GeoHealth

RESEARCH ARTICLE

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Special Collection:
Geospatial data applications for environmental justice

Key Points:

- Using satellite data and literature-derived heuristics, we accurately identified unregulated poultry Concentrated Animal Feeding Operations (CAFOs)
- Advanced data techniques show a significant overestimation of CAFO locations prior to heuristic adjustment
- We found high concentrations of poultry CAFOs in socially vulnerable areas of North Carolina and Southeast US

Supporting Information:

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

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Earth Observation Data to Support Environmental Justice: Linking Non-Permitted Poultry Operations to Social Vulnerability Indices

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Abstract Concentrated Animal Feeding Operations (CAFOs) apply massive amounts of untreated waste to nearby farmlands, with severe environmental health impacts of swine CAFOs and proximity to disadvantaged communities well documented in some US regions. Most studies documenting the impacts of CAFOs rely almost exclusively on CAFO locations known from incomplete public records. Poultry CAFOs generate dry waste and operate without federal permits; thus, their environmental justice (EJ) impacts are undocumented. North Carolina (NC), a leading poultry producer, has seen a significant increase in poultry CAFOs, particularly since the 1997 swine CAFO moratorium. Using literature-derived heuristics, this study refined the locations of poultry CAFOs derived based on Earth Observation (EO) data and deep learning, reducing the overestimation of poultry CAFO density by 54% after heuristic adjustments. We removed 51.8% of misclassified features in NC and 61.5% across the US, significantly improving data set accuracy. Spatial analysis, including Local Indicators of Spatial Association, revealed that poultry CAFOs often cluster in census tracts with high Social Vulnerability Index (SVI) scores, indicating potential EJ issues. Notably, one-third of NC's census tracts with high poultry CAFO density also have high SVI, primarily in rural eastern regions. Similar patterns were observed in the South and Southeast of the US. However, not all high-density CAFO areas correspond with high SVI, suggesting a complex relationship between CAFO locations and community vulnerabilities. This study highlights the critical need for comprehensive, high-quality data on unpermitted poultry CAFOs derived using AI algorithms to fully understand their impacts on communities and accurately inform EJ evaluations.

Plain Language Summary This study explores the environmental and social impacts of poultry concentrated animal feeding operations (CAFOs) across North Carolina and the United States. These operations, often unregulated, contribute significantly to local pollution levels, particularly in areas with high social vulnerability. Using literature-derived heuristics on Earth Observation data and deep learning techniques, we identified the precise locations of poultry CAFOs and analyzed their distribution in relation to socially vulnerable communities. The findings reveal a significant concentration of poultry CAFOs in certain regions, particularly where social vulnerabilities are already high, highlighting potential environmental justice concerns.

1. Introduction

The growth of the affluent human population has skyrocketed the demand for animal products, leading to an accelerated increase in livestock production and related environmental injustices (Herrero et al., 2015). Over 40% of US livestock production comes from Concentrated Animal Feeding Operations (CAFOs) (Copeland, 2010), which produce massive amounts of waste known to contaminate the environment. CAFOs raise large numbers of animals in confinement, generating hundreds of millions of tons of waste annually, held in lagoons or heaps, and applied essentially untreated to nearby farmlands, with the 2017 Census of Agriculture identifying several hot-spots of CAFOs in the American South and Midwest (Food & Water Watch, 2020).

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Animal confinement and waste management practices disseminate contaminants into the environment, including nutrients, pathogens, and heavy metals, chronically and episodically during extreme weather events (Christenson et al., 2022; Emanuel, 2018; Niedermeyer et al., 2020; North Carolina Conservation Network, 2021; Wing, 2002; Wing et al., 2008) creating toxic conditions for nearby communities. An extensive body of research documents CAFOs' impacts on air and water quality and related consequences for environmental and public health (Burkholder et al., 2007; Casey et al., 2015; Niedermeyer et al., 2020).

Industrialized animal agriculture has cumulative and disproportionate impacts on rural, low-income communities, communities of color, and members of Tribal Nations, raising well-documented concerns about environmental justice (EJ) (Gilio-Whitaker, 2019; Miller & Longest, 2020; Nicole, 2013; Wilson et al., 2002; Wing & Johnston, 2014; Wing, 2005; Wing et al., 2000). In NC, one of the nation's largest poultry producers, most poultry CAFOs remain unregulated by the state; however, there has been mounting political pressure for change (e.g., H. B. 722, North Carolina General Assembly, 2023). Over the past decade, impacted communities in NC have observed a dramatic rise in poultry CAFOs and have expressed concern about their disproportionate negative environmental and human health impacts on Black, Indigenous, and People of Color (Wagner et al., 2023). A 2023 journalistic investigation by the Charlotte Observer found that more than one billion chickens and turkeys generating billions of pounds of untreated waste are raised in approximately 4,700 industrialized operations in NC each year, with an estimated 230,000 people living within one mile of the operations (Off, 2023).

Human exposure to environmental hazards has typically been explored through statistical analyses of environmental hazard locations and the demographic characteristics of the places nearby (Carrel et al., 2016). Most research on the disproportionate impacts of CAFO-related hazards has been in NC and focused primarily on known swine CAFOs (~40% of them, which require a permit). These studies found that swine CAFOs are significantly more likely to be located in places where higher proportions of residents live in poverty and are non-white, making industrialized animal agriculture a major problem of EJ (Donham et al., 2007; Edwards & Ladd, 2001; Ladd & Edward, 2002; Mirabelli et al., 2006; Wing & Johnston, 2014; Wing et al., 2000). However, research conducted in the Upper Midwest, which has a different social geography, did not find an association between higher swine CAFO density and social vulnerability (Carrel et al., 2016). Deciphering if and the extent to which poultry CAFOs may be exacerbating existing or causing new environmental injustices necessitates documenting the location of these operations.

Public records of poultry CAFO locations are incomplete primarily because only CAFOs that discharge pollutants into US waters must apply for a National Pollutant Discharge Elimination System permit. Poultry CAFOs do not need a federal permit because they produce dry waste and do not discharge directly into regulated water bodies (Environmental Protection Agency, 2011) thus poultry operations across NC remain un- or under-regulated. Some states have specific regulations that might require permitting under certain conditions (e.g., Oklahoma (Felder, 2023), Nebraska (University of Nebraska–Lincoln, 2023), and Washington (Washington State Department of Ecology, 2023)). Existing regulations may be permissive or nuanced, allowing operating CAFOs to evade environmental review (Howard, 2019). For example, in Oklahoma, an industrialized poultry operation might not be considered a CAFO if they move the litter off-site (Felder, 2023), and in Washington and Nebraska, permitting could be avoided depending on the number of animals (University of Nebraska–Lincoln, 2023; Washington State Department of Ecology, 2023). Moreover, while the US Department of Agriculture's National Agricultural Statistics Service conducts a Census of Agriculture every five years, they only publish results in aggregate at the county or state level due to confidentiality and mask results in small counties (USDA, National Agricultural Statistics Service, 2019).

The lack of CAFO location data has led several agencies and organizations (e.g., EPA, Waterkeeper Alliance, Environmental Working Group) to employ individuals to scan satellite images and determine CAFO locations manually (Martin et al., 2018) in addition to on the ground monitoring that Waterkeepers and concerned citizens also conduct. However, such manual approaches are logistically difficult, non-systematically acquired, and time-consuming—it could take over seven years to classify the entire US for a fixed-time data set (Handan-Nader & Ho, 2019).

Most studies rely on CAFO locations known from public records, which are incomplete (Martin et al., 2018) thus, understanding of industrialized agriculture's negative impacts also remains incomplete. The problem of unknown CAFO locations is exacerbated in the context of poultry CAFOs, which remain undocumented and unregulated in states like NC, along with their potential impacts on marginalized communities. More than a decade ago, the

Figure 1. Examples of false positives in the poultry CAFO barn data set (Robinson et al., 2022). From left to right, these include swine CAFO barns (a), airport strips and hangars (b), and plant nurseries (c). Yellow polygons represent polygons misidentified as poultry CAFO barns. The base maps are subsets from National Agriculture Imagery Program (NAIP) data acquired over NC in 2016 (USDA Farm Production and Conservation - Business Center, Geospatial Enterprise Operations, 2016).

Government Accountability Office noted that the lack of reliable historical data on CAFOs has limited our understanding of changes in agricultural practices and associated environmental impacts over time (United States Government Accountability Office, 2008).

In response to this dearth of basic knowledge of CAFO location data, researchers have sought to manually label CAFO locations in satellite or aerial data (Handan-Nader & Ho, 2019; Martin et al., 2018) and to try to automate CAFO detection (Chugg et al., 2021; Handan-Nader & Ho, 2019; Maroney et al., 2020; Patyk et al., 2020; Robinson et al., 2022). Still, no nationwide data set records of permitted and non-permitted poultry CAFO locations and characteristics exist. Therefore, the EPA does not have accurate information to regulate them (United States Government Accountability Office, 2008).

Despite the importance of knowing CAFO locations and their characteristics for environmental governance, surprisingly, little research has been conducted in this space using machine learning (ML) and EO data (Handan-Nader & Ho, 2019). Recent advances in remote sensing and computer vision have made strides in several domains, including environmental compliance, particularly for automatic CAFO mapping (Handan-Nader & Ho, 2019; Handan-Nader et al., 2021). Mapping CAFOs in satellite data is non-trivial because CAFO facilities are variable in size (i.e., several barns for poultry or several barns and manure lagoons for swine CAFOs, Figure 1), their density in the landscape varies considerably, and other identifying features (e.g., cylindrical feeding tanks) are not always visible (Ho & Troncoso, 2019). The Microsoft for Good AI team recently developed a poultry CAFO data set across the US based on ML. However, this data set has several types of false positives (see Section 2.1.1; Robinson et al., 2022).

