissions to aerosol formation and composition?
- When and where do thermodynamic models fail to close the inorganic aerosol budget?
- What are the sources of SOA in agricultural areas?
- What conditions promote or suppress NPF in agricultural regions? How important are agricultural emissions for NPF?

#### Objective 4: Air Quality and Satellite Applications

- What is the spatiotemporal extent of exposure to primary agricultural pollutants and their secondary products?
- What are the relative contributions of CAFOs and cropland emissions to air pollution-related health damages and health inequality in the U.S.?
- What is the relationship between soil NO<sub>x</sub> emissions and TEMPO tropospheric NO<sub>2</sub> columns?
- How do satellite-inferred NH<sub>3</sub> emission estimates change with better constraints on NH<sub>3</sub> lifetimes?
- Under what conditions can satellite observations of NH<sub>3</sub>, NO<sub>2</sub>, or other species be used to infer emissions of unmeasured species such as N<sub>2</sub>O or CH<sub>4</sub>?

### Team Structure

The *Mission PI* (Wolfe) will direct mission implementation and manage science efforts on the large aircraft. The *Deputy PI for Observations* (Fischer) will assist with mission implementation and manage small aircraft science. The *Deputy PI for Modeling* (Geddes) will manage forecasting and modeling teams and contribute to modeling efforts and flight planning. Additional leadership roles, such as lead platform scientists, satellite liaisons, and agricultural outreach coordinators will be selected from the larger science team. When possible, teams of early and mid-career scientists will fill these roles. NASA's Earth Science Project Office (ESPO) will provide logistical and investigation support.

The FarmFlux science team will include weather forecasters, instrument scientists and modelers. Per EVS guidelines, science team selection will occur via a competitive NASA ROSES call. A request for proposals is anticipated in December 2024. After selection, the science team will collaborate on further refinement of the white paper, development of the detailed investigation plan, and mission execution.

### Related Activities

#### NASA

FarmFlux dovetails with several NASA initiatives in the realms of agriculture and greenhouse gas monitoring and attribution. NASA Acres<sup>1</sup> leverages satellite-derived information to inform U.S. crop production and precision agriculture. NASA Harvest<sup>2</sup> facilitates similar work but with a broader focus on global food security. The tools and deep operational knowledge developed within these consortia will be critical for optimizing crop sampling, and FarmFlux results may reveal new applications for satellite observations, particularly atmospheric trace gases. The U.S. Greenhouse Gas Center<sup>3</sup> is a collaboration among multiple U.S. agencies (NASA, EPA, NOAA, and

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<sup>1</sup> <https://www.nasaacres.org/>

<sup>2</sup> <https://nasaharvest.org/>

<sup>3</sup> <https://earth.gov/ghgcenter>

NIST) to consolidate existing greenhouse gas observations and model output and develop new infrastructure and tools to support research and policy development. With new constraints on emissions of CH<sub>4</sub> and N<sub>2</sub>O and net uptake of CO<sub>2</sub>, FarmFlux will improve emission inventories and estimates of the net climate impacts of agriculture.

## EPA

FarmFlux objectives will contribute to EPA priorities including improving air quality, quantifying nitrogen deposition, understanding PM<sub>2.5</sub> sources and composition, monitoring and reporting of agricultural emissions, and addressing environmental justice, while supporting and promoting sustainable agricultural practices. At the same time, FarmFlux objectives will benefit from ongoing monitoring and research carried out by the EPA. We anticipate leveraging available measurements from the Ammonia Monitoring Network (AMoN), while supplementing considerable gaps in this network across some of the largest agricultural areas in the country. We hope the large momentum behind FarmFlux may encourage new strategic deployments of AMoN samplers. The Clean Air Status and Trends Network (CASTNET) will also provide important baseline observations of relevant atmospheric constituents such as gaseous nitric acid (HNO<sub>3</sub>) and aerosol ammonium nitrate (NH<sub>4</sub>NO<sub>3</sub>). Enhanced reactive nitrogen monitoring by the CASTNET “nitrotrain” system (reporting HNO<sub>3</sub>, NH<sub>3</sub>, NO, NO<sub>2</sub>, NO<sub>y</sub>, and total reactive nitrogen), including potential new flux capabilities, at a relevant CASTNET location within the FarmFlux domain would be a particularly valuable partnership opportunity. FarmFlux also welcomes opportunities to build on current and upcoming EPA Strategic Research Plans.

## USDA

FarmFlux will contribute to USDA research priorities by providing facility-scale emissions estimates of major air pollutants and greenhouse gases for many animal production facilities under different environmental conditions across 5 U.S. regions. It will radically increase the existing data on relative facility-scale N<sub>2</sub>O, CH<sub>4</sub> and NH<sub>3</sub> emissions. FarmFlux will also improve our ability to measure total emission rates, and if paired with known concurrent management practices, this data may test the efficacy of potential management and mitigation strategies. The small aircraft sampling strategy is designed to enable horizontal flux calculations. With this approach, uncertainty in total flux is reduced if there is concentration information for species of interest near the surface, and emissions estimates are most useful if they can be linked to concurrent management practices. Thus, FarmFlux plans to align sampling efforts with current or planned ground-level campaigns at specific animal production facilities in our target regions.

## Ideas for Collaborative Research

FarmFlux aspires to nucleate coordinated research on agriculture - atmosphere interactions. Collaborative activities may include:

- **Additional P-3 instruments:** The P-3 can accommodate instruments beyond those directly supported by FarmFlux. Externally-funded collaborators are welcome. Of

particular interest are Priority 3 measurements and redundancy for critical Priority 1 measurements.

- **Ground-based eddy covariance** captures diurnal and seasonal patterns in fluxes over a small, well-defined footprint. Such information, if acquired for multiple species at representative sites, would complement regional-scale airborne fluxes and facilitate upscaling over larger domains and periods (Poulter et al., 2023). The atmospheric chemistry community has a long history of integrated ground campaigns in forested areas (Mao et al., 2018), but this has not been attempted for agricultural areas to our knowledge.
- **Mobile laboratories** are well suited for CAFO sampling (Golston et al., 2020; Vechi et al., 2023). Such data could complement airborne observations by generating additional flux estimates, monitoring near-source emissions over several hours while the aircraft samples downwind, and repeat sampling of facilities on days when the aircraft is elsewhere.
- **Airborne remote sensors** furnish high-resolution and real-time observations of surface and atmospheric properties. Information regarding soil moisture, surface temperature, and crop structure/health within the flux footprint of the large aircraft would enable deeper mechanistic understanding of emission and deposition drivers. Trace gas column measurements (e.g., CH<sub>4</sub> or NO<sub>2</sub>) would also strengthen connections to satellite retrievals.
- **Data analysis and modeling** beyond core FarmFlux objectives is encouraged. For example, FarmFlux will not investigate large-scale climate impacts, policy implications of emissions patterns, long-term trends, or development of novel satellite products. In the spirit of open science, FarmFlux will release data within prescribed NASA deadlines and conduct community workshops to promote new research.

## Beyond FarmFlux

FarmFlux is an ambitious effort, yet aspects of the coupled agriculture-atmosphere system will remain unexplored. Agricultural activities and impacts occur outside the FarmFlux deployment windows. For example, elevated ammonium nitrate levels in the winter are a significant issue in the Midwest (Katzman et al., 2010). Thawing soils may emit N<sub>2</sub>O at times and locations when/where FarmFlux is not sampling. Fertilization and planting also occur in the fall. CAFO sampling does not include a specific focus on poultry, which is prominent in the Southeast U.S. Also, a single year of measurements will not address interannual variability in crop production and associated emissions due to climate, economics, or other factors. Observed correlations with major drivers (e.g., temperature and soil moisture) may, to some extent, improve estimations of year-to-year variability and long-term trends. While FarmFlux cannot feasibly encompass all aspects of U.S. agriculture, the hope is to capture a representative subsample of the major components. FarmFlux will be a leap in our understanding of agricultural emissions and impacts. This is but a step along the path to finding balance between food security and environmental health.

## FarmFlux Inclusion Plan

**Context and Expectations.** Women and some ethnic (i.e., Native Americans, African Americans, and Latinx) groups continue to be marginalized in Earth Science, as are persons with disabilities and LGBTQIA+ people. The Earth Sciences are unique among STEM fields in their lack of improvement in this area over the last 40 years (Bernard & Cooperdock, 2018). Discrimination and harassment in hostile work environments are documented barriers to diversity goals (Marin-Spiotta et al., 2020, 2023). Historically minoritized trainees also have smaller professional networks and fewer role models; both factors challenge their sense of belonging. Airborne observations are a central part of scholarship across the Earth Sciences. Collaborative, multi-institutional teams carry out these campaigns. Networks take years to establish and lead to enduring collaborations. In addition to technical instruction, airborne field campaigns dramatically expand professional networks, publications, and career potential for trainees, including extended interaction at conferences and science team meetings. To meet overall diversity goals, every member of the FarmFlux team is expected to amplify and lead diversity efforts. All team members are expected to participate in evidenced-based professional development activities organized for FarmFlux.

**Goals.** FarmFlux will use evidence-based approaches to meet our inclusion goals of 1) creating a positive and inclusive working environment through a kindness framework (Estrada et al., 2018), 2) preventing all forms of harassment (Fischer et al., 2021), and 3) broadening participation through targeted recruitment, mentoring, and establishing diverse networks (Burt et al., 2023; Fischer et al., 2018; Hernandez et al., 2017, 2018, 2020).

**Activities.** Our PI team will affirm social inclusion and provide professional development on kindness, following evidence that this practice is critical for inclusive STEM excellence (Estrada et al., 2018). Upon joining the FarmFlux team, everyone (PIs, trainees, aircraft staff, etc.) will participate in professional development where they complete a social identity wheel. This social identity exercise will help participants understand how their identities are perceived and how privilege operates in the context of STEM; it will also sensitize the team to shared and different identities. Participants will also reflect on kindness that they have experienced in the workplace and be exposed to the research on kindness in STEM endeavors. This activity has already been developed through PROGRESS (PROmoting Geoscience Research Education and SuccesS, see below) and deployed in academic contexts. We anticipate some initial resistance and discomfort. To build the willingness to authentically participate, content will be presented in the context of building effective teams, without blame, and include the evidence/rationale behind the activity. We will implement best practices in preventing and responding to harassment (Fischer et al., 2021). Efforts will include 1) establishing a code of conduct, 2) developing robust safety plans, 3) implementing bystander intervention training ahead of each field deployment in conjunction with other safety training, 4) identifying mixed-gender well-trained points of contact for addressing issues as they arise, 5) collecting and sharing information on incidents of harassment after each field deployment in a way that protects team members, and 6) continuing professional development on the issue of work-place climate ahead of each field deployment, again in the context of safety and teambuilding. The FarmFlux code of conduct will follow best practices and

include clear expectations, reporting structures, and outcomes in the case of harassment. Codes of conduct reduce bias and discrimination in STEM in addition to preventing harassment (Willis et al., 2020). Bystander intervention training engenders understanding of the prevalence and impacts of harassment and teaches appropriate response strategies through practice with relevant scenarios (Berhe et al., 2020). Training will be conducted as part of the mandatory safety briefing associated with the aircraft work and can be done virtually. In this training, we will also provide information on the work environment and expectations, including photographs of locations, example schedules, and potential sampling cadences. This information will be provided in a packet, and we will review it together. This is an important aspect of inclusive onboarding, particularly from the perspective of neurodiversity. We will also have check-ins with individual instrument teams to identify individual challenges that may arise during the field campaigns and work to identify solutions. Throughout the duration of FarmFlux, we will offer complementary modules on how to interrupt bias and build anti-racist organizations (Chaudhary & Berhe, 2020).

