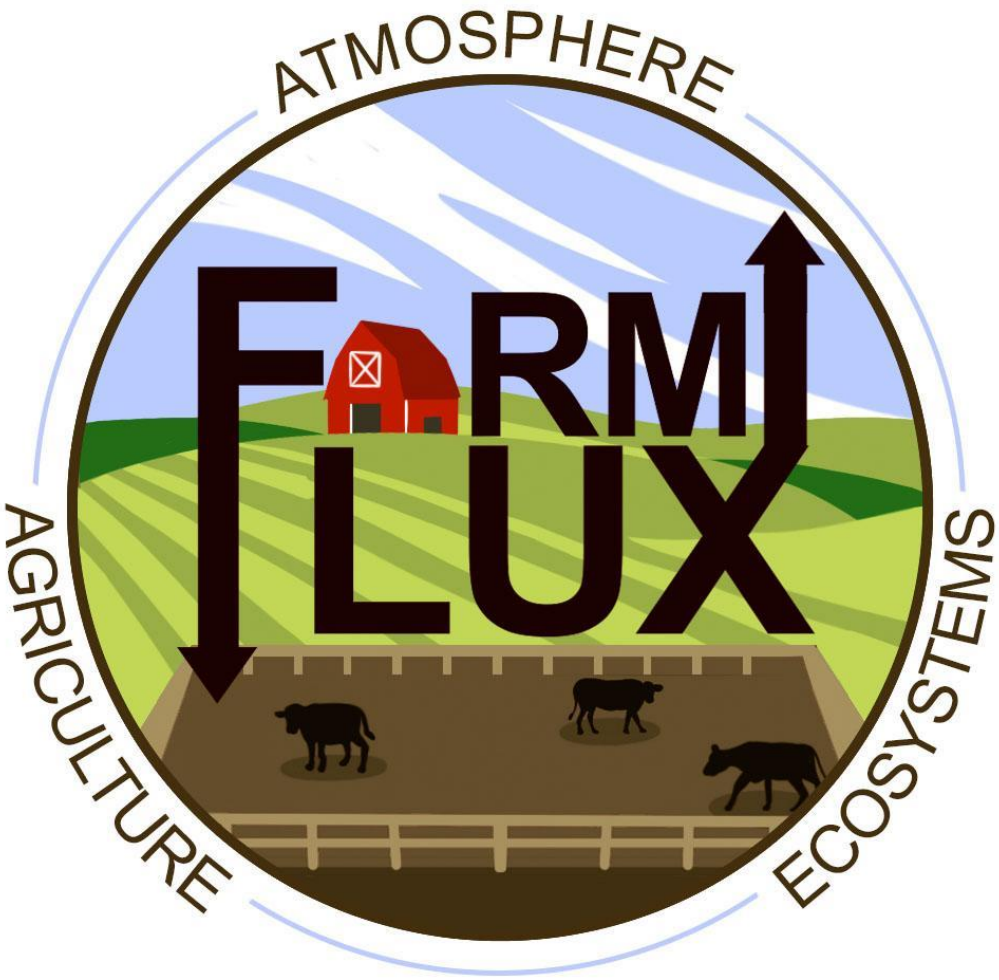

NASA Earth Venture Suborbital 4 Program

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White Paper
Finalized 10/15/2024

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 NH_3, N_2O, CH_4, C_2H_6, and aerosol size and composition. Flights will use pseudo-Lagrangian plume sampling with stacked vertical legs in the boundary layer to quantify 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 2 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 (NH_3, NO_x, N_2O, CH_4, CO_2, VOC, and O_3) with sufficient performance for eddy covariance. Priority 2 measurements include aerosol size, composition, and precursors (SO_2, 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 can also help connect soil emissions to nutrient cycling and provide a counterpoint to empirical emission parameterizations.

Table of Contents

"The real wealth of a planet is in its landscape, how we take part in that basic source of civilization–agriculture."

- *Frank Herbert,* Dune

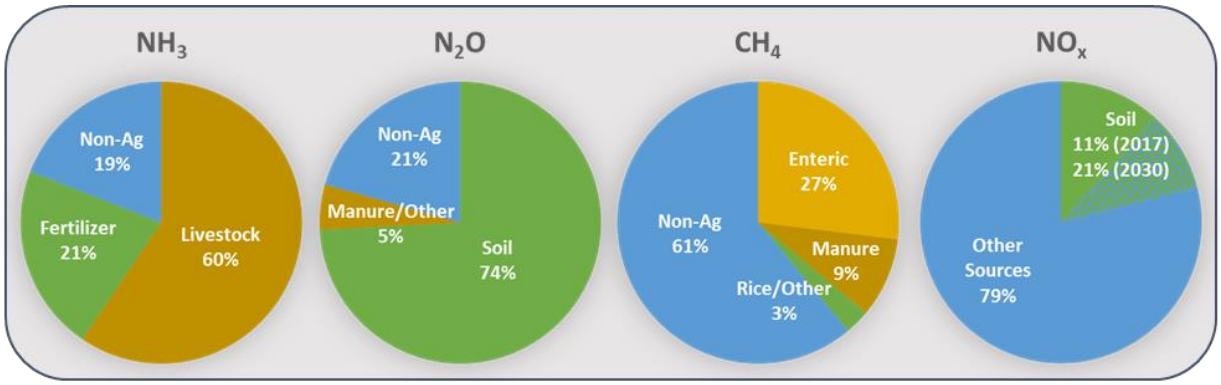

Figure 1. U.S. agriculture is a major source of reactive and greenhouse gases. *Total soil NO_x is an upper limit for agricultural influence (neglecting farm machinery and combustion-related emissions). Data derived from EPA bottom-up inventories (US EPA, 2017, 2022a).*