Based primarily on the experience and research conducted by and with communities living in the affected regions in NC, we know that there has been an increase in poultry CAFOs in these same geographies (Quincin, 2024). However, the relationship between poultry CAFO location and social vulnerabilities has not been studied systematically. This is likely due to the undocumented locations of poultry CAFOs, a knowledge gap enabled by the state's lack of regulation over this industry. This article describes a quantitative analysis of the association between social vulnerability (as measured by the Social Vulnerability Index or SVI; Flanagan et al., 2011) and poultry CAFOs at the census tract level. The specific objectives of this work were to (a) Use heuristics from the literature on poultry CAFO barn types on a recent EO-based poultry CAFO data set to produce a refined data set of poultry CAFO barns, (b) Validate the data set before and after applying the heuristics across NC and apply the heuristics US-wide, and (c) Examine the social implications of CAFOs through a quantitative analysis of the empirical relationships between EO-derived poultry CAFO density with census tract level social vulnerability indices, both in NC and US-wide.

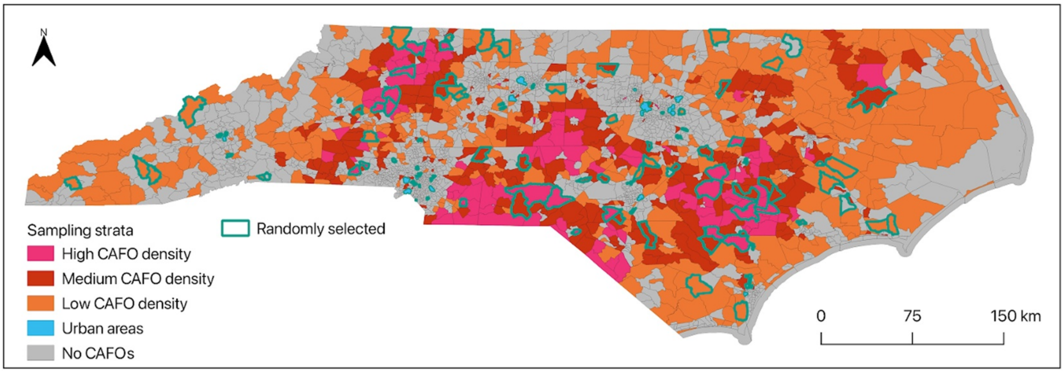

Figure 2. The distribution of the five strata and the randomly selected census tracts used for validation.

2. Methods

2.1. Data Sets

2.1.1. Robinson Data Set

We used the first national map of poultry CAFOs (Robinson et al., 2022) created using a deep-learning model. This data set consists of geolocated polygons representing poultry CAFOs. However, this effort used training data only from the Delmarva Peninsula (on the East coast of the US, occupying the vast majority of the state of Delaware and parts of the Eastern Shore of Maryland and Eastern Shore of Virginia), which lacks representativeness when applied US-wide. The data set thus produced several types of false positives (e.g., airstrips, dirt roads, swine CAFOs, plant nurseries, boats and docks in coastal or lacustrine areas, and industrial or mobile home parks, Figure 1). Given that the data set's main drawback was many false positives, we did not expand upon the data set but focused our efforts on refining the poultry CAFO data set by post-processing the results to eliminate a large number of these false positives by applying a series of literature-derived heuristics (Section 2.4).

2.1.2. National Agriculture Imagery Program (NAIP) Data

The original data set (Robinson et al., 2022) used NAIP imagery from 16 May 2016, to 4 September 2016. NAIP data have been regularly acquired in the US since 2001, with ∼1 m resolution and four bands (red, green, blue, and near-infrared) every few (∼3) years (USDA, 2009). We used the NAIP aerial imagery taken from 23 May 2016 to 11 September 2016, to perform the validation process by visually identifying poultry CAFOs for our refined data set. We accessed and downloaded the NAIP imagery as compressed county mosaics via the USDA Geospatial Data Gateway for all counties where we sampled census tracts for validation (Figure 2).

2.1.3. Environmental Justice (EJ) Indicators

We examined the environmental justice implications of poultry CAFOs using poultry CAFO barn density and the Center for Disease Control and Prevention (CDC) SVI per census tract. The SVI measures a community's ability to respond to environmental disasters, and it incorporates 16 factors, including poverty, unemployment, housing, education, age, gender, race, ethnicity, and transportation data (Flanagan et al., 2011). We utilized the 2020 data set, made available by the CDC (Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry/Geospatial Research, Analysis, and Services Program, 2021). We computed poultry CAFO barn area density per census tract as the total footprint area of barns within each tract divided by the corresponding tract area to account for the fact that larger barns will host more chickens and consequently have a higher environmental and social vulnerability impact.

2.2. Data Analysis

2.2.1. Moran's I

We used Local Moran's I to quantify the spatial co-occurrence of statistically significant SVI and poultry CAFO density clusters at the census tract level. Local Moran's I—also known as Localized Indicator of Spatial Analysis

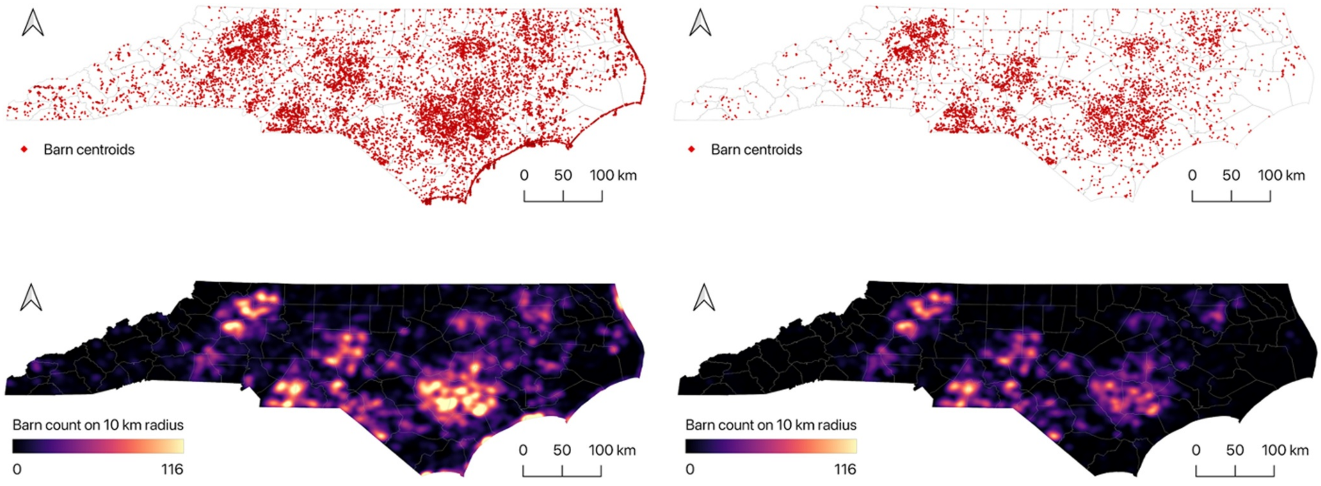

Figure 3. Barn centroid locations (top) before (left) and after (right) applying our literature-derived heuristics for NC and heat maps (using a 10 km radius) identifying high CAFO barn density areas in NC (bottom).

(LISA)—is a statistic for measuring spatial autocorrelation, that is, the extent to which a geolocated variable is clustered, dispersed, or randomly distributed at each location within a study area (Anselin, 1995). We computed Local Moran's I using the PySAL library in Python (Rey & Anselin, 2007). The five SVI variables—the index itself and the four themes that it comprises—and poultry CAFO density data were standardized (z-score standardization) before a spatial weights matrix was computed utilizing queen contiguity. This matrix was then used to compute the Local Moran's I values. For each variable, we visualized the results as LISA clusters, grouped into five categories of spatial clustering or dispersion, including High-High (HH), high values surrounded by high values (Hotspots); High-Low (HL), high values surrounded by low values (spatial outlier); Low-High (LH), low values surrounded by high value (spatial outlier); Low-Low (LL), low values surrounded by low values (Coldspots), and not significant, no statistically significant spatial autocorrelation (i.e., p-value less than 0.05). These clusters were computed at the census tract level, whereby the first quantifier—High/Low, that is, above or below the mean, respectively—refers to the value of each variable in a given tract. The second quantifier refers to the values of the same individual variable in the adjacent tracts (i.e., following queen contiguity).

We also compared the LISA clusters of HH poultry CAFO area density and the HH clusters from each one of the SVI variables (SVI itself plus the four themes). We assessed the spatial overlap between the HH clusters of the CAFO area density and each of the SVI variables by computing the number and total area of the intersecting census tracts where both variables exhibited HH clustering.

2.3. Study Area

2.3.1. North Carolina (NC)

We used NC (Figures 2 and 3) as a testbed to validate our literature-derived heuristics. NC is among the four highest poultry-producing states in the US (Figure 4) and has an established record of environmental injustices related to CAFOs (Miller & Longest, 2020; Wing et al., 2000). The vast majority of NC CAFOs are located in NC's inner Coastal Plain (southeastern NC), an area with a significant representation of low-income and minority populations (African American, Latine, Indigenous) with established records of existing, historical, underlying health disparities and social vulnerabilities (Emanuel, 2019; Lowery, 2010; Miller & Longest, 2020; Wing et al., 2000). Compounding these underlying risks, the area has experienced unprecedented flooding from hurricanes, projected to increase in frequency and intensity due to climate change (Christenson et al., 2022; Emanuel, 2018; Powell et al., 2024; USGCRP, 2017).