We will employ an external evaluation team to survey our team's behaviors after each field intensive and serve as an avenue for confidentially reporting harassment and/or discrimination. These data will be collected and analyzed using established survey scales and summary statistics that have been used with other major airborne field teams (Fischer et al., 2021). The survey will be administered and data will be analyzed by an independent evaluator with experience in formal evaluation.

FarmFlux will aim to recruit trainees and fellow PIs from a wide network and establish best practices in mentoring. There are several examples of networks that can be leveraged. 1) PROGRESS is an NSF-supported mentoring program for undergraduate women interested in the earth and environmental sciences (Burt et al., 2023; Fischer et al., 2018). The current focus of PROGRESS is to radically expand the number of student participants from historically minoritized groups and to increase the number of first-generation student participants. When Farm-Flux launches, the program will serve students in 7 U.S. regions across >30 institutions including many minority serving institutions (MSIs). The PROGRESS network offers one avenue to recruit graduate and undergraduate students for this project. 2) There are also a number of NSF- and NASA-supported REU programs with a consistent track record of placing diverse student groups in graduate programs (Burt et al., 2016). We will encourage the FarmFlux PI team to actively recruit graduate students from these programs. If they are eligible, NASA/NOAA team members will be encouraged to recruit through internal programs, such as NASA SMD's MOSAICS Program (MOSAICS, 2024). 3) The AGU BRIDGE program (AGU Bridge Program, 2024) supports many efforts to increase equity in the recruitment process for graduate students (e.g., refined holistic review process), and we will encourage PIs from BRIDGE programs to propose to FarmFlux with the goal of building new equitable partnerships (Morris, 2021).

Support mechanisms will meet culturally specific needs for trainees. Trainees supported on this project will have access to a wide mentoring network that FarmFlux leadership will facilitate through several evidence-based activities (*Effective Mentoring in STEMM*, 2017). We will lead all the students and mentors through a support network mapping exercise that helps trainees identify the types of support they need and how to build their networks. All graduate students or postdoctoral researchers on this project and their academic/research advisors will use both individual development plans (IDPs) and mentoring compacts. The trainees (students and postdoctoral researchers) supported on this project will also have access to relevant



professional development activities. We will offer a virtual professional development seminar series that includes a large topical range. Example modules include a Python bootcamp, how to give effective oral presentations, conflict resolution, and funding acquisition. We envision that these modules would be tailored to either graduate students or postdoctoral researchers, depending on the mixture of trainees on the FarmFlux team.

**Effort and Success Metrics.** Leading inclusion activities will require 0.5 months per year for one of the lead PIs. Overall effort for project participants will amount to 1-2 days per year, split into several mini workshops. Evaluation metrics including demographic information and feedback regarding mission culture and harassment will be collected annually prior to science team meetings. We will adapt strategies based on these metrics and share results with the team to foster an open culture.

## Acronyms

AGL	Above Ground Level
AEC	Airborne Eddy Covariance
AERONET	Aerosol Robotic Network
AIRS	Atmospheric Infrared Sounder
AMoN	Ammonia Monitoring Network
AOD	Aerosol Optical Depth
CAFO	Concentrated Animal Feeding Operation
CASTNET	Clean Air Status and Trends Network
CESM	Community Earth System Model
CCN	Cloud Condensation Nuclei
CMAQ	Community Multiscale Air Quality modeling system
CrIS	Cross-track Infrared Sounder (satellite instrument)
CTM	Chemical Transport Model
DNDC	Denitrification – Decomposition Model
ECOSTRESS	Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station
EMIT	Earth Surface Mineral Dust Source Investigation
EmR	Emission Ratio
EPA	Environmental Protection Agency
ESPO	Earth Science Project Office
EVS	Earth Venture Suborbital
IASI	Infrared Atmospheric Sounding Interferometer
MAIA	Multi-Angle Imager for Aerosols
MSI	Minority Serving Institution
NASA	National Aeronautics and Space Administration
NIST	National Institute of Standards and Technology
NOAA	National Oceanographic and Atmospheric Administration
NPF	New Particle Formation
NO <sub>x</sub>	Total Nitrogen Oxides (NO + NO <sub>2</sub> )
OA	Organic Aerosol
OCO2	Orbiting Carbon Observatory 2
ORCHIDEE	Organising Carbon and Hydrology in Dynamic Ecosystems
PM	Particulate Matter
PM <sub>2.5</sub>	PM with diameter < 2.5 microns
ppbv	parts per billion by volume
PROGRESS	PROMoting Geoscience Research Education and Success
RH	Relative Humidity
ROSES	Research Opportunities in Space and Earth Science
SOA	Secondary Organic Aerosol
TEMPO	Tropospheric Emissions: Monitoring of Pollution (satellite instrument)
TROPOMI	Tropospheric Monitoring Instrument
USDA	U.S. Department of Agriculture
VOCs	Volatile Organic Compounds

## References

- AGU Bridge Program. (2024). AGU. <https://www.agu.org/bridge-program>
- Aguirre-Villegas, H. A., Besson, C., & Larson, R. A. (2024). Modeling ammonia emissions from manure in conventional, organic, and grazing dairy systems and practices to mitigate emissions. *Journal of Dairy Science*, 107(1), 359–382. <https://doi.org/10.3168/jds.2023-23782>
- Almaraz, M., Bai, E., Wang, C., Trousdell, J., Conley, S., Faloon, I., & Houlton, B. Z. (2018). Agriculture is a major source of NO<sub>x</sub> pollution in California. *Science Advances*, 4(1), eaao3477. <https://doi.org/10.1126/sciadv.aao3477>
- Anthony, T. L., & Silver, W. L. (2021). Hot moments drive extreme nitrous oxide and methane emissions from agricultural peatlands. *Global Change Biology*, 27(20), 5141–5153. <https://doi.org/10.1111/gcb.15802>
- Bachy, A., Aubinet, M., Schoon, N., Amelynck, C., Bodson, B., Moureaux, C., & Heinesch, B. (2016). Are BVOC exchanges in agricultural ecosystems overestimated? Insights from fluxes measured in a maize field over a whole growing season. *Atmospheric Chemistry and Physics*, 16(8), 5343–5356. <https://doi.org/10.5194/acp-16-5343-2016>
- Balafoutis, A., Beck, B., Fountas, S., Vangeyte, J., Wal, T. V. der, Soto, I., Gómez-Barbero, M., Barnes, A., & Eory, V. (2017). Precision Agriculture Technologies Positively Contributing to GHG Emissions Mitigation, Farm Productivity and Economics. *Sustainability*, 9(8), Article 8. <https://doi.org/10.3390/su9081339>
- Beaudor, M., Vuichard, N., Lathière, J., Evangelidou, N., Van Damme, M., Clarisse, L., & Hauglustaine, D. (2023). Global agricultural ammonia emissions simulated with the ORCHIDEE land surface model. *Geoscientific Model Development*, 16(3), 1053–1081. <https://doi.org/10.5194/gmd-16-1053-2023>
- Benedict, K. B., Day, D., Schwandner, F. M., Kreidenweis, S. M., Schichtel, B., Malm, W. C., & Collett, J. L. (2013). Observations of atmospheric reactive nitrogen species in Rocky Mountain National Park and across northern Colorado. *Atmospheric Environment*, 64, 66–76. <https://doi.org/10.1016/j.atmosenv.2012.08.066>
- Berhe, A. A., Hastings, M., Schneider, B., & Marín-Spiotta, E. (2020). Changing Academic Cultures to Respond to Hostile Climates. In *Addressing Gender Bias in Science & Technology* (Vol. 1354, pp. 109–125). American Chemical Society. <https://doi.org/10.1021/bk-2020-1354.ch007>
- Bernard, R. E., & Cooperdock, E. H. G. (2018). No progress on diversity in 40 years. *Nature Geoscience*, 11(5), Article 5. <https://doi.org/10.1038/s41561-018-0116-6>
- Boersma, K. F., Eskes, H. J., & Brinkma, E. J. (2004). Error analysis for tropospheric NO<sub>2</sub> retrieval from space. *Journal of Geophysical Research: Atmospheres*, 109(D4). <https://doi.org/10.1029/2003JD003962>
- Boersma, K. F., Eskes, H. J., Richter, A., De Smedt, I., Lorente, A., Beirle, S., van Geffen, J. H. G. M., Zara, M., Peters, E., Van Roozendaal, M., Wagner, T., Maasakkers, J. D., van der A, R. J., Nightingale, J., De Rudder, A., Irie, H., Pinardi, G., Lambert, J.-C., & Compernelle, S. C. (2018). Improving algorithms and uncertainty estimates for satellite NO<sub>2</sub> retrievals: Results from the quality assurance for the essential climate variables