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_3), nitrous oxide (N_2O), and methane (CH_4) in the U.S. (Fig. 1). Managed and natural soils contributed 11% to total nitrogen oxide ($NO_x = NO + NO_2$) emissions nationally in 2017 but may be as much as 50% of total emissions in some regions (Almaraz et al., 2018; Oikawa et al., 2015). Soil NO_x will become more important as fossil fuel combustion emissions decline (Bistline et al., 2022; Geddes et al., 2022), with current trends (US EPA, 2015) suggesting the relative contribution will double by 2030. 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_3). NH_3 and NO_x are precursors to inorganic aerosol, which comprises roughly half of $PM_{2.5}$ (PM with diameter < 2.5 µm) (Mensah et al., 2012; Sorooshian et al., 2008; Young et al., 2016). The majority of the 15,000 – 29,000 deaths attributed to U.S. agriculture stem from $PM_{2.5}$ health impacts (Domingo et al., 2021; Lelieveld et al., 2015; Tschofen et al., 2019). NO_x is often a limiting factor in tropospheric O_3 production, and reductions in combustion NO_x have increased O_3 sensitivity to soil NO_x (Geddes et al., 2022). O_3 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_4 and N_2O account for 9.8% of US CO_2-equivalent greenhouse gas emissions (US EPA, 2022a). N_2O is also currently the dominant stratospheric O_3-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_3:** Models under- or over-estimate NH_3 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 $PM_{2.5}$ control decisions and critical load exceedance attribution (Gu et al., 2021; Walker et al., 2019).
- **NO_x:** Several recent studies argue that soil NO is 20 – 40% of California NO_x 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_3 by 23% (Sha et al., 2021) and are becoming relatively more important as fossil fuel NO_x declines (Geddes et al., 2022). The functional representation of soil NO_x 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_2O:** North American N_2O 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_2O 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_x 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 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 NH_3 (US EPA, 2017). CH_4 mitigation has received somewhat more attention (Hayek & Miller, 2021; US EPA, 2022b), but airborne research has historically focused on other 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). N_2O 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, including the Inflation Reduction Act (US EPA, 2022b). 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 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). 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 NO_x emissions, O_3 and 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 NH_3, a "sticky" gas that is notoriously difficult to measure at typical ambient levels (Pollack et al., 2019; Schobesberger et al., 2022). Open-path spectroscopy has also been used for ground-based NH_3 flux measurements (X. Guo et al., 2022; Pan et al., 2021; K. Sun et al., 2015), and efforts are ongoing to adapt this technology to airborne work. 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).

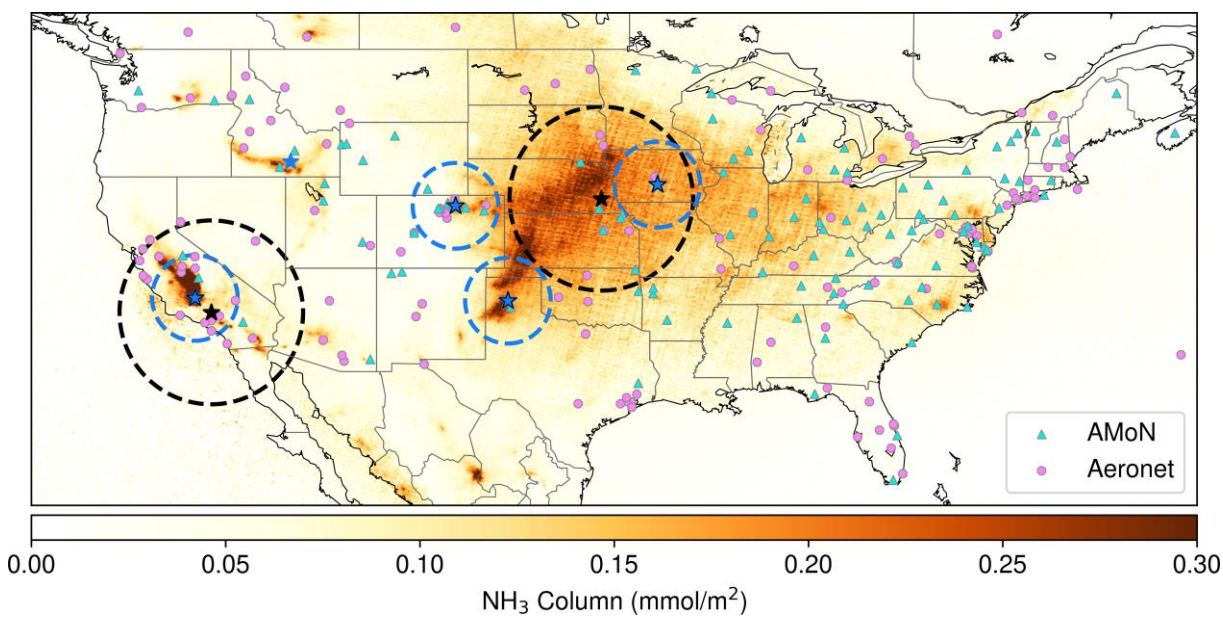

Figure 2. FarmFlux targets core U.S. agricultural emissions, including data-poor regions. *Background shows total NH_3 columns from the Cross-track Infrared Sounder (CrIS) onboard the Suomi National Polar-orbiting Partnership (S-NPP) (Cady-Pereira, 2020) oversampled over April – August 2017 to 0.05° x 0.05° (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 NH_3, N_2O, and CH_4 (Eilerman et al., 2016). Emissions of NH_3 largely stem from manure and urine. NH_3 is released during the breakdown of N-containing manure proteins, uric acid and urea. Thus 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 N_2O. It is assumed that N_2O is emitted during the nitrification (conversion of 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 NH_3, N_2O, CH_4, and 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. CH_4 is produced from enteric fermentation by ruminants (Fig. 1), largely from cattle. On a per-animal basis, dairy cows emit more 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 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 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 NH_3, CH_4 and N_2O, 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). Beef cattle, dairies, and hogs are the most significant emitters, but there may be opportunities to sample poultry in IA. To the extent possible, FarmFlux will correlate emissions with facility characteristics (number of animals, area of manure ponds, management practices, etc.). The lifetime of 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 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).