2.3.2. US-Wide

Once our literature-derived heuristics were validated for NC, we applied them to the US-wide data set to highlight the areas of high poultry CAFO density across the US. Using Moran's I, we assessed the spatial co-occurrence of

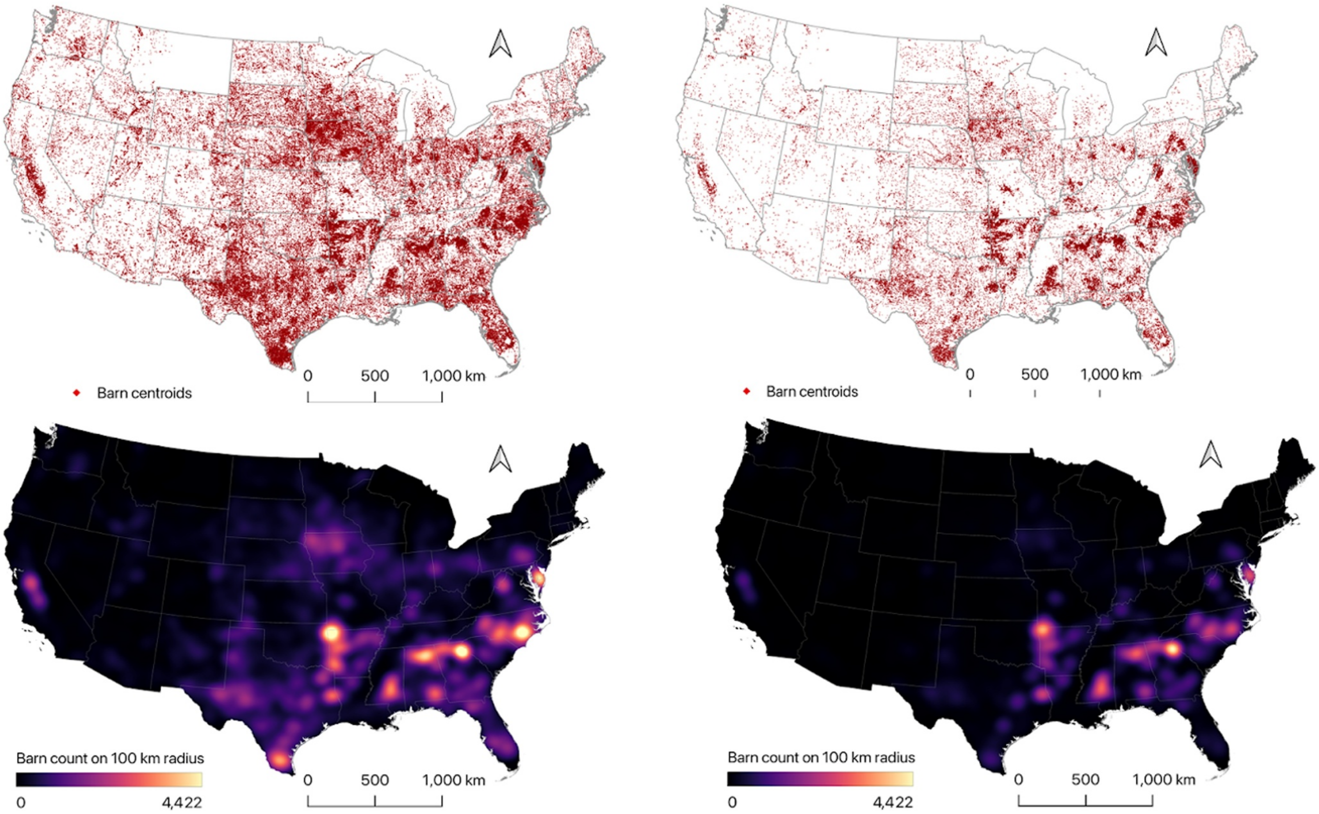

Figure 4. Barn centroid locations (top) before (left) and after (right) applying our literature-derived heuristics across the US and heat maps (using a 100 km radius) identifying high CAFO barn density areas in the US (bottom).

high poultry CAFO density with the overall 4-Theme SVI and each theme individually (i.e., Socioeconomic Status, Household Characteristics, Racial and Ethnic Minority Status, Housing Type and Transportation) across NC and US-wide. Each one of the four themes of the SVI summarizes several variables. For example, the 2020 Socioeconomic Status theme used here includes five variables: Below 150% Poverty, Unemployed, Housing Cost Burden, No High School Diploma, and No Health Insurance (Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry/Geospatial Research, Analysis, and Services Program, 2020).

2.4. Literature-Derived Heuristics

We established the need to refine the Robinson et al. (2022) data set because, for example, there were false positives corresponding to roads being misclassified as poultry barns and poultry barns occurring in water near the coastline or within inland water bodies (Figure 1). To achieve this, we conducted a literature review on poultry CAFO characteristics (Table 1), paired with several geospatial data sets (e.g., water bodies and roads). This enabled us to find where poultry CAFO barns intersected with or were close to those features (e.g., waterbodies, roads), to mark locations where poultry CAFO barns should not be present, and to remove false positives. We also constrained the area of poultry CAFO barns between 1,000 and 4,000 m^2, the width between 10 and 30 m, the length between 100 and 200 m, and the aspect ratio between 3.4 and 18. We then adjusted these ranges to reconcile differences among the references and our observations (deriving histograms to ensure most or all CAFOs were captured, followed by visual inspection and exploratory analysis of the distributions of barn characteristics distributions), ensuring suitability for a broad geographic area (US-wide).

2.5. Validation

We used after-heuristics (AH) poultry CAFO barn area density per NC census tract to construct the strata for our validation sampling design. We partitioned the tracts into five strata: the top 15% of poultry CAFO area density ("high CAFO density"), the bottom 50% ("low CAFO density"), every tract between the 15% and

Table 1
Literature-Derived Heuristics to Remove False Positives of a Machine Learning-Derived Data Set (Robinson et al., 2022) Consisting of Geolocated Polygons Representing Poultry CAFOs

Spatial feature	Criteria used	Target confounding factors	Literature source	Data set used/Other comments
Barn area	1,000–4,000 m^2	Mobile homes Swine CAFO barns	Lorencena et al., 2020; Robinson et al. (2022)	Differs from literature suggested values (2,000–3,000 m^2). Generated histograms and visual analysis, also supported by histograms in Robinson et al. (2022).
Barn length	100–200 m	Airstrips Dirt roads Airport hangars Swine CAFO barns Plant nurseries	Lorencena et al. (2020)	Generated histograms and performed visual analysis Literature suggested: 150–200 m
Barn width	10–30 m	Airstrips Dirt roads Airport hangars Swine CAFO barns Plant nurseries	Lorencena et al. (2020)	Generated histograms and performed visual analysis Literature suggested: 10–15 m
Barn aspect ratio	3.4 to 18	Swine CAFO barns Industrial and storage buildings	Soroka and Duren (2020)	Literature suggested: 3.4–20.49. Histograms provided by Robinson et al. (2022)
Barn location	At least 20 m away from roads	Roadways	Patyk et al. (2020)	Literature suggested distance to roadways. TIGER data: https://catalog.data.gov/dataset/tiger-line-shapefile-2022-nation-u-s-primary-roads
Barn location	On land	Barn polygons occurring in the ocean Barns located outside of the US border		Intersection with the US administrative area: GADM data set https://gadm.org/data.html
Barn location	At least 300 m away from the coastline	Long, narrow beaches Sand patches		Coastline data: TIGER/Line 2019 (https://catalog.data.gov/dataset/tiger-line-shapefile-2019-nation-u-s-coastline-national-shapefile)
Barn location	At least 10 m away from lakes	Barn polygons occurring within lakes Lake beaches Docks		Lakes data: HydroLAKES v1.0 https://www.hydrosheds.org/products/hydrolakes)
Barn location	At least 10 m away from rivers and streams	Surface water Long and narrow floodplains		Hydrography data: NHD Plus v2.1 https://www.epa.gov/waterdata/get-nhdplus-national-hydrography-dataset-plus-data

bottom 50% of area density ("medium CAFO density"), urban census tracts, and no poultry CAFO barns (Figure 2). The urban stratum was defined based on the 2019 National Land Cover Database (NLCD; Dewitz & U.S. Geological Survey, 2024), such that the most represented land cover classification within those tracts was either medium- or high-intensity developed areas, not including tracts with no CAFO barns. In each of the five strata, we randomly selected 25 census tracts with equal probability (i.e., simple random within each stratum). Given that the urban stratum only had 22 census tracts, we used all 22 for sampling. In comparison, each of the other four strata had 25 census tracts randomly selected, leading to 122 census tracts being used for validation as part of our ground truth (GT) data set. The GT data set was used to compare the improvement in our poultry CAFO data before and after applying the heuristics. Our GT reference data used to assess the accuracy of the poultry CAFO data set before and after applying the heuristic satisfied the requirements of reference classification/ground truth data in remote sensing (Olofsson et al., 2014). The standard for reference data is that it must be of higher quality than the map itself. That is, the reference labels can use the same imagery as the product (so "equal" in that sense, in our case, NAIP data), but the interpreter labels are of higher quality because of the intense effort to interpret them visually.