- (QA4ECV) project. *Atmospheric Measurement Techniques*, 11(12), 6651–6678. <https://doi.org/10.5194/amt-11-6651-2018>
- Brahney, J., Mahowald, N., Ward, D. S., Ballantyne, A. P., & Neff, J. C. (2015). Is atmospheric phosphorus pollution altering global alpine Lake stoichiometry? *Global Biogeochemical Cycles*, 29(9), 1369–1383. <https://doi.org/10.1002/2015GB005137>
- Brandani, C. B., Lee, M., Auvermann, B. W., Parker, D. B., Casey, K. D., Crosman, E. T., Gouvêa, V. N., Beck, M. R., Bush, K. J., Koziel, J. A., Shaw, B., & Brauer, D. (2023). Mitigating Ammonia Deposition Derived from Open-Lot Livestock Facilities into Colorado’s Rocky Mountain National Park: State of the Science. *Atmosphere*, 14(10), Article 10. <https://doi.org/10.3390/atmos14101469>
- Bunton, B., O’Shaughnessy, P., Fitzsimmons, S., Gering, J., Hoff, S., Lyngbye, M., Thorne, P. S., Wasson, J., & Werner, M. (2007). Monitoring and modeling of emissions from concentrated animal feeding operations: Overview of methods. *Environmental Health Perspectives*, 115(2), 303–307. <https://doi.org/10.1289/ehp.8838>
- Burns, A. M., Chandler, G., Dunham, K. J., & Carlton, A. G. (2023). Data Gap: Air Quality Networks Miss Air Pollution from Concentrated Animal Feeding Operations. *Environmental Science & Technology*, 57(49), 20718–20725. <https://doi.org/10.1021/acs.est.3c06947>
- Burt, M. A., Barnes, R. T., Schanz, S., Clinton, S., & Fischer, E. V. (2023, January 26). *Mentorship Builds Inclusivity and Belonging in the Geosciences*. Eos. <http://eos.org/science-updates/mentorship-builds-inclusivity-and-belonging-in-the-geosciences>
- Burt, M. A., Haacker, R., Batchelor, R. L., & Denning, A. S. (2016). Increasing the Diversity of Your Graduate Program: Translating Best Practices into Success. *Bulletin of the American Meteorological Society*, 97(7), 1169–1172. <https://doi.org/10.1175/BAMS-D-15-00004.1>
- Butterbach-Bahl, K., Baggs, E. M., Dannenmann, M., Kiese, R., & Zechmeister-Boltenstern, S. (2013). Nitrous oxide emissions from soils: How well do we understand the processes and their controls? *Philosophical Transactions of the Royal Society B: Biological Sciences*, 368(1621), 20130122. <https://doi.org/10.1098/rstb.2013.0122>
- Cady-Pereira, K. (2020). Cross-track Infrared Sounder (CrIS) Level 2 Earth System Science Profiling Algorithm Ammonia Retrieval Algorithm (ESSPA-NH3) V1 [Dataset]. In NASA GESDISC. <https://doi.org/10.5067/EHW76N16L83M>
- Cao, H., Henze, D. K., Shephard, M. W., Dammers, E., Cady-Pereira, K., Alvarado, M., Lonsdale, C., Luo, G., Yu, F., Zhu, L., Danielson, C. G., & Edgerton, E. S. (2020). Inverse modeling of NH<sub>3</sub> sources using CrIS remote sensing measurements. *Environmental Research Letters*, 15(10), 104082. <https://doi.org/10.1088/1748-9326/abb5cc>
- Cao, P., Lu, C., & Yu, Z. (2018). Historical nitrogen fertilizer use in agricultural ecosystems of the contiguous United States during 1850–2015: Application rate, timing, and fertilizer types. *Earth System Science Data*, 10(2), 969–984. <https://doi.org/10.5194/essd-10-969-2018>
- Chang, P., Zhang, S., Danabasoglu, G., Yeager, S. G., Fu, H., Wang, H., Castruccio, F. S., Chen, Y., Edwards, J., Fu, D., Jia, Y., Laurindo, L. C., Liu, X., Rosenbloom, N., Small, R. J., Xu, G., Zeng, Y., Zhang, Q., Bacmeister, J., ... Wu, L. (2020). An Unprecedented Set of High-Resolution Earth System Simulations for Understanding Multiscale Interactions in Climate Variability and Change. *Journal of Advances in Modeling Earth Systems*, 12(12), e2020MS002298. <https://doi.org/10.1029/2020MS002298>

- Chaudhary, V. B., & Berhe, A. A. (2020). Ten simple rules for building an antiracist lab. *PLOS Computational Biology*, 16(10), e1008210. <https://doi.org/10.1371/journal.pcbi.1008210>
- Chen, J., Yin, D., Zhao, Z., Kaduwela, A. P., Avise, J. C., DaMassa, J. A., Beyersdorf, A., Burton, S., Ferrare, R., Herman, J. R., Kim, H., Neuman, A., Nowak, J. B., Parworth, C., Scarino, A. J., Wisthaler, A., Young, D. E., & Zhang, Q. (2020). Modeling air quality in the San Joaquin valley of California during the 2013 Discover-AQ field campaign. *Atmospheric Environment: X*, 5, 100067. <https://doi.org/10.1016/j.aeaoa.2020.100067>
- Clark, C. M., Phelan, J., Doraiswamy, P., Buckley, J., Cajka, J. C., Dennis, R. L., Lynch, J., Nolte, C. G., & Spero, T. L. (2018). Atmospheric deposition and exceedances of critical loads from 1800–2025 for the conterminous United States. *Ecological Applications*, 28(4), 978–1002. <https://doi.org/10.1002/eap.1703>
- Clifton, O. E., Fiore, A. M., Munger, J. W., Malyshev, S., Horowitz, L. W., Shevliakova, E., Paulot, F., Murray, L. T., & Griffin, K. L. (2017). Interannual variability in ozone removal by a temperate deciduous forest. *Geophysical Research Letters*, 44(1), 542–552. <https://doi.org/10.1002/2016GL070923>
- C-MAPEX. (2012). <https://doi.org/10.5270/esa-q4tdlvo>
- Conley, S. A., Faloon, I. C., Lenschow, D. H., Campos, T., Heizer, C., Weinheimer, A., Cantrell, C. A., Mauldin, R. L., Hornbrook, R. S., Pollack, I., & Bandy, A. (2011). A complete dynamical ozone budget measured in the tropical marine boundary layer during PASE. *Journal Of Atmospheric Chemistry*, 68(1), 55–70. <https://doi.org/10.1007/s10874-011-9195-0>
- Cooter, E. J., Bash, J. O., Benson, V., & Ran, L. (2012). Linking agricultural crop management and air quality models for regional to national-scale nitrogen assessments. *Biogeosciences*, 9(10), 4023–4035. <https://doi.org/10.5194/bg-9-4023-2012>
- Dang, R., Jacob, D. J., Shah, V., Eastham, S. D., Fritz, T. M., Mickley, L. J., Liu, T., Wang, Y., & Wang, J. (2022). Background nitrogen dioxide (NO<sub>2</sub>) over the United States and its implications for satellite observations and trends: Effects of nitrate photolysis, aircraft, and open fires. *EGUsphere*, 1–21. <https://doi.org/10.5194/egusphere-2022-1198>
- Del Grosso, S. J., Ogle, S. M., Nevison, C., Gurung, R., Parton, W. J., Wagner-Riddle, C., Smith, W., Winiwarter, W., Grant, B., Tenuta, M., Marx, E., Spencer, S., & Williams, S. (2022). A gap in nitrous oxide emission reporting complicates long-term climate mitigation. *Proceedings of the National Academy of Sciences*, 119(31), e2200354119. <https://doi.org/10.1073/pnas.2200354119>
- Del Grosso, S. J., Parton, W. J., Ojima, D. S., Keough, C. A., Riley, T. H., & Mosier, A. R. (2008). Chapter 18—DAYCENT Simulated Effects of Land Use and Climate on County Level N Loss Vectors in the USA. In J. L. Hatfield & R. F. Follett (Eds.), *Nitrogen in the Environment (Second Edition)* (pp. 571–595). Academic Press. <https://doi.org/10.1016/B978-0-12-374347-3.00018-4>
- Desjardins, R. L., Worth, D. E., Pattey, E., Vanderzaag, A., Srinivasan, R., Mauder, M., Worthy, D., Sweeney, C., & Metzger, S. (2018). The challenge of reconciling bottom-up agricultural methane emissions inventories with top-down measurements. *Agricultural And Forest Meteorology*, 248(May 2017), 48–59. <https://doi.org/10.1016/j.agrformet.2017.09.003>
- Domingo, N. G. G., Balasubramanian, S., Thakrar, S. K., Clark, M. A., Adams, P. J., Marshall, J. D., Muller, N. Z., Pandis, S. N., Polasky, S., Robinson, A. L., Tessum, C. W., Tilman, D., Tschopen, P., & Hill, J. D. (2021). Air quality–related health damages of food. *Proceedings*



- of the National Academy of Sciences, 118(20), e2013637118. <https://doi.org/10.1073/pnas.2013637118>
- Donahue, N. M., Epstein, S. A., Pandis, S. N., & Robinson, A. L. (2011). *And Physics A two-dimensional volatility basis set: 1. Organic-aerosol mixing thermodynamics*. 3303–3318. <https://doi.org/10.5194/acp-11-3303-2011>
- Eberwein, J. R., Homyak, P. M., Carey, C. J., Aronson, E. L., & Jenerette, G. D. (2020). Large nitrogen oxide emission pulses from desert soils and associated microbiomes. *Biogeochemistry*, 149(3), 239–250. <https://doi.org/10.1007/s10533-020-00672-9>
- Effective Mentoring in STEMM: Practice, Research, and Future Directions: Proceedings of a Workshop in Brief* (with National Academies of Sciences, Engineering, and Medicine). (2017). National Academies Press. <https://doi.org/10.17226/24815>
- Eilerman, S. J., Peischl, J., Neuman, J. A., Ryerson, T. B., Aikin, K. C., Holloway, M. W., Zondlo, M. A., Golston, L. M., Pan, D., Floerchinger, C., & Herndon, S. (2016). Characterization of ammonia, methane, and nitrous oxide emissions from concentrated animal feeding operations in northeastern Colorado. *Environmental Science & Technology*, 50(20), 10885–10893. <https://doi.org/10.1021/acs.est.6b02851>
- Erismann, J. W., Sutton, M. A., Galloway, J., Klimont, Z., & Winiwarter, W. (2008). How a century of ammonia synthesis changed the world. *Nature Geoscience*, 1(10), Article 10. <https://doi.org/10.1038/ngeo325>
- Estrada, M., Eroy-Reveles, A., & Matsui, J. (2018). The Influence of Affirming Kindness and Community on Broadening Participation in STEM Career Pathways. *Social Issues and Policy Review*, 12(1), 258–297. <https://doi.org/10.1111/sipr.12046>
- Fischer, E. V., Adams, A., Barnes, R., Bloodhart, B., Burt, M., Clinton, S., Godfrey, E., Pollack, I., & Hernandez, P. R. (2018, April 3). *Welcoming Women into the Geosciences*. Eos. <http://eos.org/science-updates/welcoming-women-into-the-geosciences>
- Fischer, E. V., Bloodhart, B., Rasmussen, K., Pollack, I. B., Hastings, M. G., Marin-Spiotta, E., Desai, A. R., Schwarz, J. P., Nesbitt, S., & Hence, D. (2021). Leveraging Field-Campaign Networks to Identify Sexual Harassment in Atmospheric Science and Pilot Promising Interventions. *Bulletin of the American Meteorological Society*, 102(11), E2137–E2150. <https://doi.org/10.1175/BAMS-D-19-0341.1>
- Franks, P. J., Bonan, G. B., Berry, J. A., Lombardozzi, D. L., Holbrook, N. M., Herold, N., & Oleson, K. W. (2018). Comparing optimal and empirical stomatal conductance models for application in Earth system models. *Global Change Biology*, 24(12), 5708–5723. <https://doi.org/10.1111/gcb.14445>
- Gao, Y., Wu, Y., Guo, X., Kou, W., Zhang, S., Leung, L. R., Chen, X., Lu, J., Diffenbaugh, N. S., Horton, D. E., Yao, X., Gao, H., & Wu, L. (2023). More Frequent and Persistent Heatwaves Due To Increased Temperature Skewness Projected by a High-Resolution Earth System Model. *Geophysical Research Letters*, 50(18), e2023GL105840. <https://doi.org/10.1029/2023GL105840>
- Garcia, E., Hill, T. C. J., Prenni, A. J., DeMott, P. J., Franc, G. D., & Kreidenweis, S. M. (2012). Biogenic ice nuclei in boundary layer air over two U.S. High Plains agricultural regions. *Journal of Geophysical Research: Atmospheres*, 117(D18). <https://doi.org/10.1029/2012JD018343>
- Ge, X., Wexler, A. S., & Clegg, S. L. (2011). Atmospheric amines – Part I. A review. *Atmospheric Environment*, 45(3), 524–546. <https://doi.org/10.1016/j.atmosenv.2010.10.012>