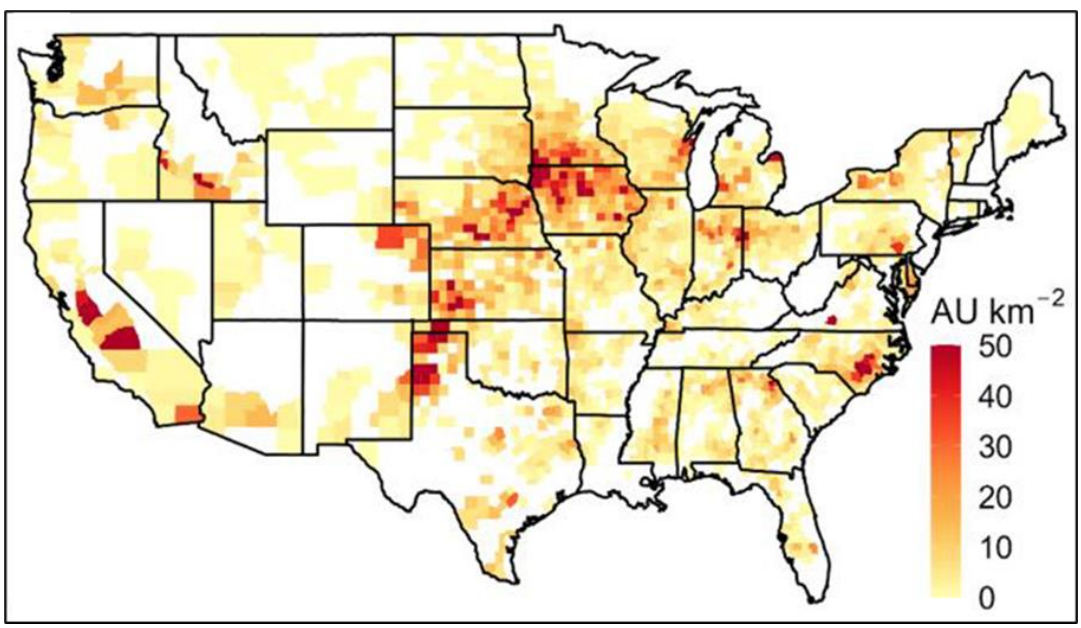

Figure 3. 2017 county-level animal unit (AU) concentrations. *1 AU = 1000 pounds live weight, or roughly 1 cattle, 2.5 swine, or 30 - 125 chickens. Adapted from Burns et al. (2023).*

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). Tillage practices also vary significantly (Azzari et al., 2019; Wade et al., 2015).

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. NH_3, N_2O, and NO emissions (Fig. 1). Soil NH_3 emission rates depend on fertilizer application methods, meteorology, soil properties, and vegetation (Wyer et al., 2022). N_2O 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 NO emissions depend on similar factors, but the