In each of the 122 sampled census tracts, two analysts visually counted and digitized poultry CAFO barns in QGIS (QGIS Development Team, 2024), creating rectangular polygons around the perimeter of apparent poultry CAFO barns. To avoid bias, the analysts were unaware of the strata to which the census tracts belonged. While identifying poultry CAFOs from NAIP aerial imagery was relatively straightforward, to ensure the classifications were consistent between the two analysts, both analysts counted and digitized the poultry CAFO barns for the same first 25 tracts (randomly selected) and compared the results. Disagreement between the two analysts was rare. The team consulted and provided feedback at the end of digitizing the 25 tracts to ensure consistency between the analysts, who continued digitizing the remaining 97 tracts separately. Further, when the analysts were unsure of their digitizing, those examples were reviewed and agreed upon across the team to maintain consistency in counting and digitizing. The characteristics used for visually identifying poultry CAFO barns included their shape (i.e., long and thin rectangular barns), color and texture (to exclude abandoned barns), the presence of feed silos, truck roads to the barns, other barns in their vicinities (most CAFOs have multiple barns), propane tanks used for heating mainly in western NC, and absence of manure lagoons, which are characteristic for swine CAFOs.

To assess per census tract accuracy, we used three primary metrics, including mean deviation (MD), mean absolute deviation (MAD), and root mean square error (RMSE, see formulas below). For the formulas, we defined y_k = GT (ground truth) value and x_k = BH (before heuristics) or AH (after heuristics) value for census tract k, and N = number of census tracts in the full population. The formulas below are presented in terms of the population parameter of the accuracy metric, which we then estimated from the stratified sample.

Mean deviation (MD): $\mathrm{MD} = \frac{1}{N}\sum_{k=1}^{N}\left(x_k - y_k\right)$

Mean absolute deviation (MAD): $\mathrm{MAD} = \frac{1}{N}\sum_{k=1}^{N}\left|x_k - y_k\right|$

Root mean square error (RMSE): $\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(x_k - y_k\right)^2}$

MAD and RMSE remove the impact that the after-heuristic and before-heuristic values can be greater than or less than the ground-truth values so that large positive and large negative differences with ground-truth will cancel in the MD metric. RMSE weights outliers (large deviations) more heavily than MAD because the deviations are squared. The stratified estimator of the population mean of z_k is shown below, where $\bar{z}_h$ is the sample mean of z_k in stratum h and N_h is the number of census tracts in stratum h (i.e., the stratum size of the population). z_k is defined differently to estimate each agreement measure, as shown in Supporting Information S1.

$$\hat{\bar{Z}} = \frac{1}{N}\sum_{h=1}^{H} N_h \bar{z}_h$$

3. Results

3.1. Refined Data Set

We applied a series of heuristics on an EO-based data set that mapped poultry CAFOs across NC and the US. The heuristics used were chosen based on existing literature, which described the characteristics of poultry CAFO barns (Table 1). These characteristics included area, width, length, and aspect ratio of poultry barns. Across NC, we removed 14,242 poultry CAFO barns (51.8% of the original 27,514 polygons) that were identified as false positives based on our heuristics across NC. Based on the validation sample data and the reference classification of poultry CAFO barns, the estimated number of barns was 12,847 for the AH classification compared to 12,216 based on the GT classification for NC (Table 2). Based on the BH classification, the estimated number was more than double the total count from the GT labels. Across the US, the number of poultry CAFO barns removed was 221,915 (61.5% of the original 360,857 polygons). After applying our literature-derived heuristics, the total number of poultry CAFO barns was 13,272 for NC and 138,942 for the US. The results indicate that the barn geometry criteria (width, length, area, and aspect ratio; see Table 1) effectively removed outliers, as evidenced by the similar mean values and the reduced standard deviation of barn area per tract AH when compared to BH, both in NC and in the US (see Table S1 and Table S2 in Supporting Information S1).

3.2. Validation

The sample validation demonstrated an accuracy improvement in all three features measured: number of poultry CAFO barns, area of barns, and barn area density estimates before and after applying heuristics. Applying heuristics reduced the overestimation of poultry CAFO density per census tract by 54%, aligning the AH density estimates much closer to the GT estimates than the agreement of the BH estimates with the GT estimates. Specifically, the Mean Deviation (MD) for the total count declined from 13,060 for BH to 631 for AH, indicating a substantial decrease in the overall bias. Similarly, the Mean Absolute Deviation (MAD) and Root Mean Square Error (RMSE) metrics showed that AH values were more accurate, with MAD decreasing from 13,711 (BH) to 3,627 (AH) and RMSE reducing substantially as well. These metrics from the accuracy assessment support that the heuristics corrected large discrepancies in the BH product for the number of barns, area of barns, and barn density; therefore, the refined AH data set better reflects the actual conditions on the ground.

3.3. Poultry CAFO Area Density in NC and the Contiguous United States (CONUS)

Descriptive mapping of poultry CAFO barn density at the census tract scale suggests a non-random and uneven distribution of poultry CAFOs in NC and across CONUS (Figures 3 and 4). In NC, most poultry CAFOs are located in the eastern, south-central, and western parts of the state, with higher densities than the rest of NC. The lowest densities of poultry CAFOs in NC are found in areas surrounding NC's larger cities, including Raleigh-Durham, Charlotte, and Asheville. Across the US, high densities of poultry CAFOs are found predominantly in rural areas of the US South, Southeast, and the Midwest, including NC, the Delmarva Peninsula, north central Iowa, eastern Oklahoma, northern and southern parts of Georgia, Alabama, Mississippi, Louisiana, and western Arkansas.

3.4. Association Between Areas of High Poultry CAFO Density and SVI

We found that poultry CAFOs cluster in certain NC and USA regions. We applied Local Indicators of Spatial Association (LISA) and Local Moran's I to identify clustering patterns of poultry CAFOs. Our analysis revealed that these facilities tend to cluster in regions of NC characterized by high racial and minority populations and low socioeconomic status, as defined by SVI's themes, and high social vulnerability, particularly in the southeastern part of the state (Figure 5). We have also produced similar maps for the other two SVI themes (Household Characteristics and Housing Type, and Transportation; see Supporting Information S1). Socioeconomic Status and Racial and Minority Status were the themes with more discernible spatial clusters that match the barn area density in NC (Figure 5). Across the US, these high densities of poultry CAFOs are located in areas with populations of high social vulnerability in eastern NC, eastern Oklahoma, and southern Georgia, among others (Figure 6). When comparing HH poultry CAFO area density census tracts with census tracts of HH SVI, we identified areas of significant spatial correlation between the variables. In NC, one-third of the HH poultry CAFO area density census tracts overlapped with census tracts of HH SVI, whereas for the CONUS, this overlap is only 17%. For both NC and the US, tracts of HH SVI's Theme 3, Racial and Ethnic Minority Status, overlapped the

Table 2
Comparison of GT, BH, and AH Estimates of Total Count and Total Area of Poultry CAFO Barns Based on the Sample, As Well As Estimates of Mean (Per Census Tract) Count, Mean Area, and Mean Density in NC

COUNT	Estimated total	SE	Estimated mean	SE
Ground truth	12,216	1,647	4.57	0.62
Before heuristics	25,276	3,164	9.46	1.18
After heuristics	12,847	1,615	4.81	0.6
AREA (m^2)	Estimated total	SE	Estimated mean	SE
Ground truth	2.748×10^7	3.855×10^6	10,287	1,443
Before heuristics	5.218×10^7	6.651×10^6	19,532	2,489
After heuristics	3.335×10^7	4.269×10^6	12,485	1,598
DENSITY			Estimated mean	SE
Ground truth			9.1×10^{-5}	8.4×10^{-6}
Before heuristics			2.81×10^{-4}	5.21×10^{-5}
After heuristics			1.28×10^{-4}	5.8×10^{-6}

most (30%) with areas of HH poultry CAFO area density. In terms of area, 36% and 21% of the total area of census tracts of HH poultry CAFO area density overlapped with census tracts of HH SVI across NC and the US, respectively. Among the SVI themes, Theme 3, Racial and Ethnic Minority Status, had the highest area overlap (43%) across NC, followed by SVI's Theme 2, Socioeconomic Status (31%). Across the US, SVI's Theme 2, Household Characteristics, had the highest area overlap (29%), followed closely by Racial and Ethnic Minority Status and Socioeconomic Status, each with 26% area overlap.

4. Discussion

We used literature-derived heuristics (Table 1) to remove the large proportion of false positives in a US-wide poultry CAFO data set that was developed based on a deep-learning model trained on the Delmarva Peninsula and applied across the entire US using NAIP data (Robinson et al., 2022). Applying the heuristics improved the AH data set as quantified by our validation, which showed a 54% reduction in the overestimation of poultry CAFO density per census tract compared to the BH data set (Table 2). For example, Figure 7 shows that the majority of AH barn density estimates have lower errors than BH estimates per census tract. The larger errors are in the BH estimates, specifically in the urban tracts and in some of the high-density tracts. The improvement in the CAFO density estimates was more prominent in urban areas (Figure 7), likely due to urban areas having a higher density and overall more features that can be misidentified as poultry CAFO barns. We used the AH data set to identify co-occurrence clusters of areas of high poultry CAFO density and high CDC SVI in NC and US-wide. We chose NC to validate our data because NC is one of the largest poultry-producing states in the US, experiences environmental injustices amplified by climate-driven hazards such as increased hurricane flooding, and has a high proportion of private well water users who are at risk of drinking water contamination by CAFO waste.