- Geddes, J. A., Pusede, S. E., & Wong, A. Y. H. (2022). Changes in the relative importance of biogenic isoprene and soil NO<sub>x</sub> emissions on ozone concentrations in nonattainment areas of the United States. *Journal of Geophysical Research: Atmospheres*, 127(13), e2021JD036361. <https://doi.org/10.1029/2021JD036361>
- Golston, L. M., Pan, D., Sun, K., Tao, L., Zondlo, M. A., Eilerman, S. J., Peischl, J., Neuman, J. A., & Floerchinger, C. (2020). Variability of ammonia and methane emissions from animal feeding operations in northeastern Colorado. *Environmental Science & Technology*, 54(18), 11015–11024. <https://doi.org/10.1021/acs.est.0c00301>
- Goodkind, A. L., Tessum, C. W., Coggins, J. S., Hill, J. D., & Marshall, J. D. (2019). *Fine-scale damage estimates of particulate matter air pollution reveal opportunities for location-specific mitigation of emissions*. <https://doi.org/10.1073/pnas.1816102116>
- Gordon, H., Kirkby, J., Baltensperger, U., Bianchi, F., Breitenlechner, M., Curtius, J., Dias, A., Dommen, J., Donahue, N. M., Dunne, E. M., Duplissy, J., Ehrhart, S., Flagan, R. C., Frege, C., Fuchs, C., Hansel, A., Hoyle, C. R., Kulmala, M., Kürten, A., ... Carslaw, K. S. (2017). Causes and importance of new particle formation in the present-day and preindustrial atmospheres. *Journal of Geophysical Research: Atmospheres*, 122(16), 8739–8760. <https://doi.org/10.1002/2017JD026844>
- Gu, B., Zhang, L., Van Dingenen, R., Vieno, M., Van Grinsven, H. J., Zhang, X., Zhang, S., Chen, Y., Wang, S., Ren, C., Rao, S., Holland, M., Winiwarter, W., Chen, D., Xu, J., & Sutton, M. A. (2021). Abating ammonia is more cost-effective than nitrogen oxides for mitigating PM<sub>2.5</sub> air pollution. *Science*, 374(6568), 758–762. <https://doi.org/10.1126/science.abf8623>
- Guenet, B., Gabrielle, B., Chenu, C., Arrouays, D., Balesdent, J., Bernoux, M., Bruni, E., Caliman, J.-P., Cardinael, R., Chen, S., Ciais, P., Desbois, D., Fouche, J., Frank, S., Henault, C., Lugato, E., Naipal, V., Nesme, T., Obersteiner, M., ... Zhou, F. (2021). Can N<sub>2</sub>O emissions offset the benefits from soil organic carbon storage? *Global Change Biology*, 27(2), 237–256. <https://doi.org/10.1111/gcb.15342>
- Guo, H., Sullivan, A. P., Campuzano-Jost, P., Schroder, J. C., Lopez-Hilfiker, F. D., Dibb, J. E., Jimenez, J. L., Thornton, J. A., Brown, S. S., Nenes, A., & Weber, R. J. (2016). Fine particle pH and the partitioning of nitric acid during winter in the northeastern United States. *Journal of Geophysical Research: Atmospheres*, 121(17), 10,355–10,376. <https://doi.org/10.1002/2016JD025311>
- Guo, L., Chen, J., Luo, D., Liu, S., Lee, H. J., Motallebi, N., Fong, A., Deng, J., Rasool, Q. Z., Avise, J. C., Kuwayama, T., Croes, B. E., & FitzGibbon, M. (2020). Assessment of nitrogen oxide emissions and San Joaquin Valley PM<sub>2.5</sub> impacts from soils in California. *Journal of Geophysical Research: Atmospheres*, 125(24), e2020JD033304. <https://doi.org/10.1029/2020JD033304>
- Hacker, J. M., Chen, D., Bai, M., Ewenz, C., Junkermann, W., Lieff, W., McManus, B., Neininger, B., Sun, J., Coates, T., Denmead, T., Flesch, T., McGinn, S., Hill, J., Hacker, J. M., Chen, D., Bai, M., Ewenz, C., Junkermann, W., ... Hill, J. (2016). Using airborne technology to quantify and apportion emissions of CH<sub>4</sub> and NH<sub>3</sub> from feedlots. *Animal Production Science*, 56(3), 190–203. <https://doi.org/10.1071/AN15513>
- Hall, S. J., Reyes, L., Huang, W., & Homyak, P. M. (2018). Wet Spots as Hotspots: Moisture Responses of Nitric and Nitrous Oxide Emissions From Poorly Drained Agricultural Soils. *Journal of Geophysical Research: Biogeosciences*, 123(12), 3589–3602. <https://doi.org/10.1029/2018JG004629>

- Handan-Nader, C., & Ho, D. E. (2019). Deep learning to map concentrated animal feeding operations. *Nature Sustainability*, 2(4), Article 4. <https://doi.org/10.1038/s41893-019-0246-x>
- Hannun, R. A., Wolfe, G. M., Kawa, S. R., Hanisco, T. F., Newman, P. A., Alfieri, J. G., Barrick, J., Clark, K. L., DiGangi, J. P., Diskin, G. S., King, J., Kustas, W. P., Mitra, B., Noormets, A., Nowak, J. B., Thornhill, K. L., & Vargas, R. (2020). Spatial heterogeneity in CO<sub>2</sub>, CH<sub>4</sub>, and energy fluxes: Insights from airborne eddy covariance measurements over the Mid-Atlantic region. *Environmental Research Letters*, 15(3), 35008. <https://doi.org/10.1088/1748-9326/ab7391>
- Hayek, M. N., & Miller, S. M. (2021). Underestimates of methane from intensively raised animals could undermine goals of sustainable development. *Environmental Research Letters*, 16(6), 063006. <https://doi.org/10.1088/1748-9326/ac02ef>
- Hernandez, P. R., Adams, A. S., Barnes, R. T., Bloodhart, B., Burt, M., Clinton, S. M., Du, W., Henderson, H., Pollack, I., & Fischer, E. V. (2020). Inspiration, inoculation, and introductions are all critical to successful mentorship for undergraduate women pursuing geoscience careers. *Communications Earth & Environment*, 1(1), Article 1. <https://doi.org/10.1038/s43247-020-0005-y>
- Hernandez, P. R., Bloodhart, B., Adams, A. S., Barnes, R. T., Burt, M., Clinton, S. M., Du, W., Godfrey, E., Henderson, H., Pollack, I. B., & Fischer, E. V. (2018). Role modeling is a viable retention strategy for undergraduate women in the geosciences. *Geosphere*, 14(6), 2585–2593. <https://doi.org/10.1130/GES01659.1>
- Hernandez, P. R., Bloodhart, B., Barnes, R. T., Adams, A. S., Clinton, S. M., Pollack, I., Godfrey, E., Burt, M., & Fischer, E. V. (2017). Promoting professional identity, motivation, and persistence: Benefits of an informal mentoring program for female undergraduate students. *PLOS ONE*, 12(11), e0187531. <https://doi.org/10.1371/journal.pone.0187531>
- Herrera, S. A., Diskin, G. S., Harward, C., Sachse, G., De Wekker, S. F. J., Yang, M., Choi, Y., Wisthaler, A., Mallia, D. V., & Pusede, S. E. (2021). Wintertime nitrous oxide emissions in the San Joaquin Valley of California estimated from aircraft observations. *Environmental Science & Technology*, 55(8), 4462–4473. <https://doi.org/10.1021/acs.est.0c08418>
- Hiller, R. V., Neininger, B., Brunner, D., Gerbig, C., Bretscher, D., Künzle, T., Buchmann, N., & Eugster, W. (2014). Aircraft-based CH<sub>4</sub> flux estimates for validation of emissions from an agriculturally dominated area in Switzerland. *Journal of Geophysical Research: Atmospheres*, 119(8), 4874–4887. <https://doi.org/10.1002/2013jd020918>
- Huber, D. E., Steiner, A. L., & Kort, E. A. (2020). Daily cropland soil NO<sub>x</sub> emissions identified by TROPOMI and SMAP. *Geophysical Research Letters*, 47(22), e2020GL089949. <https://doi.org/10.1029/2020GL089949>
- Huber, D. E., Steiner, A. L., & Kort, E. A. (2023). Sensitivity of Modeled Soil NO<sub>x</sub> Emissions to Soil Moisture. *Journal of Geophysical Research: Atmospheres*, 128(7), e2022JD037611. <https://doi.org/10.1029/2022JD037611>
- Hudman, R. C., Russell, A. R., Valin, L. C., & Cohen, R. C. (2010). Interannual variability in soil nitric oxide emissions over the United States as viewed from space. *Atmospheric Chemistry And Physics*, 10(20), 9943–9952. <https://doi.org/10.5194/acp-10-9943-2010>
- Hutjes, R. W. A., Vellinga, O. S., Gioli, B., & Miglietta, F. (2010). Dis-aggregation of airborne flux measurements using footprint analysis. *Agricultural and Forest Meteorology*, 150(7), 966–983. <https://doi.org/10.1016/j.agrformet.2010.03.004>