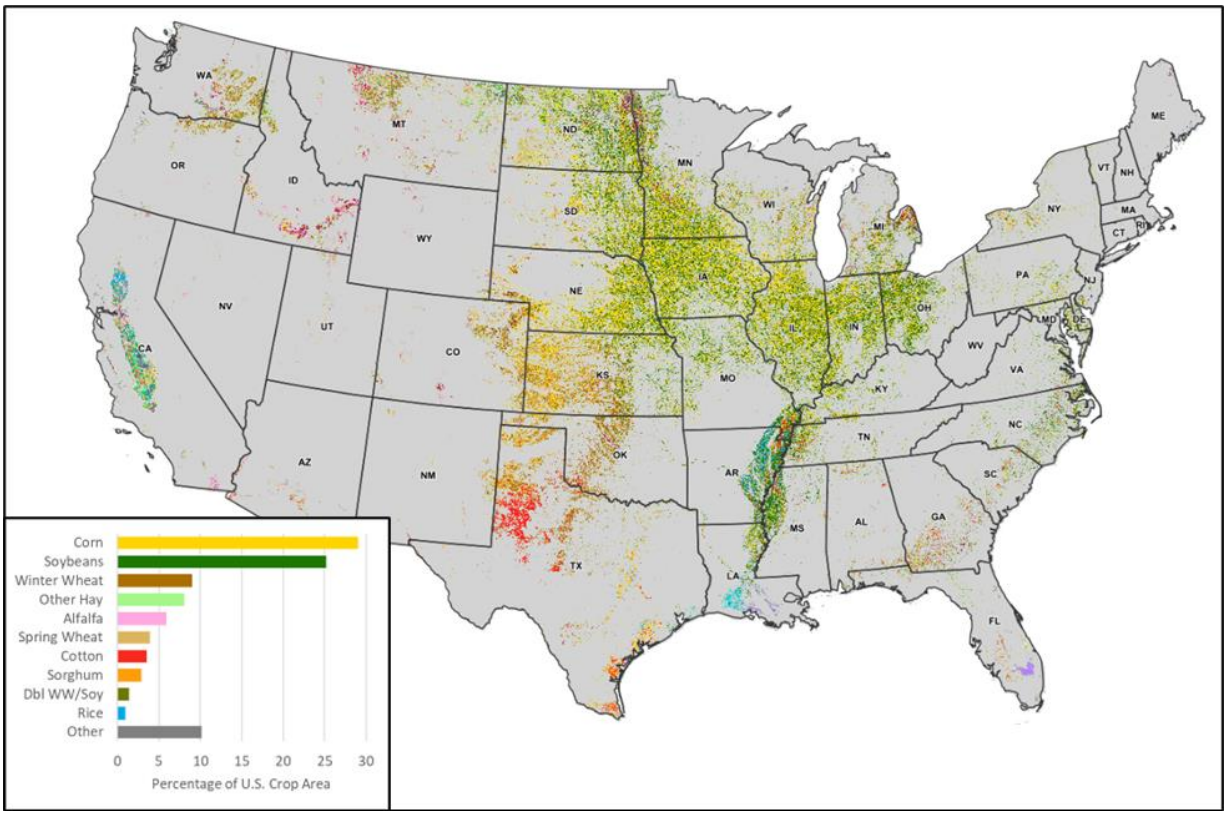

Figure 4. 2023 U.S. crop distribution. *Inset shows land cover of top 10 crops in 2023, with colors corresponding to those in the map (USDA, 2024b).*

functional relationships of NO and N_2O emissions differ (Hall et al., 2018). Soil N emissions can also spike following wetting of dried soils (Eberwein et al., 2020), but this response varies with species, temperature, and history (e.g. due to substrate depletion) (Hickman et al., 2018; McCalley & Sparks, 2008; Soper et al., 2016). 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_4 and other VOC. Anaerobic conditions - typically related to surface inundation - promote CH_4 production (Oertel et al., 2016). Rice paddies and drained peatlands account for 3% of U.S. CH_4 emissions (Fig. 1), and CH_4 emissions can occur in hot moments similar to N_2O (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_2 (Franks et al., 2018) and is a conduit for both nutrients (NH_3, CO_2) and hazardous gases (O_3). Several metrics exist for assessing crop ozone exposure (Lefohn et al., 2018), but results differ between metrics (Tai et al., 2021) and data to validate model estimates is limited (Clifton et al., 2020). 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_2O (Yang et al., 2021; Ye et al., 2017). NH_3 dry deposition occurs in tandem with emission, and the net flux can change signs over a short period (Pan et al., 2021; Pleim et al., 2013).

FarmFlux will quantify the bidirectional exchange of gases over major crop systems. Target species include all those listed above: NH_3, N_2O, NO_x, CH_4, VOCs, O_3, CO_2, and H_2O. 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 may 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)
- Tillage practices (e.g., no-till or strip-till)
- 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_2 and H_2O 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

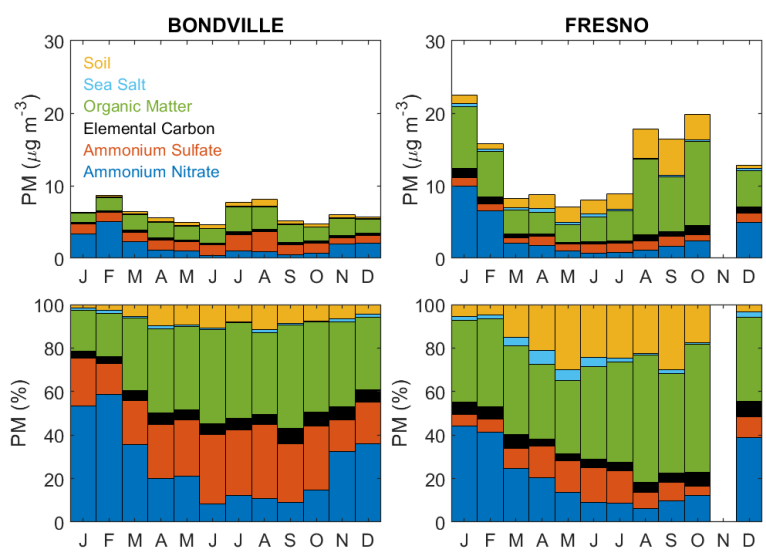

Figure 5. PM varies across seasons and locations. *2021 seasonal $PM_{2.5}$ mass (top) and percentage (bottom) for Bondville, IL (left) and Fresno, CA (right) from the IMPROVE (Interagency Monitoring of Protected Visual Environments) network (Malm et al., 1994). Fresno is an agriculturally impacted urban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

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 organic and inorganic aerosol (Montoya-Aguilera et al., 2018) and serve as an important sink of NO_x and NH_3 emitted by agricultural operations (Nenes et al., 2021). Acid availability can limit inorganic PM in 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., NH_3, HNO_3, H_2SO_4, VOC), T, RH, and other aerosol constituents (H. Guo et al., 2016). FarmFlux will collect a nearly comprehensive dataset for such analyses (all species except H_2SO_4). Sampling in CA and the Midwest will also provide a range of contrasting conditions for aerosol formation and loss (Nenes et al., 2021; S. Wang et al., 2011). 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 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 15 – 29 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 NH_3 (Fig. 2) and attributed deaths (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). 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, NH_3 emissions are aggregated to the county level (~1000 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 NH_3 columns suggest that inventories underestimate NH_3 point source emissions by orders of magnitude; however, order-of-magnitude uncertainties in 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 NO_x emissions may have a discernible influence on tropospheric NO_2 columns (Huber et al., 2023), but other sources of "background" 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). Most CH_4 satellite retrievals lack the sensitivity for agricultural sources, but MethaneSAT may make this possible.