Poultry production in NC in CAFOs was not evenly distributed in space. There are three clusters of High-High (HH), high poultry CAFO density per census tract surrounded by other high poultry CAFO density (Hotspots) in NC, including the state's southeastern part and the central and western parts of NC (Figures 2 and 3). This pattern differs from the geographic distribution of swine CAFOs, which are concentrated in the eastern part of the state (Montefiore et al., 2022). Poultry CAFO concentrations are more widespread across the state compared to swine CAFOs, and they tend to be clustered in rural regions. The clusters of HH poultry CAFO density in the Coastal Plain of NC occurred in areas of low socioeconomic status and high SVI (Figure 5), similar to what others have found in the literature for NC (Donham et al., 2007; Edwards & Ladd, 2001; Ladd & Edward, 2002; Mirabelli et al., 2006; Wing & Johnston, 2014; Wing et al., 2000). Specifically, when overlapping HH poultry CAFO area density tracts with tracts of HH SVI and HH themes scores, Racial and Ethnic Minority Status had the highest overlap in NC in terms of both by number (30%) and area (43%) of census tracts, and one-third of HH poultry

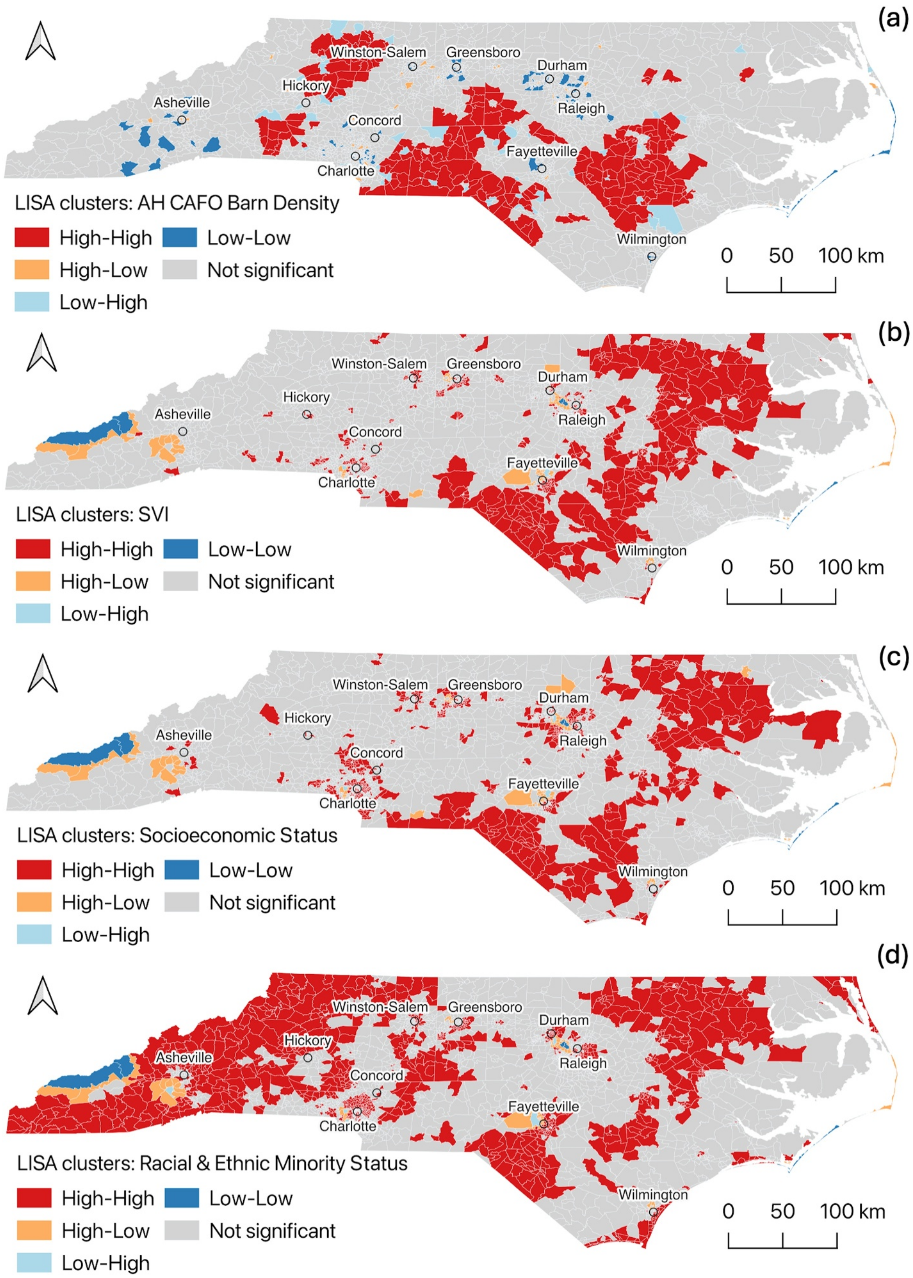

Figure 5. LISA clusters in NC of (a) poultry CAFO barn density, (b) the CDC Social Vulnerability Index (SVI) for 2020, (c) SVI's Socioeconomic Status scores, and (d) SVI's Racial and Ethnic Minority Status scores. All variables are aggregated by the 2020 U.S. Census Tracts. LISA clusters show high values surrounded by high values (red, High-High, also termed hotspots); high values surrounded by low values (orange, High-Low, spatial outliers); low values surrounded by high values (light blue, Low-High, spatial outliers); and low values surrounded by low values (dark blue, Low-Low, also termed coldspots). The remaining areas do not have statistically significant spatial autocorrelation (light gray). The names of the 10 most populous cities are included for reference.

CAFO area density tracts overlapped with tracts of HH SVI. Similar relationships were observed between swine CAFO exposure and race and income in Mississippi (Wilson et al., 2002). Socioeconomic status and racial minorities are among the four themes of variables that comprise the SVI, and they have been documented as important in characterizing social vulnerabilities (Tate et al., 2021); such vulnerabilities are further compounded by the ecological risks shouldered by these communities, who reside in lowland regions increasingly impacted by hurricane and flooding events, heat indices, and loss of biodiversity.

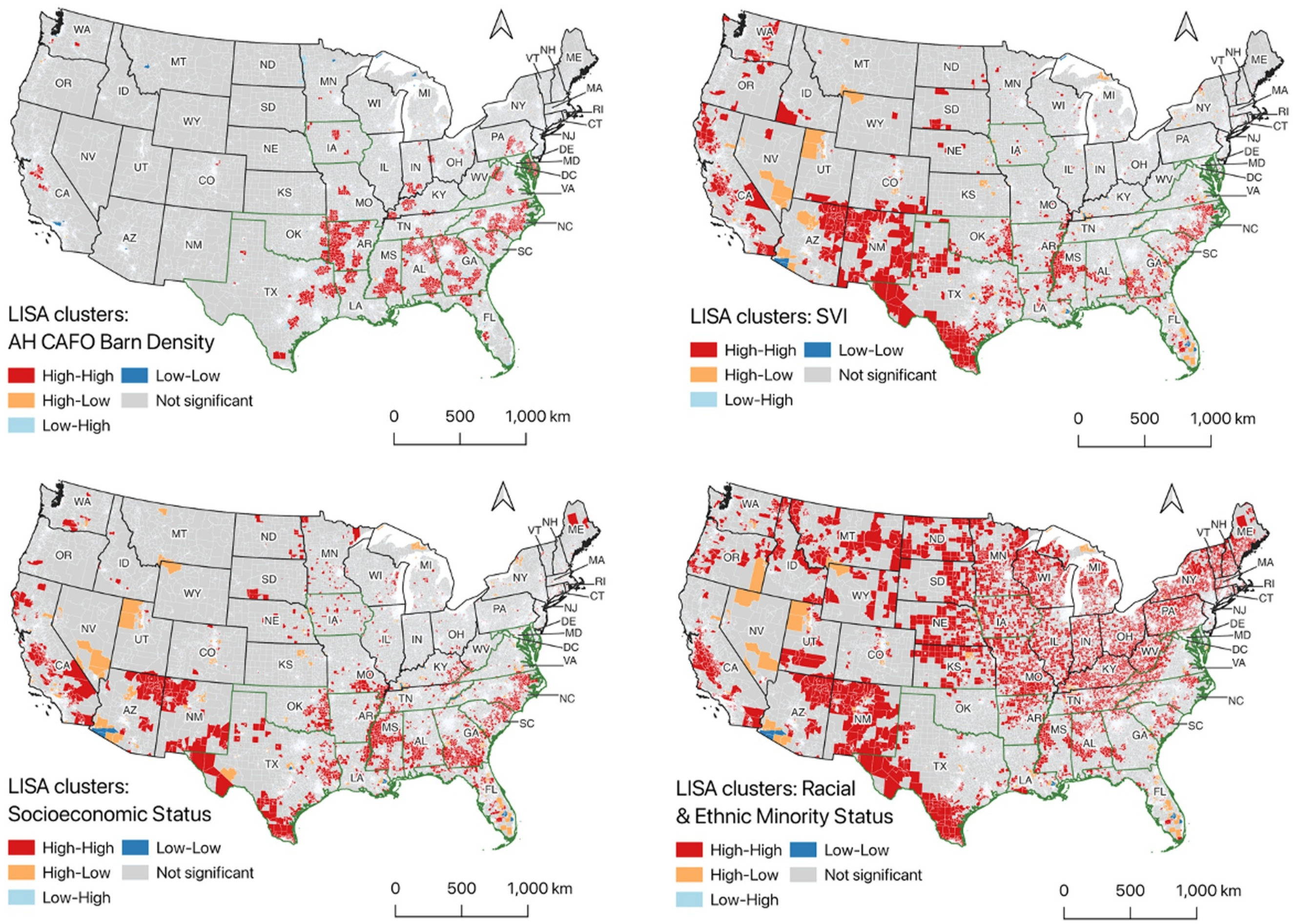

Figure 6. LISA clusters in the contiguous US of CAFO barn density (top left), the CDC Social Vulnerability Index (SVI) for 2020 (top right), SVI's Socioeconomic Status scores (bottom left), and SVI's Racial and Ethnic Minority Status (bottom right) scores. All variables are aggregated by the 2020 U.S. Census Tracts. LISA clusters show high values surrounded by high values (red, High-High, also termed hotspots); high values surrounded by low values (orange, High-Low, spatial outliers); low values surrounded by high values (light blue, Low-High, spatial outliers); and low values surrounded by low values (dark blue, Low-Low, also termed coldspots). The remaining areas do not have statistically significant spatial autocorrelation (light gray). The 2-letter state codes and their boundaries (black) are included for reference. The states mentioned in the text are outlined in green.