- Juncosa Calahorano, J. F., Pollack, I. B., Sullivan, A. P., Roscioli, J. R., Caulton, D. R., McCabe, M. E., Li, E., Pierce, J. R., & Fischer, E. V. (2023). Summertime airborne measurements of ammonia emissions from cattle feedlots and dairies in northeastern Colorado. *Journal of Geophysical Research*, submitted (M.S. no. 2023JD039043).
- Juncosa Calahorano, J. F., Sullivan, A. P., Pollack, I. B., Roscioli, R., McCabe, M. E., Steinmann, K., Caulton, D. R., Li, E., Pierce, J. R., Naimie, L., Pan, D., Collett, J., & Fischer, E. V. (2024a). Anatomy of a summertime upslope event in northeastern Colorado: Ammonia (NH<sub>3</sub>) transport to the Rocky Mountains. *Environmental Science & Technology*, es-2023-10902r.R1.
- Juncosa Calahorano, J. F., Sullivan, A. P., Pollack, I. B., Roscioli, R., McCabe, M. E., Steinmann, K., Caulton, D. R., Li, E., Pierce, J. R., Naimie, L., Pan, D., Collett, J., & Fischer, E. V. (2024b). Near source ammonia (NH<sub>3</sub>) deposition observed from in situ measurements in plumes from large beef cattle facilities. *Journal Of Geophysical Research-Atmospheres*, 2024JD041559 (in review).
- Justice40 Initiative / Environmental Justice. (2022). The White House. <https://www.whitehouse.gov/environmentaljustice/justice40/>
- Karamchandani, P., Seigneur, C., Vijayaraghavan, K., & Wu, S.-Y. (2002). Development and application of a state-of-the-science plume-in-grid model. *Journal of Geophysical Research: Atmospheres*, 107(D19), ACH 12-1-ACH 12-13. <https://doi.org/10.1029/2002JD002123>
- Karl, T., Apel, E., Hodzic, A., Riemer, D. D., Blake, D. R., & Wiedinmyer, C. (2009). Emissions of volatile organic compounds inferred from airborne flux measurements over a megacity. *Atmospheric Chemistry And Physics*, 9(1), 271–285.
- Karl, T., Guenther, A., Turnipseed, A., Patton, E. G., & Jardine, K. (2008). Chemical sensing of plant stress at the ecosystem scale. *Biogeosciences*, 5(5), 1287–1294. <https://doi.org/10.5194/bg-5-1287-2008>
- Karydis, V. A., Tsimpidi, A. P., Pozzer, A., Astitha, M., & Lelieveld, J. (2016). Effects of mineral dust on global atmospheric nitrate concentrations. *Atmospheric Chemistry and Physics*, 16(3), 1491–1509. <https://doi.org/10.5194/acp-16-1491-2016>
- Katzman, T. L., Rutter, A. P., Schauer, J. J., Lough, G. C., Kolb, C. J., & Klooster, S. V. (2010). PM<sub>2.5</sub> and PM<sub>10-2.5</sub> Compositions during Wintertime Episodes of Elevated PM Concentrations across the Midwestern USA. *Aerosol and Air Quality Research*, 10(2), 140–153. <https://doi.org/10.4209/aaqr.2009.10.0063>
- Kelly, J. T., Parworth, C. L., Zhang, Q., Miller, D. J., Sun, K., Zondlo, M. A., Baker, K. R., Wisthaler, A., Nowak, J. B., Pusede, S. E., Cohen, R. C., Weinheimer, A. J., Beyersdorf, A. J., Tonnesen, G. S., Bash, J. O., Valin, L. C., Crawford, J. H., Fried, A., & Walega, J. G. (2018). Modeling NH<sub>4</sub>NO<sub>3</sub> over the San Joaquin Valley during the 2013 DISCOVER-AQ campaign. *Journal of Geophysical Research: Atmospheres*, 123(9), 4727–4745. <https://doi.org/10.1029/2018JD028290>
- Kharol, S. K., Shephard, M. W., McLinden, C. A., Zhang, L., Sioris, C. E., O'Brien, J. M., Vet, R., Cady-Pereira, K. E., Hare, E., Siemons, J., & Krotkov, N. A. (2018). Dry deposition of reactive nitrogen from satellite observations of ammonia and nitrogen dioxide over North America. *Geophysical Research Letters*, 45(2), 1157–1166. <https://doi.org/10.1002/2017GL075832>
- Kiendler-scharr, A., Wildt, J., Dal Maso, M., Hohaus, T., Kleist, E., Mentel, T. F., Tillmann, R., Uerlings, R., Schurr, U., Wahner, A., Maso, M. D., Hohaus, T., Kleist, E., Mentel, T. F.,

- Kiendler-scharr, A., Tillmann, R., Uerlings, R., Schurr, U., & Wahner, A. (2009). New particle formation in forests inhibited by isoprene emissions. *Nature*, 461(7262), 381–384. <https://doi.org/10.1038/nature08292>
- Kille, N., Baidar, S., Handley, P., Ortega, I., Sinreich, R., Cooper, O. R., Hase, F., Hannigan, J. W., Pfister, G., & Volkamer, R. (2017). The CU mobile Solar Occultation Flux instrument: Structure functions and emission rates of NH<sub>3</sub>, NO<sub>2</sub> and C<sub>2</sub>H<sub>6</sub>. *Atmospheric Measurement Techniques*, 10(1), 373–392. <https://doi.org/10.5194/amt-10-373-2017>
- Kim, H. S., Song, C. H., Park, R. S., Huey, G., & Ryu, J. Y. (2009). Investigation of ship-plume chemistry using a newly-developed photochemical/dynamic ship-plume model. *Atmospheric Chemistry and Physics*, 9(19), 7531–7550. <https://doi.org/10.5194/acp-9-7531-2009>
- Kim, Y., Park, O., Park, S. H., Kim, M. J., Kim, J.-J., Choi, J.-Y., Lee, D., Cho, S., & Shim, S. (2022). PM<sub>2.5</sub> pH estimation in Seoul during the KORUS-AQ campaign using different thermodynamic models. *Atmospheric Environment*, 268, 118787. <https://doi.org/10.1016/j.atmosenv.2021.118787>
- Kljun, N., Calanca, P., Rotach, M. W., & Schmid, H. P. (2015). A simple two-dimensional parameterisation for Flux Footprint Prediction (FFP). *Geoscientific Model Development*, 8(11), 3695–3713. <https://doi.org/10.5194/gmd-8-3695-2015>
- Kuhn, U., Sintermann, J., Spirig, C., Jocher, M., Ammann, C., & Neftel, A. (2011). Basic biogenic aerosol precursors: Agricultural source attribution of volatile amines revised. *Geophysical Research Letters*, 38(16), L16811. <https://doi.org/10.1029/2011GL047958>
- Kupper, T., Häni, C., Neftel, A., Kincaid, C., Bühler, M., Amon, B., & VanderZaag, A. (2020). Ammonia and greenhouse gas emissions from slurry storage—A review. *Agriculture, Ecosystems & Environment*, 300, 106963. <https://doi.org/10.1016/j.agee.2020.106963>
- Lambert, A., Hallar, A. G., Garcia, M., Strong, C., Andrews, E., & Hand, J. L. (2020). Dust Impacts of Rapid Agricultural Expansion on the Great Plains. *Geophysical Research Letters*, 47(20), e2020GL090347. <https://doi.org/10.1029/2020GL090347>
- Lavaine, E., Majerus, P., & Treich, N. (2020). Health, air pollution, and animal agriculture. *Review of Agricultural, Food and Environmental Studies*, 101(4), 517–528. <https://doi.org/10.1007/s41130-020-00124-w>
- Lawrence, N. C., Tenesaca, C. G., VanLoocke, A., & Hall, S. J. (2021). Nitrous oxide emissions from agricultural soils challenge climate sustainability in the US Corn Belt. *Proceedings of the National Academy of Sciences*, 118(46), e2112108118. <https://doi.org/10.1073/pnas.2112108118>
- Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., & Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*, 525(7569), Article 7569. <https://doi.org/10.1038/nature15371>
- Leytem, A. B., Bjorneberg, D. L., Rotz, C. A., Moraes, L. E., Kebreab, E., & Dungan, R. S. (2018). Ammonia emissions from dairy lagoons in the Western U.S. *Transactions of the ASABE*, 61(3), 1001–1015. <https://doi.org/10.13031/trans.12646>
- Leytem, A. B., Dungan, R. S., & Bjorneberg, D. L. (2009). Seasonal and spatial distribution of ambient ammonia concentrations measured at a large open-lot dairy. *The Professional Animal Scientist*, 25(6), 786–793. [https://doi.org/10.15232/S1080-7446\(15\)30790-7](https://doi.org/10.15232/S1080-7446(15)30790-7)
- Li, E., Pierce, J. R., Juncosa Calahorrano, J. F., Sullivan, A. P., Pollack, I. B., Roscioli, J. R., Caulton, D. R., McCabe, M. E., Jathar, S. H., & Fischer, E. V. (2024). Inorganic Nitrogen Gas-Aerosol Partitioning in and Around Animal Feeding Operations in Northeastern



- Colorado in Late Summer 2021. *Journal of Geophysical Research: Atmospheres*, 129(12), e2023JD040507. <https://doi.org/10.1029/2023JD040507>
- Li, J., Carlson, B. E., Yung, Y. L., Lv, D., Hansen, J., Penner, J. E., Liao, H., Ramaswamy, V., Kahn, R. A., Zhang, P., Dubovik, O., Ding, A., Lacis, A. A., Zhang, L., & Dong, Y. (2022). Scattering and absorbing aerosols in the climate system. *Nature Reviews Earth & Environment*, 3(6), 363–379. <https://doi.org/10.1038/s43017-022-00296-7>
- Li, Y., Thompson, T. M., Van Damme, M., Chen, X., Benedict, K. B., Shao, Y., Day, D., Boris, A., Sullivan, A. P., Ham, J., Whitburn, S., Clarisse, L., Coheur, P.-F., & Collett Jr., J. L. (2017). Temporal and spatial variability of ammonia in urban and agricultural regions of northern Colorado, United States. *Atmospheric Chemistry and Physics*, 17(10), 6197–6213. <https://doi.org/10.5194/acp-17-6197-2017>
- Liu, X., Zhang, X., Huang, Y., Chen, K., Wang, L., Ma, J., Huang, T., Zhao, Y., Gao, H., Tao, S., Liu, J., Jian, X., & Luo, J. (2021). The direct radiative forcing impact of agriculture-emitted black carbon associated with India's green revolution. *Earth's Future*, 9(6), e2021EF001975. <https://doi.org/10.1029/2021EF001975>
- Loubet, B., Buysse, P., Gonzaga-Gomez, L., Lafouge, F., Ciuraru, R., Decuq, C., Kammer, J., Bsaibes, S., Boissard, C., Durand, B., Gueudet, J.-C., Fanucci, O., Zurfluh, O., Abis, L., Zannoni, N., Truong, F., Baisnée, D., Sarda-Estève, R., Staudt, M., & Gros, V. (2022). Volatile organic compound fluxes over a winter wheat field by PTR-Qi-TOF-MS and eddy covariance. *Atmospheric Chemistry and Physics*, 22(4), 2817–2842. <https://doi.org/10.5194/acp-22-2817-2022>
- Luo, L., Ran, L., Rasool, Q. Z., & Cohan, D. S. (2022). Integrated modeling of U.S. agricultural soil emissions of reactive nitrogen and associated impacts on air pollution, health, and climate. *Environmental Science & Technology*, 56(13), 9265–9276. <https://doi.org/10.1021/acs.est.1c08660>
- Malm, W. C., Sisler, J. F., Huffman, D., Eldred, R. A., & Cahill, T. A. (1994). Spatial and seasonal trends in particle concentration and optical extinction in the United States. *Journal of Geophysical Research: Atmospheres*, 99(D1), 1347–1370. <https://doi.org/10.1029/93JD02916>
- Maltz, M. R., Carey, C. J., Freund, H. L., Botthoff, J. K., Hart, S. C., Stajich, J. E., Aarons, S. M., Aciego, S. M., Blakowski, M., Dove, N. C., Barnes, M. E., Pombubpa, N., & Aronson, E. L. (2022). Landscape topography and regional drought alters dust microbiomes in the Sierra Nevada of California. *Frontiers in Microbiology*, 13, 856454. <https://doi.org/10.3389/fmicb.2022.856454>
- Mao, J., Carlton, A., Cohen, R. C., Brune, W. H., Brown, S. S., Wolfe, G. M., Jimenez, J. L., Pye, H. O. T., Lee Ng, N., Xu, L., McNeill, V. F., Tsigaridis, K., McDonald, B. C., Warneke, C., Guenther, A., Alvarado, M. J., de Gouw, J., Mickley, L. J., Lebensperger, E. M., ... Horowitz, L. W. (2018). Southeast Atmosphere Studies: Learning from model-observation syntheses. *Atmospheric Chemistry And Physics*, 18(4), 2615–2651. <https://doi.org/10.5194/acp-18-2615-2018>
- Marin-Spiotta, E., Barnes, R. T., Berhe, A. A., Hastings, M. G., Mattheis, A., Schneider, B., & Williams, B. M. (2020). Hostile climates are barriers to diversifying the geosciences. *Advances in Geosciences*, 53, 117–127. Diversity and equality in the geosciences (EGU2019 EOS6.1 & US4, AGU2018 ED41B, JpGU2019 U-02) -. <https://doi.org/10.5194/adgeo-53-117-2020>