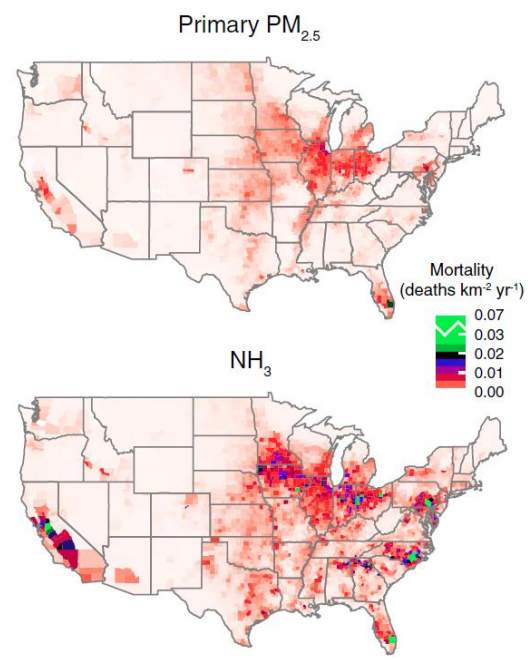

Figure 6. Agriculture costs lives. *Mortality attributed to primary $PM_{2.5}$ (top) and secondary $PM_{2.5}$ from NH_3 (bottom). Maps show where the impact originates, not necessarily where it is experienced (Domingo et al., 2021).*

FarmFlux will advance new satellite data applications over agricultural areas. Point source NH_3 and CH_4 emission rates acquired via Objective 1 provide indirect constraints on satellite-based estimates (which require months or years of oversampling). Regional fluxes of NH_3, NO_x, and other gases can validate or serve as

input for inversions. 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., linking surface N_2O with NO_2 and NH_3). Evaluation of satellite-based proxies for aerosol emission sensitivity (Dang et al., 2023) will also be possible. 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_3 products from infrared sounders (CrIS, IASI, AIRS) and NO_2, HCHO, and O_3 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).

Because of the need to prioritize observations, it is likely that only portions of Objective 4 will be accomplished by FarmFlux measurement and modeling teams. The data, however, will be available to the community to pursue future applications.

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^{2}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.

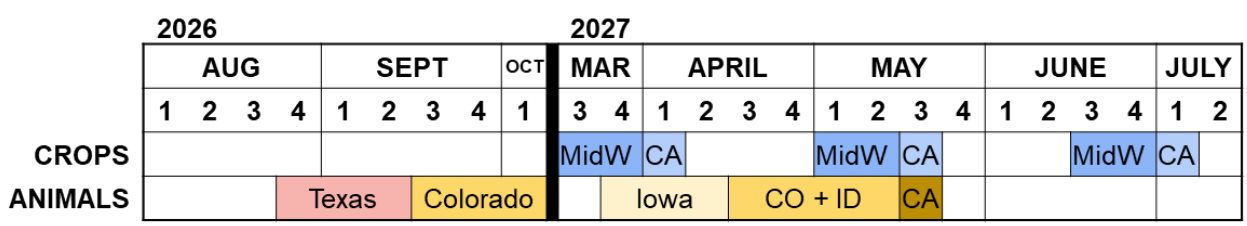

Figure 7. Notional FarmFlux deployment schedule.

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 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-MAPExp*, 2012; Hacker et al., 2016; Staebler et al., 2009). Animal feeding operations are large sources of NH_3, N_2O, and CH_4 (Miller et al., 2015; Nowak et al., 2012). CH_4 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_3 to CH_4 to constrain NH_3 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_2H_6) is needed to partition observed CH_4 between feedlot and oil and gas sources (McCabe et al., 2023). NH_3 reacts rapidly with sulfuric and nitric acids to form fine PM. Thus, a full understanding of NH_3 emissions necessitates sampling of NH_x (NH_3 + NH_4^+), 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_3 likely contribute to significant fine particulate matter formation (Benedict et al., 2013; E. Li et al., 2024;

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_3	1	60 pptv	15%	1 Hz	1
N_2O	1	30 ppt	10%	1 Hz	1
CH_4	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_3	2	200 pptv	20%	1 min	3
NO, NO_2	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

Nowak et al., 2012; Schiferl et al., 2014). HNO_3 measurements would help constrain thermodynamic modeling of ammonium nitrate formation. NO_x 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_4 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.

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

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. Poultry operations in IA are also significant and may be sampled if suitable facilities are identified.

Flight Planning

FarmFlux will identify and prioritize facilities using a combination of oversampled CrIS 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^{2}Am (Fig. 9). First, the aircraft approaches a target facility from the top of the boundary layer. Once the pilot visually