Poultry production in CAFOs is spatially clustered in certain areas of the US. We identified several clusters of HH poultry CAFO density nationally across the US, including the Coastal Plain in southeastern NC, the Delmarva Peninsula, Iowa, and several areas of the US south and southeast (Figures 4 and 6). Only some HH poultry CAFO density areas coincided with areas of HH clusters of SVI, particularly in the eastern NC, but not in the major urban areas or areas of the western NC, which also have high poultry CAFO barn densities but not high SVI. When overlapping HH poultry CAFO tracts with tracts of HH SVI, the overall overlap was 17% and 21%, respectively, by number and area of census tract. Among the four SVI themes, similar to NC, Racial and Ethnic Minority Status had the highest overlap by area and the second highest, together with Socioeconomic Status by number of census tracts overlapped. The presence of poultry CAFOs can provide economic benefits to operators and some members of local communities who may be directly employed in the industry or who may benefit indirectly via CAFO-related economic activity (e.g., providing infrastructure or purchasing feed and supplies; Environmental Protection Agency, 2001). However, occupational studies acknowledge that jobs directly associated with CAFOs are accompanied by elevated health and safety risks (e.g., Mitloehner & Calvo, 2008; Moore et al., 2021; Ramos et al., 2016).

Although our work indicates potential for environmental injustice, other factors should also be considered. First, the fact that not all locations of high poultry CAFO densities are associated with areas of high social vulnerability could suggest that accounting for places where manure is sprayed or discarded, which can be further away from a

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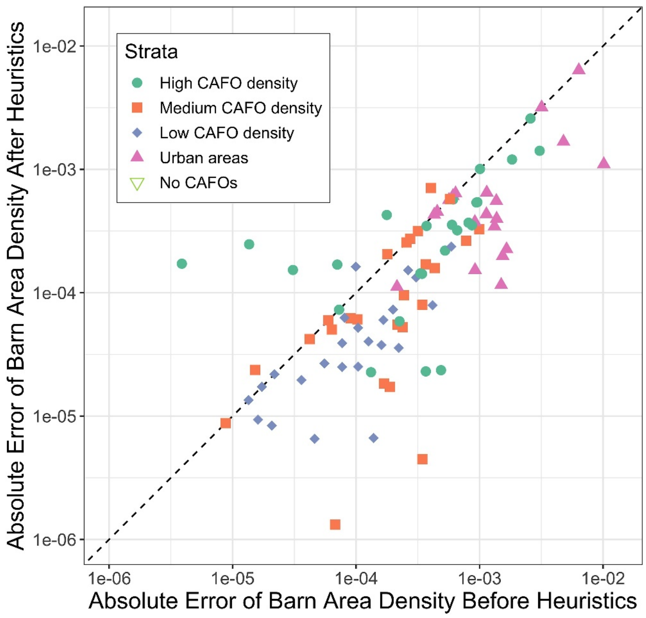

Figure 7. Comparison of the absolute errors of both barn area density estimates, after heuristics (AH, *y*-axis) and before heuristics (BH, *x*-axis), per census tract. The color and shape of the points show their strata. The dashed line represents the 1:1 line. The density estimates are log-transformed for better visualization, showing the larger errors occurring in BH estimates within census tracts of Urban areas, and of High CAFO density. It also shows that most BH estimates have higher errors than the AH estimates.

CAFO, may be important. Poultry CAFOs store dry waste in open heaps, which is then often applied to agricultural lands as fertilizer—the distance between the CAFO and the point of application is typically greater than 15 km (Miralha et al., 2022). Poultry CAFOs are not approved for discharging into US waters, and they do not typically need a federal permit to operate, thus potentially leading to further inequalities.

Second, while most studies, primarily conducted in NC and areas of the US South and mainly focused on swine CAFOs, demonstrated a positive association between areas of high CAFO density and high SVI, this relationship does not hold throughout the US. For example, a study focused on swine CAFOs in Iowa did not find a significant relationship between swine CAFOs and hotpots of poverty and non-white populations, unlike in NC (Carrel et al., 2016). The authors attributed this to the different geography and demography of Iowa, as well as other parts of the Upper Midwest, where minorities are located mainly in urban areas rather than rural areas such as in the southeastern US (e.g., NC), with rural areas having high revenue due to their corn and soy production (Carrel et al., 2016).

Third, EJ is not usually a factor of one polluting industry but multiple compounded social, economic, and environmental hazards and inequities captured in the SVI. This research underscores the critical need to understand the EJ implications of poultry CAFO locations to effectively document and address the accumulation and exacerbation of social and environmental harms, particularly in areas where swine CAFOs and their impacts have already been established (e.g., eastern NC), as well as emerging new areas. For example, NC's Governor's Office recently committed (see Executive Order 292; Office of the Governor of North Carolina, 2023) to advancing EJ across state agencies, including developing an EJ mapping tool and cumulative impact assessment. This commitment highlights the urgency of incorporating data on poultry CAFO locations. Such inclusion is essential for prioritizing regulatory efforts and for comprehensive EJ assessments. Furthermore, the expansion of poultry CAFOs across NC, known for hazardous waste issues and potential aggravation of existing environmental injustices—especially in hurricane-prone eastern NC—calls for a regulatory review to mitigate new and ongoing harms in vulnerable communities. This work provides foundational data for guiding policy decisions and further research into the spatial dynamics of CAFO impacts within diverse ecological and social landscapes.

Fourth, ideally, a finer-scale analysis at the census block might be preferable over census tracts to capture finer spatial links to SVI. The size of census tracts is a function of the number of people in a tract (on average, a tract represents 4,000 people); thus, their size can vary. If census tract sizes are large and heterogeneous, they can mask those effects by averaging across a larger area. In contrast, a census block is the smallest geographic unit used by the United States Census Bureau, typically bounded by visible features such as streets and roads or non-visible boundaries like property lines. However, SVI data at the block level are lacking compared to data at the tract level.

Understanding the impacts of CAFOs on community health relies on updated, high quality and publicly available data on the location of poultry CAFOs. EO data and ML represent one of the few ways to quantify the presence of CAFOs, their expansion over time, and facility establishment and closing. While the data set utilized here relied on NAIP imagery, a source of imagery only available in the US, the approach could be applied to other areas worldwide where high numbers of CAFOs occur (e.g., Western Europe, Australia, New Zealand) using other sources of high-resolution satellite imagery, such as PlanetScope data. This is important given the increase in intensive industrialized farming worldwide (Ilea, 2009). This global applicability highlights the role of integrating regional-specific EO data with global environmental monitoring efforts to enhance the efficacy of policy-making (Tulbure et al., 2022). The lack of readily available data on unpermitted and unregulated poultry CAFO locations highlights the importance of EO-derived data using artificial intelligence algorithms. Our work highlights the importance of a full record of high-quality, openly accessible data of non-permitted poultry CAFO locations to assess their environmental impacts and intersections with social vulnerabilities accurately. Moreover, it closes the widely documented "technology gap" between the public (NGOs, civil society, and regulators) and private sectors (Newcombe, 2018) regarding access to EO-derived data sets.

Future work could use this or similar data sets to link CAFO locations to water quality and community health impacts. Contaminants released from CAFO waste reach shallow, unconfined aquifers (Miller & Longest, 2020) and are discharged into wetlands, streams, and coastal waters used for recreation (Burkholder et al., 2007; Karr et al., 2001). Ground- and surface waters impacted by CAFOs have increased levels of nitrate (Amato et al., 2020; Hubbard et al., 2020; Mallin et al., 2015; Mallin & McIver, 2018) and microbes (Christenson et al., 2022; Mallin et al., 2015; Mallin & McIver, 2018), threatening aquatic ecosystems and human health (Burkholder et al., 2007; Casey et al., 2015; Wing et al., 2000). However, most studies rely on publicly available CAFO locations to investigate associations with water quality and may underestimate impacts due to exposure misclassification because of incomplete data on CAFO locations. Using complete and accurate CAFO locations to understand water quality impacts is particularly important in areas where residents use private wells for drinking water. For example, NC has over 3 million private well users, the second highest of all US states (George et al., 2023; Gibson & Pieper, 2017), with many residents in disadvantaged communities relying on untreated drinking water from private wells that the Safe Drinking Water Act does not regulate. Well owners are expected to conduct their own testing but rarely have access to the information and resources needed to do so (Fizer et al., 2018; Stillo et al., 2019). Accurate spatial data can help identify communities where CAFO exposure, socioeconomic vulnerability, and water quality risks co-occur.