- Marin-Spiotta, E., Diaz-Vallejo, E. J., Barnes, R. T., Mattheis, A., Schneider, B., Berhe, A. A., Hastings, M. G., Williams, B. M., & Magley, V. (2023). Exclusionary Behaviors Reinforce Historical Biases and Contribute to Loss of Talent in the Earth Sciences. *Earth's Future*, 11(3), e2022EF002912. <https://doi.org/10.1029/2022EF002912>
- McCabe, M. E., Pollack, I. B., Fischer, E. V., & Caulton, D. R. (2023). Technical note: Isolating methane emissions from animal feeding operations in an interfering location. *Atmospheric Chemistry And Physics*, 23(13), 7479–7494. <https://doi.org/10.5194/acp-23-7479-2023>
- McGrath, J. M., Betzelberger, A. M., Wang, S., Shook, E., Zhu, X.-G., Long, S. P., & Ainsworth, E. A. (2015). An analysis of ozone damage to historical maize and soybean yields in the United States. *Proceedings of the National Academy of Sciences*, 112(46), 14390–14395. <https://doi.org/10.1073/pnas.1509777112>
- Medel-Jiménez, F., Piringer, G., Gronauer, A., Barta, N., Neugschwandtner, R. W., Krexner, T., & Kral, I. (2022). Modelling soil emissions and precision agriculture in fertilization life cycle assessment—A case study of wheat production in Austria. *Journal of Cleaner Production*, 380, 134841. <https://doi.org/10.1016/j.jclepro.2022.134841>
- Mensah, A. A., Holzinger, R., Otjes, R., Trimborn, A., Mentel, T. F., ten Brink, H., Henzing, B., & Kiendler-Scharr, A. (2012). Aerosol chemical composition at Cabauw, The Netherlands as observed in two intensive periods in May 2008 and March 2009. *Atmospheric Chemistry and Physics*, 12(10), 4723–4742. <https://doi.org/10.5194/acp-12-4723-2012>
- Metzger, S., Junkermann, W., Mauder, M., Butterbach-Bahl, K., Widemann, B. T. Y., Neidl, F., Schafer, K., Wieneke, S., Zheng, X. H., Schmid, H. P., Foken, T., Climate, B., & Development, M. (2013). Spatially explicit regionalization of airborne flux measurements using environmental response functions. *Biogeosciences*, 10(4), 2193–2217. <https://doi.org/10.5194/bg-10-2193-2013>
- Miller, D. J., Sun, K., Tao, L., Pan, D., Zondlo, M. A., Nowak, J. B., Liu, Z., Diskin, G., Sachse, G., Beyersdorf, A., Ferrare, R., & Scarino, A. J. (2015). Ammonia and methane dairy emission plumes in the San Joaquin Valley of California from individual feedlot to regional scales. *Journal of Geophysical Research: Atmospheres*, 120(18), 9718–9738. <https://doi.org/10.1002/2015JD023241>
- Misztal, P. K., Avise, J. C., Karl, T., Scott, K., Jonsson, H. H., Guenther, A. B., & Goldstein, A. H. (2016). Evaluation of regional isoprene emission factors and modeled fluxes in California. *Atmospheric Chemistry And Physics*, 16(15), 9611–9628. <https://doi.org/10.5194/acp-16-9611-2016>
- Misztal, P. K., Karl, T., Weber, R., Jonsson, H. H., Guenther, A. B., & Goldstein, A. H. (2014). *Airborne flux measurements of biogenic isoprene over California*. 10631–10647. <https://doi.org/10.5194/acp-14-10631-2014>
- Montoya-Aguilera, J., Hinks, M. L., Aiona, P. K., Wingen, L. M., Horne, J. R., Zhu, S., Dabdub, D., Laskin, A., Laskin, J., Lin, P., & Nizkorodov, S. A. (2018). Reactive Uptake of Ammonia by Biogenic and Anthropogenic Organic Aerosols. In *Multiphase Environmental Chemistry in the Atmosphere* (Vol. 1299, pp. 127–147). American Chemical Society. <https://doi.org/10.1021/bk-2018-1299.ch007>
- Morris, V. R. (2021). Combating Racism in the Geosciences: Reflections From a Black Professor. *AGU Advances*, 2(1), e2020AV000358. <https://doi.org/10.1029/2020AV000358>
- MOSAICS. (2024). <https://science.nasa.gov/researchers/smd-bridge-program/>
- NASA SPoRT-LiS Soil Moisture Products. (2024). Drought.Gov. <https://www.drought.gov/data-maps-tools/nasa-sport-lis-soil-moisture-products>

- Nenes, A., Pandis, S. N., Kanakidou, M., Russell, A. G., Song, S., Vasilakos, P., & Weber, R. J. (2021). Aerosol acidity and liquid water content regulate the dry deposition of inorganic reactive nitrogen. *Atmospheric Chemistry and Physics*, 21(8), 6023–6033. <https://doi.org/10.5194/acp-21-6023-2021>
- Niederbacher, B., Winkler, J. B., & Schnitzler, J. P. (2015). Volatile organic compounds as non-invasive markers for plant phenotyping. *Journal of Experimental Botany*, 66(18), 5403–5416. <https://doi.org/10.1093/jxb/erv219>
- Novak, G. A., Fite, C. H., Holmes, C. D., Veres, P. R., Neuman, J. A., Faloona, I., Thornton, J. A., Wolfe, G. M., Vermeuel, M. P., Jernigan, C. M., Peischl, J., Ryerson, T. B., Thompson, C. R., Bourgeois, I., Warneke, C., Gkatzelis, G. I., Coggon, M. M., Sekimoto, K., Bui, T. P., ... Bertram, T. H. (2021). Rapid cloud removal of dimethyl sulfide oxidation products limits SO<sub>2</sub> and cloud condensation nuclei production in the marine atmosphere. *Proceedings of the National Academy of Sciences*, 118(42). <https://doi.org/10.1073/pnas.2110472118>
- Nowak, J. B., Neuman, J. A., Bahreini, R., Middlebrook, A. M., Holloway, J. S., McKeen, S. A., Parrish, D. D., Ryerson, T. B., & Trainer, M. (2012). Ammonia sources in the California South Coast Air Basin and their impact on ammonium nitrate formation. *Geophysical Research Letters*, 39(7). <https://doi.org/10.1029/2012GL051197>
- Oertel, C., Matschullat, J., Zurba, K., Zimmermann, F., & Erasmi, S. (2016). Greenhouse gas emissions from soils—A review. *Geochemistry*, 76(3), 327–352. <https://doi.org/10.1016/j.chemer.2016.04.002>
- Oikawa, P. Y., Ge, C., Wang, J., Eberwein, J. R., Liang, L. L., Allsman, L. A., Grantz, D. A., & Jenerette, G. D. (2015). Unusually high soil nitrogen oxide emissions influence air quality in a high-temperature agricultural region. *Nature Communications*, 6(1), Article 1. <https://doi.org/10.1038/ncomms9753>
- Park, M., Joo, H. S., Lee, K., Jang, M., Kim, S. D., Kim, I., Borlaza, L. J. S., Lim, H., Shin, H., Chung, K. H., Choi, Y.-H., Park, S. G., Bae, M.-S., Lee, J., Song, H., & Park, K. (2018). Differential toxicities of fine particulate matters from various sources. *Scientific Reports*, 8(1), Article 1. <https://doi.org/10.1038/s41598-018-35398-0>
- Pfannerstill, E. Y., Arata, C., Zhu, Q., Schulze, B. C., Woods, R., Seinfeld, J. H., Bucholtz, A., Cohen, R. C., & Goldstein, A. H. (2023). Volatile organic compound fluxes in the agricultural San Joaquin Valley – spatial distribution, source attribution, and inventory comparison. *Atmospheric Chemistry and Physics*, 23(19), 12753–12780. <https://doi.org/10.5194/acp-23-12753-2023>
- Pleim, J. E., Bash, J. O., Walker, J. T., & Cooter, E. J. (2013). Development and evaluation of an ammonia bidirectional flux parameterization for air quality models. *Journal of Geophysical Research: Atmospheres*, 118(9), 3794–3806. <https://doi.org/10.1002/jgrd.50262>
- Pleim, J. E., Ran, L., Appel, W., Shephard, M. W., & Cady-Pereira, K. (2019). New bidirectional ammonia flux model in an air quality model coupled with an agricultural model. *Journal of Advances in Modeling Earth Systems*, 11(9), 2934–2957. <https://doi.org/10.1029/2019MS001728>
- Pollack, I. B., Lindaas, J., Roscioli, J. R., Agnese, M., Permar, W., Hu, L., & Fischer, E. V. (2019). Evaluation of ambient ammonia measurements from a research aircraft using a closed-path QC-TILDAS operated with active continuous passivation. *Atmospheric Measurement Techniques*, 12(7), 3717–3742. <https://doi.org/10.5194/amt-12-3717-2019>