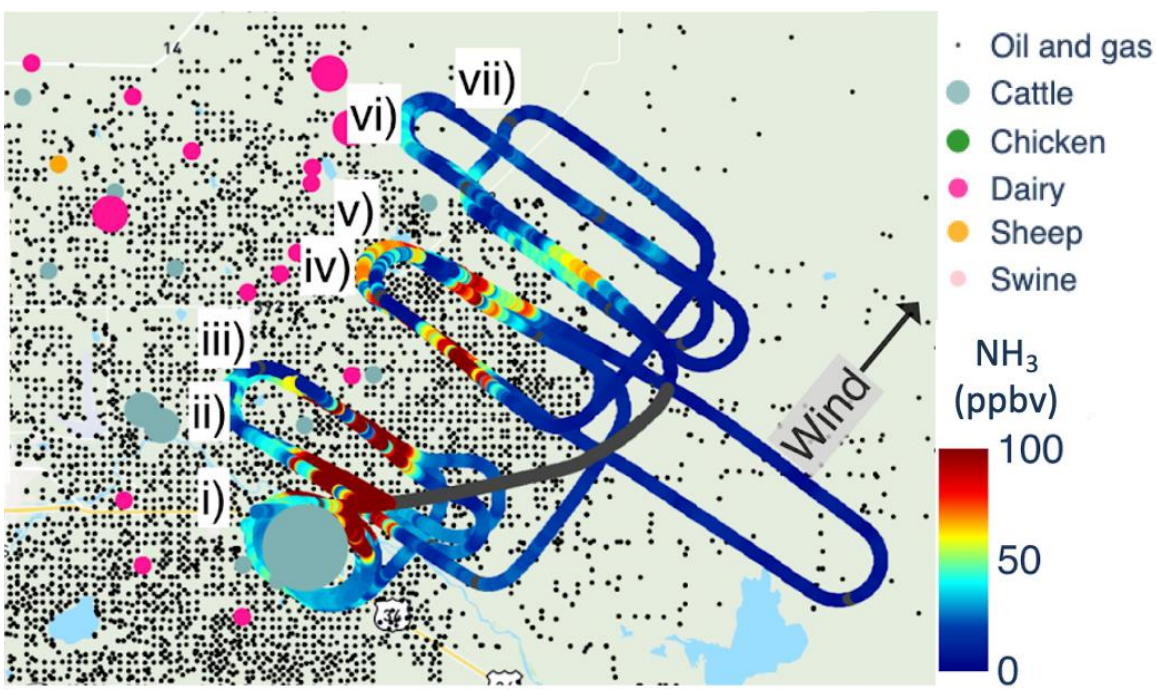

Figure 9. Small aircraft can densely sample agricultural point sources*. Example flight pattern for the small aircraft based on observations collected in the Colorado Front Range in August 2021. (Juncosa Calahorano et al., 2023). The flight track is colored by observed NH_3. Colored and sized dots represent 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.*

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 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. 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 NH_3 relative to 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 will be 6 - 8 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 ample 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 (NO_x, NH_3, and N_2O) are major emissions over fertilized lands. CH_4 is emitted from rice patties and other inundated areas. CO_2

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
Temperature, Pressure	1	0.05 K, 0.003 mb	0.3 K, 0.3 mb	10 Hz	2,3
Horizontal, vertical winds	1	0.1, 0.05 m s^{-1}	1, 0.3 m s^{-1}	10 Hz	2,3
water vapor	1	100 ppmv	5%	10 Hz	2,3
NH_3	1	20 pptv	15%	5 Hz	2,3
NO, NO_2	1	1, 10 pptv	10%	5 Hz	2,3
CO_2, CH_4, N_2O	1	200, 3, 0.4 ppbv	1%	5 Hz	2
VOC (C_1-C_2 alcohols, aldehydes, acids; acetone; terpenes)	1	1 – 100 pptv (varies by species)	15%	5 Hz	2,3
Ozone	1	0.1 ppbv	5%	5 Hz	2
CO	1	1 ppbv	2%	1 Hz	2
Aerosol size (3 nm – 5 µm)	2	NA	15%	0.1 Hz	3
Speciated aerosol mass (< 1 µm)	2	100 ng m^{-3}	35%	1 Hz	3
SO_2	2	50 pptv	15%	1 Hz	3
HNO_3	2	50 pptv	30%	1 Hz	2,3
Coarse-mode aerosol size	3	NA	NA	0.1 Hz	3
f(RH)	3	NA	NA	0.1 Hz	3
aerosol scattering, extinction	3	1 Mm^{-1}	20%	1 Hz	3
aerosol absorption	3	0.2 Mm^{-1}	20%	0.1 Hz	3
Black carbon	3	50 ng m^{-3}	25%	1 Hz	3
single particle composition	3	100 ng m^{-3}	50%	Variable	3
Bioaerosol content	3	NA	20%	1 Hz	3
CCN	3	NA	20%	1 Hz	3
organic nitrates	3	10 pptv	30%	5 Hz	2
Amines	3	10 pptv	20%	1 Hz	2,3
HONO	3	5 pptv	15%	5 Hz	2
Total oxidized nitrogen (NO_y)	3	20 pptv	15%	5 Hz	2
^{15}NO	3	1 pptv	10%	0.1 Hz	2
Ethane	3	0.2 ppbv	10%	1 Hz	2
Pesticides	3	NA	NA	1 min	2,3
Spectral actinic flux	3	80° SZA equivalent	10%	1 Hz	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. O_3 and CO are fundamental tracers for anthropogenic influence. O_3 deposition fluxes are also of interest for vegetation health. Previous work has demonstrated AEC applications for NH_3 (Schobesberger et al., 2022), NO_x (Q. Zhu et al., 2023), N_2O (Wilkerson et al., 2019), VOCs (Pfannerstill et al., 2023; Wolfe et al., 2015), O_3 (Conley et al., 2011), and CO_2/CH_4 (Desjardins et al., 2018; Hannun et al., 2020; Wolfe et al., 2018). Precision values in Table 2 are approximate. FarmFlux is pushing the limit of state-of-the-art instrumentation, and it is likely that measuring fluxes for all species over all regions will not be possible. Even mixing ratio measurements in these regions, however, will be valuable.

Priority 2: Size measurements from 3 nm to 5 µm will span ultrafine, accumulation, and some coarse-mode aerosol to constrain new particle formation (NPF), direct emission (dust/combustion), and secondary production. At this size cut, we will likely miss a significant portion of coarse-mode dust. 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 SO_2 and HNO_3, are also needed to constrain thermodynamic aerosol models. Hygroscopicity (f(RH)) well 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 (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}NO, a stable isotope of nitric oxide, would facilitate discrimination of 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 N_2O 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 3-week intensives over a single year (Fig. 7). Each deployment consists of 2 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-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 (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).