5. Summary

In this study, we identify the regions in NC and across CONUS—based on the 2020 census tracts—that are more exposed to environmental justice issues driven by the prevalence of poultry CAFOs. We achieved this goal by structuring this research in two stages. In the first stage, we refined a deep-learning generated data set of poultry CAFO barns by applying a set of heuristics to remove different types of misclassified features, including swine CAFOs, dirt roads, and storage facilities, that otherwise would hinder further analyses. In the second stage, we analyzed the environmental justice impact of the locations of these poultry CAFOs using the CDC's SVI. We utilized Moran's I, a spatial statistics technique, to identify clusters of census tracts with a high density of poultry CAFO barns and high SVI scores. Identifying vulnerable communities can help local environmental justice organizations better understand residents' problems and allocate appropriate funding for solutions.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data sets used in this study are freely available. The original poultry CAFO data set is provided by Robinson et al. (2022) at the following GitHub page: https://github.com/microsoft/poultry-cafos/, and the Social Vulnerability Index is available from the Center for Disease Control (Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry/Geospatial Research, Analysis, and Services Program, 2021).

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References

Amato, H. K., Wong, N. M., Pelc, C., Taylor, K., Price, L. B., Altabet, M., et al. (2020). Effects of concentrated poultry operations and cropland manure application on antibiotic resistant *Escherichia coli* and nutrient pollution in Chesapeake bay watersheds. *Science of the Total Environment*, *735*(September), 139401. https://doi.org/10.1016/j.scitotenv.2020.139401

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Burkholder, J. A., Libra, B., Weyer, P., Heathcote, S., Kolpin, D., Thorne, P. S., & Wichman, M. (2007). Impacts of waste from concentrated animal feeding operations on water quality. *Environmental Health Perspectives*, *115*(2), 308–312. https://doi.org/10.1289/ehp.8839

Carrel, M., Young, S., & Tate, E. (2016). Pigs in space: Determining the environmental justice landscape of swine concentrated animal feeding operations (CAFOs) in Iowa. *International Journal of Environmental Research and Public Health*, *13*(9), 849. https://doi.org/10.3390/ijerph13090849

Casey, J. A., Kim, B. F., Larsen, J., Price, L. B., & Nachman, K. E. (2015). Industrial food animal production and community health. *Current Environmental Health Reports*, *2*(3), 259–271. https://doi.org/10.1007/s40572-015-0061-0

Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry/Geospatial Research, Analysis, and Services Program. (2020). CDC/ATSDR social vulnerability index (SVI) 2020 documentation. Retrieved from https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2020.html

Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry/Geospatial Research, Analysis, and Services Program. (2021). CDC/ATSDR social vulnerability index 2020 database NC. Retrieved from https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html

Christenson, E., Wickersham, L., Jacob, M., & Stewart, J. (2022). A watershed study assessing effects of commercial hog operations on microbial water quality in North Carolina, USA. *Science of the Total Environment*, *838*(September), 156085. https://doi.org/10.1016/j.scitotenv.2022.156085

Chugg, B., Anderson, B., Eicher, S., Lee, S., & Ho, D. E. (2021). Enhancing environmental enforcement with near real-time monitoring: Likelihood-based detection of structural expansion of intensive livestock farms. *International Journal of Applied Earth Observation and Geoinformation*, *103*(December), 102463. https://doi.org/10.1016/j.jag.2021.102463

Copeland, C. (2010). *Animal waste and water quality: EPA regulation of concentrated animal feeding operations (CAFOs) CRS Report for Congress CRS-RL31851*. Congressional Research Service. Retrieved from https://nationalaglawcenter.org/wp-content/uploads/assets/crs/RL31851.pdf

Dewitz, J., & U.S. Geological Survey (2024). National land cover database (NLCD) 2019 products (Ver. 3.0, February 2024). [Object]. https://doi.org/10.5066/P9KZCM54

Donham, K. J., Wing, S., Osterberg, D., Flora, J. L., Hodne, C., Thu, K. M., & Thorne, P. S. (2007). Community health and socioeconomic issues surrounding concentrated animal feeding operations. *Environmental Health Perspectives*, *115*(2), 317–320. https://doi.org/10.1289/ehp.8836

Edwards, B., & Ladd, A. (2001). *Race, class, political capacity and the spatial distribution of swine Waste in North Carolina, 1982-1997* (Vol. 9, pp. 51–70). North Carolina Geographer.

Emanuel, R. E. (2018). Climate change in the lumbee river watershed and potential impacts on the Lumbee tribe of North Carolina. *Journal of Contemporary Water Research & Education*, *163*(1), 79–93. https://doi.org/10.1111/j.1936-704X.2018.03271.x

Emanuel, R. E. (2019). Water in the Lumbee world: A river and its people in a time of change. *Environmental History*, *24*(1), 25–51. https://doi.org/10.1093/envhis/emy129

Environmental Protection Agency. (2001). *Economic analysis for the proposed revisions to the national pollutant discharge elimination system and the effluent guidelines for concentrated animal feeding operations*. U.S. Environmental Protection Agency. EPA-821-R-01-001 Retrieved from https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=20002OV9.txt

Environmental Protection Agency. (2011). *"National pollutant discharge elimination system (NPDES) concentrated animal feeding operation (CAFO) reporting rule." Proposed rule 76 FR 65431*. Federal Register. Retrieved from https://www.federalregister.gov/documents/2011/10/21/2011-27189/national-pollutant-discharge-elimination-system-npdes-concentrated-animal-feeding-operation-cafo

Felder, B. (2023). *Oklahoma's permit system ushered in new wave of industrial poultry farm growth*. Investigate Midwest, October 2023. Retrieved from https://investigatemidwest.org/2023/10/05/oklahomas-permit-system-ushered-in-new-wave-of-industrial-poultry-farm-growth/

Fizer, C., Bruine de Bruin, W., & Stillo, F. (2018). Barriers to managing private wells and septic systems in underserved communities: Mental models of homeowner decision making. *Journal of Environmental Health*, *81*(5), 8–40.

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2011). A social vulnerability index for disaster management. *Journal of Homeland Security and Emergency Management*, *8*(1). https://doi.org/10.2202/1547-7355.1792

Food & Water Watch. (2020). Factory farm nation: 2020 Edition.

George, A., Gray, K., Wait, K., Gallagher, D., Edwards, M., Currie, J., et al. (2023). Drinking water disparities in North Carolina communities served by private wells. *Environmental Justice, June, env.2022.0100*. https://doi.org/10.1089/env.2022.0100

Gibson, J. M. D., & Pieper, K. J. (2017). Strategies to improve private-well water quality: A North Carolina perspective. *Environmental Health Perspectives*, *125*(7). http://dx.doi.org.prox.lib.ncsu.edu/10.1289/EHP890

Gilio-Whitaker, D. (2019). *As long as grass grows: The indigenous fight for environmental justice, from colonization to standing rock*. Beacon Press.

Handan-Nader, C., & Ho, D. E. (2019). Deep learning to map concentrated animal feeding operations. *Nature Sustainability*, *2*(4), 298–306. https://doi.org/10.1038/s41893-019-0246-x

Handan-Nader, C., Ho, D. E., & Liu, L. Y. (2021). Deep learning with satellite imagery to enhance environmental enforcement. In *Data science applied to sustainability analysis* (pp. 205–228). Elsevier. https://doi.org/10.1016/B978-0-12-817976-5.00011-5

Herrero, M., Wirsenius, S., Henderson, B., Rigolot, C., Thornton, P., Havlík, P., et al. (2015). Livestock and the environment: What have we learned in the past decade? *Annual Review of Environment and Resources*, *40*(1), 177–202. https://doi.org/10.1146/annurev-environ-031113-093503

Ho, M., & Troncoso, J. (2019). Object localization of concentrated animal feeding operations.

Howard, C. (2019). *Illinois has open door for CAFOs*. Free Community Word. Retrieved from http://thecommunityword.com/online/blog/2019/07/31/illinois-has-open-door-for-cafos/ 31 July 2019.

Hubbard, L. E., Givens, C. E., Griffin, D. W., Iwanowicz, L. R., Meyer, M. T., & Kolpin, D. W. (2020). Poultry litter as potential source of pathogens and other contaminants in groundwater and surface water proximal to large-scale confined poultry feeding operations. *Science of the Total Environment*, *735*(September), 139459. https://doi.org/10.1016/j.scitotenv.2020.139459

Ilea, R. C. (2009). Intensive livestock farming: Global trends, increased environmental concerns, and ethical solutions. *Journal of Agricultural and Environmental Ethics*, *22*(2), 153–167. https://doi.org/10.1007/s10806-008-9136-3

Karr, J. D., Showers, W. J., Wendell Gilliam, J., & Scott Andres, A. (2001). Tracing nitrate transport and environmental impact from intensive swine farming using delta nitrogen-15. *Journal of Environmental Quality*, *30*(4), 1163–1175. https://doi.org/10.2134/jeq2001.3041163x

Ladd, A. E., & Edward, B. (2002). Corporate swine and capitalist pigs: A decade of environmental injustice and protest in North Carolina. *Social Justice 29*, *3*(89), 26–46.

Lorencena, M. C., Southier, L. F. P., Casanova, D., Ribeiro, R., & Teixeira, M. (2020). A framework for modelling, control and supervision of poultry farming. *International Journal of Production Research*, *58*(10), 3164–3179. https://doi.org/10.1080/00207543.2019.1630768

Lowery, M. M. (2010). *Lumbee Indians in the Jim Crow South: Race, identity, and the making of a nation*. Chapel Hill: University of North Carolina Press.