- Pollack, I. B., McCabe, M. E., Caulton, D. R., & Fischer, E. V. (2022). Enhancements in ammonia and methane from agricultural sources in the northeastern Colorado Front Range using observations from a small research aircraft. *Environmental Science & Technology*, 56(4), 2236–2247. <https://doi.org/10.1021/acs.est.1c07382>
- Poulter, B., Adams-Metayer, F. M., Amaral, C., Barenblitt, A., Campbell, A., Charles, S. P., Roman-Cuesta, R. M., D’Ascanio, R., Delaria, E. R., Doughty, C., Fatoyinbo, T., Gewirtzman, J., Hanisco, T. F., Hull, M., Kawa, S. R., Hannun, R., Lagomasino, D., Lait, L., Malone, S. L., ... Zhang, Z. (2023). Multi-scale observations of mangrove blue carbon ecosystem fluxes: The NASA Carbon Monitoring System BlueFlux field campaign. *Environmental Research Letters*, 18(7), 075009. <https://doi.org/10.1088/1748-9326/acdae6>
- Rappert, S., & Müller, R. (2005). Odor compounds in waste gas emissions from agricultural operations and food industries. *Waste Management*, 25(9), 887–907. <https://doi.org/10.1016/j.wasman.2005.07.008>
- Rasool, Q. Z., Zhang, R., Lash, B., Cohan, D. S., Cooter, E. J., Bash, J. O., & Lamsal, L. N. (2016). Enhanced representation of soil NO emissions in the Community Multiscale Air Quality (CMAQ) model version 5.0.2. *Geoscientific Model Development*, 9(9), 3177–3197. <https://doi.org/10.5194/gmd-9-3177-2016>
- Ravishankara, A. R., Daniel, J. S., & Portmann, R. W. (2009). Nitrous oxide (N<sub>2</sub>O): The dominant ozone-depleting substance emitted in the 21<sup>st</sup> century. *Science*, 326(5949), 123–125. <https://doi.org/10.1126/science.1176985>
- Ruhl, J. B. (2000). Farms, their environmental harms, and environmental law. *Ecology Law Quarterly*, 27(2), 263–348. <https://doi.org/10.2139/ssrn.186848>
- Schiferl, L. D., Heald, C. L., Nowak, J. B., Holloway, J. S., Neuman, J. A., Bahreini, R., Pollack, I. B., Ryerson, T. B., Wiedinmyer, C., & Murphy, J. G. (2014). An investigation of ammonia and inorganic particulate matter in California during the CalNex campaign. *Journal of Geophysical Research: Atmospheres*, 119(4), 1883–1902. <https://doi.org/10.1002/2013JD020765>
- Schobesberger, S., D’Ambro, E. L., Vettikkat, L., Lee, B. H., Peng, Q., Bell, D. M., Shilling, J. E., Shrivastava, M., Pekour, M., Fast, J., & Thornton, J. A. (2022). Airborne flux measurements of ammonia over the Southern Great Plains using chemical ionization mass spectrometry. *Atmospheric Measurement Techniques Discussions*, 1–35. <https://doi.org/10.5194/amt-2022-244>
- Schulze, B. C., Ward, R. X., Pfannerstill, E. Y., Zhu, Q., Arata, C., Place, B., Nussbaumer, C., Wooldridge, P., Woods, R., Bucholtz, A., Cohen, R. C., Goldstein, A. H., Wennberg, P. O., & Seinfeld, J. H. (2023). Methane Emissions from Dairy Operations in California’s San Joaquin Valley Evaluated Using Airborne Flux Measurements. *Environmental Science & Technology*, 57(48), 19519–19531. <https://doi.org/10.1021/acs.est.3c03940>
- Seinfeld, J. H., Bretherton, C., Carslaw, K. S., Coe, H., DeMott, P. J., Dunlea, E. J., Feingold, G., Ghan, S., Guenther, A. B., Kahn, R., Kraucunas, I., Kreidenweis, S. M., Molina, M. J., Nenes, A., Penner, J. E., Prather, K. A., Ramanathan, V., Ramaswamy, V., Rasch, P. J., ... Wood, R. (2016). Improving our fundamental understanding of the role of aerosol–cloud interactions in the climate system. *Proceedings of the National Academy of Sciences*, 113(21), 5781–5790. <https://doi.org/10.1073/pnas.1514043113>
- Sha, T., Ma, X., Zhang, H., Janecek, N., Wang, Y., Wang, Y., Castro García, L., Jenerette, G. D., & Wang, J. (2021). Impacts of soil NO<sub>x</sub> Emission on O<sub>3</sub> air quality in rural California.

- Environmental Science & Technology*, 55(10), 7113–7122.  
<https://doi.org/10.1021/acs.est.0c06834>
- Sharkey, A. M., Hartig, A. M., Dang, A. J., Chatterjee, A., Williams, B. J., & Parker, K. M. (2022). Amine Volatilization from Herbicide Salts: Implications for Herbicide Formulations and Atmospheric Chemistry. *Environmental Science & Technology*, 56(19), 13644–13653.  
<https://doi.org/10.1021/acs.est.2c03740>
- Shephard, M. W., Dammers, E., Cady-Pereira, K. E., Kharol, S. K., Thompson, J., Gainariu-Matz, Y., Zhang, J., McLinden, C. A., Kovachik, A., Moran, M., Bittman, S., Sioris, C. E., Griffin, D., Alvarado, M. J., Lonsdale, C., Savic-Jovcic, V., & Zheng, Q. (2020). Ammonia measurements from space with the Cross-track Infrared Sounder: Characteristics and applications. *Atmospheric Chemistry and Physics*, 20(4), 2277–2302.  
<https://doi.org/10.5194/acp-20-2277-2020>
- Shiraiwa, M., Ueda, K., Pozzer, A., Lammel, G., Kampf, C. J., Fushimi, A., Enami, S., Arangio, A. M., Fröhlich-Nowoisky, J., Fujitani, Y., Furuyama, A., Lakey, P. S. J., Lelieveld, J., Lucas, K., Morino, Y., Pöschl, U., Takahama, S., Takami, A., Tong, H., ... Sato, K. (2017). Aerosol Health Effects from Molecular to Global Scales. *Environmental Science & Technology*, 51(23), 13545–13567. <https://doi.org/10.1021/acs.est.7b04417>
- Socorro, J., Durand, A., Temime-Roussel, B., Gligorovski, S., Wortham, H., & Quivet, E. (2016). The persistence of pesticides in atmospheric particulate phase: An emerging air quality issue. *Scientific Reports*, 6(1), Article 1. <https://doi.org/10.1038/srep33456>
- Song, C. H., Chen, G., Hanna, S. R., Crawford, J., & Davis, D. D. (2003). Dispersion and chemical evolution of ship plumes in the marine boundary layer: Investigation of O<sub>3</sub>/NO<sub>y</sub>/HO<sub>x</sub> chemistry. *Journal of Geophysical Research: Atmospheres*, 108(D4), 4143.  
<https://doi.org/10.1029/2002JD002216>
- Song, Y., Xue, C., Zhang, Y., Liu, P., Bao, F., Li, X., & Mu, Y. (2023). Measurement report: Exchange fluxes of HONO over agricultural fields in the North China Plain. *Atmospheric Chemistry and Physics*, 23(24), 15733–15747. <https://doi.org/10.5194/acp-23-15733-2023>
- Sorooshian, A., Murphy, S. M., Hersey, S., Gates, H., Padro, L. T., Nenes, A., Brechtel, F. J., Jonsson, H., Flagan, R. C., & Seinfeld, J. H. (2008). Comprehensive airborne characterization of aerosol from a major bovine source. *Atmospheric Chemistry and Physics*, 8(17), 5489–5520. <https://doi.org/10.5194/acp-8-5489-2008>
- Staebler, R. M., McGinn, S. M., Crenna, B. P., Flesch, T. K., Hayden, K. L., & Li, S.-M. (2009). Three-dimensional characterization of the ammonia plume from a beef cattle feedlot. *Atmospheric Environment*, 43(38), 6091–6099.  
<https://doi.org/10.1016/j.atmosenv.2009.08.045>
- Steinkamp, J., & Lawrence, M. G. (2011). Improvement and evaluation of simulated global biogenic soil NO emissions in an AC-GCM. *Atmospheric Chemistry And Physics*, 11(12), 6063–6082. <https://doi.org/10.5194/acp-11-6063-2011>
- Stevens, C. J., & Quinton, J. N. (2009). Policy implications of pollution swapping. *Physics and Chemistry of the Earth, Parts A/B/C*, 34(8), 589–594.  
<https://doi.org/10.1016/j.pce.2008.01.001>
- Su, C., Kang, R., Zhu, W., Huang, W., Song, L., Wang, A., Liu, D., Quan, Z., Zhu, F., Fu, P., & Fang, Y. (2020).  $\delta^{15}\text{N}$  of Nitric Oxide Produced Under Aerobic or Anaerobic Conditions From Seven Soils and Their Associated N Isotope Fractionations. *Journal of Geophysical Research: Biogeosciences*, 125(9), e2020JG005705.  
<https://doi.org/10.1029/2020JG005705>



- Sun, H., Eastham, S., & Keith, D. (2022). Developing a plume-in-grid model for plume evolution in the stratosphere. *Journal of Advances in Modeling Earth Systems*, 14(4), e2021MS002816. <https://doi.org/10.1029/2021MS002816>
- Sun, K., Zhu, L., Cady-Pereira, K., Chan Miller, C., Chance, K., Clarisse, L., Coheur, P.-F., González Abad, G., Huang, G., Liu, X., Van Damme, M., Yang, K., & Zondlo, M. (2018). A physics-based approach to oversample multi-satellite, multispecies observations to a common grid. *Atmospheric Measurement Techniques*, 11(12), 6679–6701. <https://doi.org/10.5194/amt-11-6679-2018>
- TEMPO Green Paper. (2024, August). [https://weather.ndc.nasa.gov/tempo/green\\_paper.html](https://weather.ndc.nasa.gov/tempo/green_paper.html)
- Tessum, C. W., Hill, J. D., & Marshall, J. D. (2017). InMAP: A model for air pollution interventions. *PLOS ONE*, 12(4), e0176131. <https://doi.org/10.1371/journal.pone.0176131>
- The Future of Atmospheric Chemistry Research: Remembering Yesterday, Understanding Today, Anticipating Tomorrow* (with NASM). (2016). National Academies Press. <https://doi.org/10.17226/23573>
- Tschofen, P., Azevedo, I. L., & Muller, N. Z. (2019). Fine particulate matter damages and value added in the US economy. *Proceedings of the National Academy of Sciences*, 116(40), 19857–19862. <https://doi.org/10.1073/pnas.1905030116>
- US EPA. (2017, June 30). *2017 National Emissions Inventory (NEI) Data* [Other Policies and Guidance]. <https://www.epa.gov/air-emissions-inventories/2017-national-emissions-inventory-nei-data>
- US EPA. (2022a, February 3). *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2020* [Reports and Assessments]. <https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2020>
- US EPA. (2022b, September 28). *Greenhouse Gas Reduction Fund* [Overviews and Factsheets]. <https://www.epa.gov/inflation-reduction-act/greenhouse-gas-reduction-fund>
- USDA. (2024a). *2022 Census of Agriculture* (AC-22-A-51). [https://www.nass.usda.gov/Publications/AgCensus/2022/index.php#full\\_report](https://www.nass.usda.gov/Publications/AgCensus/2022/index.php#full_report)
- USDA. (2024b). *CropScape—NASS CDL Program*. <https://nassgeodata.gmu.edu/CropScape/>
- USDA ERS. (2024). Land and Natural Resources. <https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/land-and-natural-resources/>
- USDA-ERS. (2023). *Irrigation & Water Use*. <https://www.ers.usda.gov/topics/farm-practices-management/irrigation-water-use.aspx>
- Van Damme, M., Clarisse, L., Heald, C. L., Hurtmans, D., Ngadi, Y., Clerbaux, C., Dolman, A. J., Erisman, J. W., & Coheur, P. F. (2014). Global distributions, time series and error characterization of atmospheric ammonia (NH<sub>3</sub>) from IASI satellite observations. *Atmospheric Chemistry and Physics*, 14(6), 2905–2922. <https://doi.org/10.5194/acp-14-2905-2014>
- Van Damme, M., Clarisse, L., Stavrou, T., Wichink Kruit, R., Sellekaerts, L., Viatte, C., Clerbaux, C., & Coheur, P.-F. (2022). On the weekly cycle of atmospheric ammonia over European agricultural hotspots. *Scientific Reports*, 12(1), 12327. <https://doi.org/10.1038/s41598-022-15836-w>
- Van Damme, M., Clarisse, L., Whitburn, S., Hadji-Lazaro, J., Hurtmans, D., Clerbaux, C., & Coheur, P.-F. (2018). Industrial and agricultural ammonia point sources exposed. *Nature*, 564(7734), Article 7734. <https://doi.org/10.1038/s41586-018-0747-1>
- Vechi, N. T., Mellqvist, J., Samuelsson, J., Offerle, B., & Scheutz, C. (2023). Ammonia and methane emissions from dairy concentrated animal feeding operations in California, using