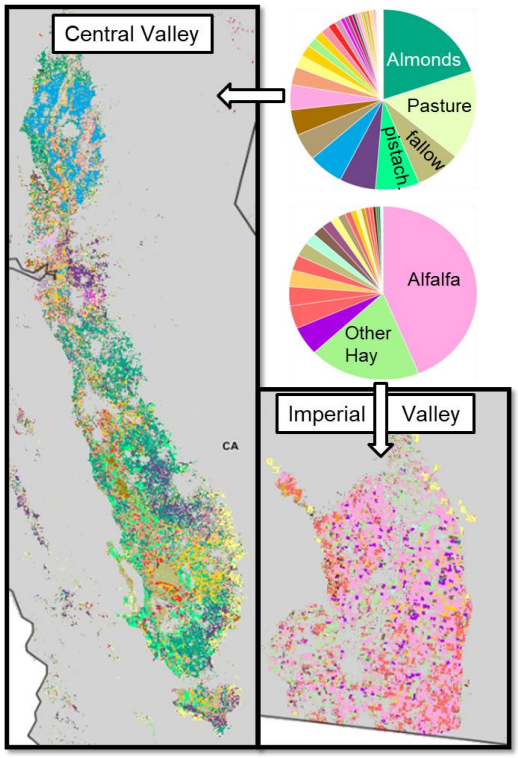

Figure 10. 2023 CA crop distribution *in the Central Valley (left and top pie chart) and Imperial Valley (right and bottom pie chart) for 2023 (USDA, 2024b).*

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, tillage, 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. Methods also exist to derive tillage information from satellite imagery (Azzari et al., 2019; Cambron et al., 2024). 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 NO_x
Imperial Valley	Alfalfa	Water management; NO_2 hotspot in TEMPO

Flights will sample across gradients in crop cover 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.

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 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.

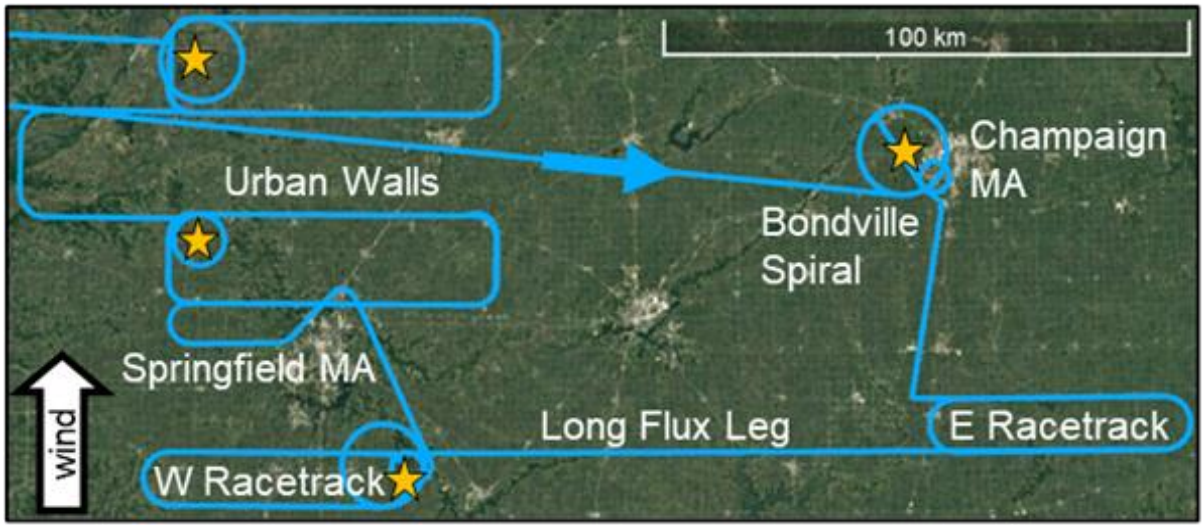

Figure 11. The large aircraft simultaneously addresses multiple FarmFlux objectives*. Example flight plan for central IL. Blue arrow: flight direction. MA: missed approach. Stars: vertical profiles. Racetracks and urban walls consist of 3 sets of stacked legs at altitudes of 1000' - 3000' AGL. Corn and soy farms dominate land cover. As drawn, this flight plan is 6.7 hours with the P-3 and yields 500 km of surface flux data.*

Modeling and Analysis Tools

Models

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

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 can 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 depending on sample altitude, wind speed, and atmospheric stability. Figure 12 shows the contributions of different crop classes within a hypothetical footprint for the "long flux leg" from Fig. 11, revealing the dominance of corn and soy with smaller contributions from forest, pasture, and other land types. Fluxes also change with altitude (vertical flux divergence) which can be accounted for by measuring fluxes at multiple altitudes 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, 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 FarmFlux science team will share code and work collaboratively to improve existing methodology and develop flux data products for wider community use.

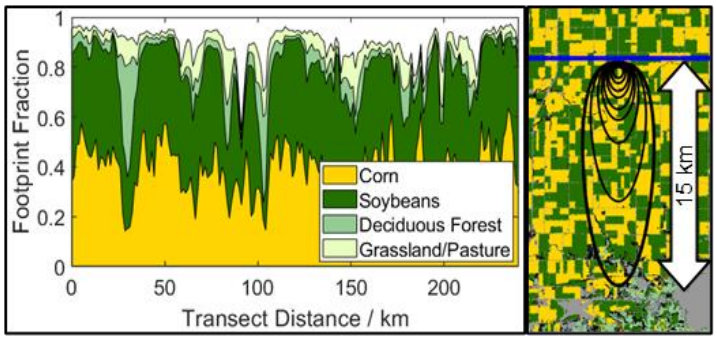

Figure 12. AEC footprints capture heterogeneity in surface fluxes. *(Left) Estimated fractional land cover contributions to flux footprint for the "long flux leg" (Fig. 11) based on 2022 CropScape data (USDA, 2024b). (Right) Example 2-D footprint. Contours represent 10-percentile contributions in 10%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

Ancillary Datasets

Connecting observations to surface processes and properties is a critical challenge for FarmFlux. Desired information for animal facilities includes number of animals, area of manure lagoons, and management activities coincident with sampling. For croplands, desired information includes crop type and stage, fertilizer application (amount, method), soil moisture and type, and other management practices (tillage, irrigation, etc.). Meteorology, both current and historical, is also relevant. As discussed above, this data may or may not be readily available. For example, privacy concerns prevent USDA and EPA from reporting the location and size of individual CAFOs (GAO, 2008; USDA, 2024c). The availability and granularity of crop system information varies by region and often depends on engagement of agricultural scientists with local communities. FarmFlux is developing a network of relationships to identify and access this information where it exists. Realistically, however, it is unlikely that we will have all data needed to fully explain variability in observations.