Mallin, M. A., & McIver, M. R. (2018). Season matters when sampling streams for swine CAFO waste pollution impacts. *Journal of Water and Health*, *16*(1), 78–86. https://doi.org/10.2166/wh.2017.194

Mallin, M. A., McIver, M. R., Robuck, A. R., & Dickens, A. K. (2015). Industrial swine and poultry production causes chronic nutrient and fecal microbial stream pollution. *Water, Air, & Soil Pollution*, *226*(12), 407. https://doi.org/10.1007/s11270-015-2669-y

Maroney, S., McCool-Eye, M. J., Fox, A., & Burdett, C. (2020). Using object-based image analysis to map commercial poultry operations from high resolution imagery to support animal health outbreaks and events. *Geospatial Health*, *15*(2). https://doi.org/10.4081/gh.2020.919

Martin, K. L., Emanuel, R. E., & Vose, J. M. (2018). Terra incognita: The unknown risks to environmental quality posed by the spatial distribution and abundance of concentrated animal feeding operations. *Science of the Total Environment*, *642*, 887–893. https://doi.org/10.1016/j.scitotenv.2018.06.072

Miller, D. L., & Longest, R. (2020). Reconciling environmental justice with climate change mitigation: A case study of NC swine CAFOs. *Vermont Journal of Environmental Law*, *21*, 523–543.

Mirabelli, M. C., Wing, S., Marshall, S. W., & Wilcosky, T. C. (2006). Race, poverty, and potential exposure of middle-school students to air emissions from confined swine feeding operations. *Environmental Health Perspectives*, *114*(4), 591–596. https://doi.org/10.1289/ehp.8586

Miralha, L., Sidique, S., & Muenich, R. L. (2022). The spatial organization of CAFOs and its relationship to water quality in the United States. *Journal of Hydrology*, *613*(October), 128301. https://doi.org/10.1016/j.jhydrol.2022.128301

Mitloehner, F. M., & Calvo, M. S. (2008). Worker health and safety in concentrated animal feeding operations. *Journal of Agricultural Safety and Health*, *14*(2), 163–187. https://doi.org/10.13031/2013.24349

Montefiore, L. R., Nelson, N. G., Dean, A., & Sharara, M. (2022). Reconstructing the historical expansion of industrial swine production from landsat imagery. *Scientific Reports*, *12*(1), 1736. https://doi.org/10.1038/s41598-022-05789-5

Moore, T. C., Fong, J., Rosa Hernández, A. M., & Pogreba-Brown, K. (2021). CAFOs, novel influenza, and the need for one health approaches. *One Health*, *13*(December), 100246. https://doi.org/10.1016/j.onehlt.2021.100246

Newcombe, T. (2018). *Is government ready for AI?* Government Technology. Retrieved from https://www.govtech.com/products/is-government-ready-for-ai.html

Nicole, W. (2013). CAFOs and environmental justice: The case of North Carolina. *Environmental Health Perspectives*, *121*(6). https://doi.org/10.1289/ehp.121-a182

Niedermeyer, J. A., Miller, W. G., Yee, E., Harris, A., Emanuel, R. E., Jass, T., et al. (2020). Search for campylobacter spp. reveals high prevalence and pronounced genetic diversity of Arcobacter Butzleri in floodwater samples associated with hurricane florence in North Carolina, USA. In C. A. Elkins (Ed.), *Applied and environmental microbiology* (Vol. 86(20), pp. e01118-20). https://doi.org/10.1128/AEM.01118-20

North Carolina Conservation Network. (2021). Concerns with directed biogas projects in North Carolina. Retrieved from https://www.ncconservationnetwork.org/wp-content/uploads/2021/03/biogaspositionpaperNC33021.pdf

North Carolina General Assembly. (2023). House bill 722. Retrieved from https://www.ncleg.gov/Sessions/2023/Bills/House/PDF/H722v0.pdf

Off, G. (2023). *Big poultry: How a secretive industry rules the roost in North Carolina*. The Charlotte Observer, 2023. Retrieved from https://www.charlotteobserver.com/news/state/north-carolina/article267887592.html

Office of the Governor of North Carolina. (2023). Executive order no. 292: Advancing environmental justice for North Carolina. Retrieved from https://governor.nc.gov/executive-order-no-292/open

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148*(May), 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Patyk, K. A., McCool-Eye, M. J., South, D. D., Burdett, C. L., Maroney, S. A., Fox, A., et al. (2020). Modelling the domestic poultry population in the United States: A novel approach leveraging remote sensing and synthetic data methods. *Geospatial Health*, *15*(2). https://doi.org/10.4081/gh.2020.913

Powell, D. E., Currie, J., Koonce, D. M., Legerton, M., & Witter, R. (2024). *Renewable ruse: Bioenergy development in North Carolina's coastal plains*. Engaging Science, Technology, & Society.

QGIS Development Team. (2024). *QGIS geographic information system*. QGIS Association. Retrieved from https://www.qgis.org

Quincin, A. (2024). 'Nobody's listening:' NC department of environmental quality fails to regulate water and air pollution from poultry farming. Retrieved from https://mediahub.unc.edu/nobodys-listening-nc-department-of-environmental-quality-fails-to-regulate-water-and-air-pollution-from-poultry-farming

Ramos, A., Fuentes, A., & Trinidad, N. (2016). Perception of job-related risk, training, and use of personal protective equipment (PPE) among Latino immigrant hog CAFO workers in Missouri: A pilot study. *Safety Now*, *2*(4), 25. https://doi.org/10.3390/safety2040025

Rey, S., & Anselin, L. (2007). PySAL: A python library of spatial analytical methods. *The Review of Regional Studies*, *37*(1). https://doi.org/10.52324/001c.8285

Robinson, C., Ben, C., Anderson, B., Lavista Ferres, J. M., & Ho, D. E. (2022). Mapping industrial poultry operations at scale with deep learning and aerial imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *15*, 7458–7471. https://doi.org/10.1109/JSTARS.2022.3191544

Soroka, A. M., & Duren, Z. L. (2020). *Poultry feeding operations on the Delaware, Maryland, and Virginia Peninsula from 2016 to 2017*. U.S. Geological Survey. https://doi.org/10.5066/P9MO25Z7

Stillo, F., de Bruin, W. B., Zimmer, C., & Gibson, J. M. D. (2019). Well water testing in African-American communities without municipal infrastructure: Beliefs driving decisions. *Science of the Total Environment*, *686*(October), 1220–1228. https://doi.org/10.1016/j.scitotenv.2019.05.317

Tate, E., Rahman, M. A., Emrich, C. T., & Sampson, C. C. (2021). Flood exposure and social vulnerability in the United States. *Natural Hazards*, *106*(1), 435–457. https://doi.org/10.1007/s11069-020-04470-2

Tulbure, M. G., Hostert, P., Kuemmerle, T., & Broich, M. (2022). Regional matters: On the usefulness of regional land-cover datasets in times of global change. In M. Disney & J. Hernández-Stefanoni (Eds.), *Remote sensing in ecology and conservation* (Vol. 8(3), pp. 272–283). https://doi.org/10.1002/rse2.248

United States Government Accountability Office. (2008). *Concentrated animal feeding operations: EPA needs more information and a clearly defined strategy to protect air and water quality from pollutants of concern*. Report to Congressional Requesters GAO-08-944. Retrieved from https://www.gao.gov/products/gao-08-944

University of Nebraska–Lincoln. (2023). “Do i need a permit?” 2023. Retrieved from https://water.unl.edu/article/animal-manure-management/do-i-need-permit

USDA. (2009). National agriculture imagery program (NAIP), information sheet. Retrieved from https://www.fsa.usda.gov/Internet/FSA_File/naip_2009_info_final.pdf

USDA Farm Production and Conservation - Business Center. (2016). *Geospatial enterprise operations*. National Agriculture Imagery Program (NAIP) 2016 Data.

USDA, National Agricultural Statistics Service. (2019). 2017 census of agriculture, Appendix A. Census of agriculture methodology. Retrieved from https://www.nass.usda.gov/Publications/AgCensus/2017/Full_Report/Volume_1,_Chapter_1_US/usappxa.pdf

USGCRP. (2017). *Climate science special report*. U.S. Global Change Research Program. Retrieved from https://science2017.globalchange.gov/chapter/7/

Wagner, A., Off, G., & Alexander, A. (2023). *Civil rights complaint takes aim at North Carolina’s lack of poultry farm regulations*. The Charlotte Observer. Retrieved from https://www.charlotteobserver.com/news/state/north-carolina/article274850381.html

Washington State Department of Ecology. (2023). Concentrated animal feeding operation. Retrieved from https://ecology.wa.gov/regulations-permits/permits-certifications/concentrated-animal-feeding-operation

Wilson, S. M., Howell, F., Wing, S., & Sobsey, M. (2002). Environmental injustice and the Mississippi hog industry. *Environmental Health Perspectives*, *110*(2), 195–201. https://doi.org/10.1289/ehp.02110s2195

Wing, S. (2002). Social responsibility and research ethics in community-driven studies of industrialized hog production. *Environmental Health Perspectives*, *110*(5), 437–444. https://doi.org/10.1289/ehp.02110437

Wing, S. (2005). Environmental justice, science, and public health. *Essay on Environmental Justice, Essays on the Future of Environmental Health Research* (pp. 54–63).

Wing, S., Cole, D., & Grant, G. (2000). Environmental injustice in North Carolina’s Hog industry. *Environmental Health Perspectives*, *108*(3), 225–231. https://doi.org/10.1289/ehp.00108225

Wing, S., Horton, R. A., Marshall, S. W., Thu, K., Tajik, M., Schinasi, L., & Schiffman, S. S. (2008). Air pollution and odor in communities near industrial swine operations. *Environmental Health Perspectives*, *116*(10), 1362–1368. https://doi.org/10.1289/ehp.11250

Wing, S., & Johnston, J. (2014). *Industrial hog operations in North Carolina disproportionately impact African-Americans, Hispanics, and American Indians*. Chapel Hill: University of North Carolina at Chapel Hill. Retrieved from https://www.ncpolicywatch.com/wp-content/uploads/2014/09/UNC-Report.pdf