- mobile optical remote sensing. *Atmospheric Environment*, 293, 119448. <https://doi.org/10.1016/j.atmosenv.2022.119448>
- Vinken, G. C. M., Boersma, K. F., Maasakkers, J. D., Adon, M., & Martin, R. V. (2014). Worldwide biogenic soil NO<sub>x</sub> emissions inferred from OMI NO<sub>2</sub> observations. *Atmospheric Chemistry and Physics*, 14(18), 10363–10381. <https://doi.org/10.5194/acp-14-10363-2014>
- Vira, J., Hess, P., Ossohou, M., & Galy-Lacaux, C. (2022). Evaluation of interactive and prescribed agricultural ammonia emissions for simulating atmospheric composition in CAM-chem. *Atmospheric Chemistry and Physics*, 22(3), 1883–1904. <https://doi.org/10.5194/acp-22-1883-2022>
- Wagner-Riddle, C., Congreves, K. A., Abalos, D., Berg, A. A., Brown, S. E., Ambadan, J. T., Gao, X., & Tenuta, M. (2017). Globally important nitrous oxide emissions from croplands induced by freeze–thaw cycles. *Nature Geoscience*, 10(4), 279–283. <https://doi.org/10.1038/ngeo2907>
- Waldrip, H. M., Cole, N. A., & Todd, R. W. (2015). Review: Nitrogen sustainability and beef cattle feedyards: II. Ammonia emissions. *The Professional Animal Scientist*, 31(5), 395–411. <https://doi.org/10.15232/pas.2015-01395>
- Walker, J. T., Beachley, G., Zhang, L., Benedict, K. B., Sive, B. C., & Schwede, D. B. (2020). A review of measurements of air-surface exchange of reactive nitrogen in natural ecosystems across North America. *Science of The Total Environment*, 698, 133975. <https://doi.org/10.1016/j.scitotenv.2019.133975>
- Walker, J. T., Bell, M. D., Schwede, D., Cole, A., Beachley, G., Lear, G., & Wu, Z. (2019). Aspects of uncertainty in total reactive nitrogen deposition estimates for North American critical load applications. *Science of The Total Environment*, 690, 1005–1018. <https://doi.org/10.1016/j.scitotenv.2019.06.337>
- Wang, M., Kong, W., Marten, R., He, X.-C., Chen, D., Pfeifer, J., Heitto, A., Kontkanen, J., Dada, L., Kürten, A., Yli-Juuti, T., Manninen, H. E., Amanatidis, S., Amorim, A., Baalbaki, R., Baccarini, A., Bell, D. M., Bertozzi, B., Bräkling, S., ... Donahue, N. M. (2020). Rapid growth of new atmospheric particles by nitric acid and ammonia condensation. *Nature*, 581(7807), Article 7807. <https://doi.org/10.1038/s41586-020-2270-4>
- Wang, R., Guo, X., Pan, D., Kelly, J. T., Bash, J. O., Sun, K., Paulot, F., Clarisse, L., Van Damme, M., Whitburn, S., Coheur, P.-F., Clerbaux, C., & Zondlo, M. A. (2021). Monthly patterns of ammonia over the contiguous United States at 2-km resolution. *Geophysical Research Letters*, 48(5), e2020GL090579. <https://doi.org/10.1029/2020GL090579>
- Wang, S. L., Heisey, P., Schimmelpfennig, D., & Ball, E. (2015). *Agricultural Productivity Growth in the United States: Measurement, Trends, and Drivers* (ERR-189; p. ERR-189). U.S. Department of Agriculture, Economic Research Service. <https://www.ers.usda.gov/publications/pub-details/?pubid=45390>
- Wang, Y., Ge, C., Garcia, L. C., Jenerette, G. D., Oikawa, P. Y., & Wang, J. (2021). Improved modelling of soil NO<sub>x</sub> emissions in a high temperature agricultural region: Role of background emissions on NO<sub>2</sub> trend over the US. *Environmental Research Letters*, 16(8), 084061. <https://doi.org/10.1088/1748-9326/ac16a3>
- Wesely, M. L. (1989). Parameterization of surface resistances to gaseous dry deposition in regional-scale numerical models. *Atmospheric Environment*, 23(6), 1293–1304. [https://doi.org/10.1016/0004-6981\(89\)90153-4](https://doi.org/10.1016/0004-6981(89)90153-4)

- Wilkerson, J., Dobosy, R., Sayres, D. S., Healy, C., Dumas, E., Baker, B., & Anderson, J. G. (2019). Permafrost nitrous oxide emissions observed on a landscape scale using the airborne eddy-covariance method. *Atmospheric Chemistry and Physics*, 19(7), 4257–4268. <https://doi.org/10.5194/acp-19-4257-2019>
- Willis, L. M., Mehta, D., & Davis, A. (2020). Twelve Principles Trainees, Pls, Departments, and Faculties Can Use to Reduce Bias and Discrimination in STEM. *ACS Central Science*, 6(12), 2294–2300. <https://doi.org/10.1021/acscentsci.0c01120>
- Wolfe, G. M., Hanisco, T. F., Arkinson, H. L., Bui, T. P., Crounse, J. D., Guenther, A., Hall, S. R., Huey, G., Jacob, D. J., Karl, T., Kim, P. S., Liu, X., Marvin, M. R., Mikoviny, T., Misztal, P. K., Nguyen, T. B., Peischl, J., Pollack, I., Teng, A., ... Wisthaler, A. (2015). Quantifying sources and sinks of reactive gases in the lower atmosphere using airborne flux observations. *Geophysical Research Letters*, 42(April), 8231–8240. <https://doi.org/10.1002/2015GL065839>
- Wolfe, G. M., Kawa, S. R., Hanisco, T. F., Hannun, R. A., Newman, P. A., Swanson, A., Bailey, S., Barrick, J., Thornhill, K. L., Diskin, G., DiGangi, J., Nowak, J. B., Sorenson, C., Bland, G., Yungel, J. K., & Swenson, C. A. (2018). The NASA Carbon Airborne Flux Experiment (CARAFE): Instrumentation and methodology. *Atmospheric Measurement Techniques*, 11(3), 1757–1776. <https://doi.org/10.5194/amt-11-1757-2018>
- Wong, A. Y. H., Geddes, J. A., Ducker, J. A., Holmes, C. D., Fares, S., Goldstein, A. H., Mammarella, I., & Munger, J. W. (2022). New evidence for the importance of non-stomatal pathways in ozone deposition during extreme heat and dry anomalies. *Geophysical Research Letters*, 49(8), e2021GL095717. <https://doi.org/10.1029/2021GL095717>
- Wyer, K. E., Kelleghan, D. B., Blanes-Vidal, V., Schaubberger, G., & Curran, T. P. (2022). Ammonia emissions from agriculture and their contribution to fine particulate matter: A review of implications for human health. *Journal of Environmental Management*, 323, 116285. <https://doi.org/10.1016/j.jenvman.2022.116285>
- Xia, Y., Kwon, H., & Wander, M. (2021). Developing county-level data of nitrogen fertilizer and manure inputs for corn production in the United States. *Journal of Cleaner Production*, 309, 126957. <https://doi.org/10.1016/j.jclepro.2021.126957>
- Xu, R., Tian, H., Pan, N., Thompson, R. L., Canadell, J. G., Davidson, E. A., Nevison, C., Winiwarter, W., Shi, H., Pan, S., Chang, J., Ciais, P., Dangal, S. R. S., Ito, A., Jackson, R. B., Joos, F., Lauerwald, R., Lienert, S., Maavara, T., ... Zhou, F. (2021). Magnitude and uncertainty of nitrous oxide emissions from North America based on bottom-up and top-down approaches: Informing future research and national inventories. *Geophysical Research Letters*, 48(23), e2021GL095264. <https://doi.org/10.1029/2021GL095264>
- Xue, C., Ye, C., Zhang, C., Catoire, V., Liu, P., Gu, R., Zhang, J., Ma, Z., Zhao, X., Zhang, W., Ren, Y., Krysztofiak, G., Tong, S., Xue, L., An, J., Ge, M., Mellouki, A., & Mu, Y. (2021). Evidence for Strong HONO Emission from Fertilized Agricultural Fields and its Remarkable Impact on Regional O<sub>3</sub> Pollution in the Summer North China Plain. *ACS Earth and Space Chemistry*, 5(2), 340–347. <https://doi.org/10.1021/acsearthspacechem.0c00314>
- Yang, Y., Liu, L., Zhang, F., Zhang, X., Xu, W., Liu, X., Wang, Z., & Xie, Y. (2021). Soil Nitrous Oxide Emissions by Atmospheric Nitrogen Deposition over Global Agricultural Systems. *Environmental Science & Technology*, 55(8), 4420–4429. <https://doi.org/10.1021/acs.est.0c08004>

- Ye, C., Zhang, N., Gao, H., & Zhou, X. (2017). Photolysis of Particulate Nitrate as a Source of HONO and NO<sub>x</sub>. *Environmental Science & Technology*, 51(12), 6849–6856. <https://doi.org/10.1021/acs.est.7b00387>
- Young, D. E., Kim, H., Parworth, C., Zhou, S., Zhang, X., Cappa, C. D., Seco, R., Kim, S., & Zhang, Q. (2016). Influences of emission sources and meteorology on aerosol chemistry in a polluted urban environment: Results from DISCOVER-AQ California. *Atmospheric Chemistry and Physics*, 16(8), 5427–5451. <https://doi.org/10.5194/acp-16-5427-2016>
- Yuan, B., Coggon, M. M., Koss, A. R., Warneke, C., Eilerman, S., Peischl, J., Aikin, K. C., Ryerson, T. B., & de Gouw, J. A. (2017). Emissions of volatile organic compounds (VOCs) from concentrated animal feeding operations (CAFOs): Chemical compositions and separation of sources. *Atmospheric Chemistry and Physics*, 17(8), 4945–4956. <https://doi.org/10.5194/acp-17-4945-2017>
- Zaady, E., Sarig, S., & Katra, I. (2022). Dust particles as a pesticide's carrier in agro-ecosystems; qualitative and quantitative analysis. *Agronomy*, 12(8), Article 8. <https://doi.org/10.3390/agronomy12081826>
- Zhang, L., Brook, J. R., & Vet, R. (2003). A revised parameterization for gaseous dry deposition in air-quality models. *Atmospheric Chemistry And Physics*, 3, 2067–2082. <https://doi.org/10.5194/acp-3-2067-2003>
- Zhu, L., Henze, D., Bash, J., Jeong, G.-R., Cady-Pereira, K., Shephard, M., Luo, M., Paulot, F., & Capps, S. (2015). Global evaluation of ammonia bidirectional exchange and livestock diurnal variation schemes. *Atmospheric Chemistry and Physics*, 15(22), 12823–12843. <https://doi.org/10.5194/acp-15-12823-2015>
- Zhu, Q., Place, B., Pfannerstill, E. Y., Tong, S., Zhang, H., Wang, J., Nussbaumer, C. M., Wooldridge, P., Schulze, B. C., Arata, C., Bucholtz, A., Seinfeld, J. H., Goldstein, A. H., & Cohen, R. C. (2023). Direct observations of NO<sub>x</sub> emissions over the San Joaquin Valley using airborne flux measurements during RECAP-CA 2021 field campaign. *Atmospheric Chemistry and Physics Discussions*, 1–21. <https://doi.org/10.5194/acp-2023-3>