Model products and inputs can serve as a reasonable – and in some cases preferable – alternative to actual surface data. Measured emissions and deposition will be evaluated against model simulations, and underlying such models are parameterizations with gridded inputs (Cooter et al., 2012; Pleim et al., 2019). If the goal is to improve modeled surface fluxes, then it is sensible to evaluate observations with the same level of information available to those models.

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 below is only a starting point and by no means exhaustive.

Objective 1: Livestock

- What are the magnitudes of the emission fluxes of NH_3, N_2O, CH_4 and other trace gases from cattle, dairy, hog and poultry operations? How do emissions vary with time of day, season, environmental conditions, and management practices?

- What is the lifetime of 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 (NH_3, N_2O, 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 NO_x and N_2O?
- 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 exposure metrics capture this accurately?
- What is the net 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_x emissions and TEMPO NO_2 columns?
- How do satellite-inferred NH_3 emission estimates change with better constraints on NH_3 lifetimes?
- Under what conditions can satellite observations of NH_3, NO_2, or other species be used to infer emissions of unmeasured species such as N_2O or CH_4?

Related Activities

NASA

FarmFlux dovetails with several NASA initiatives in the realms of agriculture and greenhouse gas monitoring and attribution. NASA Acres[1] leverages satellite-derived information to inform U.S. crop production and precision agriculture. NASA Harvest[2] 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 uses for satellite observations, such as improved tracking of fertilizer application. The U.S. Greenhouse Gas Center[3] is a collaboration among multiple U.S. agencies (NASA, EPA, NOAA, and 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_4 and N_2O and net uptake of CO_2, FarmFlux will improve emission inventories and estimates of the net climate impacts of agriculture. This work also builds on the insights into large-scale greenhouse gas transport gained from the NASA ACT-America mission (Davis et al., 2021; Eckl et al., 2021).

EPA

FarmFlux objectives will contribute to EPA priorities including improving air quality, quantifying nitrogen deposition, understanding $PM_{2.5}$ sources and composition, and monitoring and reporting of agricultural emissions, 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_3) and aerosol ammonium nitrate (NH_4NO_3). Enhanced reactive nitrogen monitoring by the CASTNET "nitrotrain" system (reporting HNO_3, NH_3, NO, NO_2, NO_y, 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 significantly increase the existing data on relative facility-scale N_2O, CH_4 and NH_3 emissions. FarmFlux will also improve our ability to measure total emission rates, and if paired with known concurrent management

[1] https://www.nasaacres.org/
[2] https://nasaharvest.org/
[3] https://earth.gov/ghgcenter

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.

Beyond FarmFlux

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 2/3 measurements and redundancy for critical Priority 1 measurements (Table 2).
- **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. While FarmFlux cannot support such work directly, we can help coordinate these efforts and overfly for intercomparisons.
- **Mobile laboratories** are well suited for CAFO sampling (Golston et al., 2020; Vechi et al., 2023) and field-scale crop sampling. 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. Mobile labs could also acquire measurements outside of the FarmFlux operations area (discussed further below).
- **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_4 or NO_2) 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.

Study Limitations

FarmFlux is an ambitious effort, but we cannot cover all facets of this complex system. Budget realities[4] require that we prioritize areas with the largest emissions and balance costs between data acquisition and analysis. Here we acknowledge aspects that will remain to be explored by collaborators or future work.

Locations: CAFO sampling does not include a specific focus on poultry, which is prominent in the Southeast U.S. We also cannot cover several regions with significant agriculture-related mortality (Fig. 6), including hog farms in NC, dairies in southeast PA, and cattle in FL and NE.

Timing: Agricultural activities and impacts occur outside the FarmFlux deployment windows. For example, elevated ammonium nitrate levels in the winter are a significant health issue in the Midwest (Katzman et al., 2010). Thawing soils may emit N_2O at times and locations when/where FarmFlux is not sampling. Fertilization and planting also occur in the fall. 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.

Measurements: FarmFlux focuses on near-surface processes and will only conduct limited vertical profiling. This may reduce the utility of data for some applications, such as satellite product validation and transport model inversions. We also cannot support most Tier 3 measurements (Tables 1 and 2) or ground-based observations, both of which would add significant synergistic value. As noted above, we are hopeful that other agencies and collaborators will step up to fill these gaps.

Analysis: FarmFlux will focus first on data quality and second on interpretation within the context of the immediate objectives and questions laid out above. It is unlikely that FarmFlux will support broader-scale analysis such as evaluation of climate impacts, though the data may be suitable for such applications.

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, which is a step along the path to finding balance between food security and environmental health.

[4] Accounting for inflation and reduced funding, the FarmFlux budget is 35% of the amount allotted to EVS-1 missions.

Team Structure

The *FarmFlux 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.

The FarmFlux inclusion plan has been redacted by Executive decree. To the extent allowable, FarmFlux leadership will facilitate a safe environment and a cohesive team where all members contribute to mission success.

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_x	Total Nitrogen Oxides ($NO + NO_2$)
OA	Organic Aerosol
OCO2	Orbiting Carbon Observatory 2
ORCHIDEE	Organising Carbon and Hydrology in Dynamic Ecosystems
PM	Particulate Matter
$PM_{2.5}$	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

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