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A spatially explicit dataset of agriculture liming across the contiguous United States

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Abstract. Agricultural lime has historically been applied to croplands in the United States to counteract soil acidification and enhance soil fertility, with important consequences for crop productivity and Earth's carbon cycle. Previous works on agricultural liming have largely focused on either region-specific case studies or national-level estimates of total application rates, leaving a major gap in understanding the spatial variability in lime application. This study addresses this gap by presenting the first spatially explicit dataset of agricultural lime application across the contiguous United States (https://doi.org/10.5281/zenodo.15758274, Tsao et al., 2026). The dataset comprises state-level data for 1930–1950 and a more detailed county-level dataset for 1954–1987, enabling comprehensive spatial-temporal analyses at multiple scales. Counties in the Midwest region exhibited the highest total amounts of lime applied in the latter half of the twentieth century, reflecting intensive agricultural activity. These counties were characterized by higher overall lime application rates (amount of lime applied per unit of limed area each year) but relatively lower lime-treated fraction (ratio of limed area to total cropland area each year). In contrast, counties in the southeastern coastal region exhibited lower lime application rates per unit of limed area but with a higher lime-treated fraction within the agricultural areas. We used a machine learning framework to assess if the spatial variation of lime application from our dataset can be explained by agricultural and environmental factors with known agronomic relationships. Our results show that the total amount of lime applied for each county, as well as the application rate and treated fraction, can be reasonably explained with regional climatic conditions, soil properties, and agricultural management practices (such as crop production, fertilizer use, and soil pH recommendations). Spatiotemporal integration of the data product results in a revised national estimate of total lime application, with a range of 15–25 million metric tons per year (Mt yr^{-1}) between 1954–1987. This study establishes a critical observational baseline of historical agricultural lime application and highlights the need for further research into its long-term environmental impacts.

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1 Introduction

Agricultural lime has been historically applied to the surface of cropland to enhance soil pH and increase yields (Tennant, 1799; Johnston, 1849). Soils can naturally acidify through a range of processes, including atmospheric deposition of strong acids, nitrification, sulfur oxidation, and release of organic acids by roots, microorganisms, and decomposing organic matter (Goulding, 2016). In croplands, soil acidification is intensified by repeated addition of nitrogen fertilizers, which promotes the release of hydrogen ions (H^+) via nitrification and by removal of base cations in crop biomass (Guo et al., 2010). Approximately 50 % of global arable land is considered acidic (pH < 5.5) (von Uexküll and Mutert, 1995). As soil pH decreases, excess hydrogen ions replace base cations such as calcium (Ca^{2+}) and magnesium (Mg^{2+}), causing their leaching and leading to a relative abundance of toxic elements like aluminum (Al^{3+}), which can be detrimental to crop growth (Fageria and Baligar, 2008). In response, lime application has become a common strategy to mitigate the issue of soil acidification in croplands where access is available. When lime is applied to soil, the Ca^{2+} and Mg^{2+} it releases can displace H^+, effectively reducing soil acidity (Hooda and Alloway, 1996). Repeated nitrogen application and harvest increase soil acidity, prompting periodic lime applications to restore soil pH towards neutral (pH ∼ 7). In addition to counteracting soil pH decline, liming also replenishes key nutrients like Ca^{2+}, Mg^{2+}, and potassium (K) (Han et al., 2019), improves soil fertility and crop yield (Pagani and Mallarino, 2012), and has become an essential practice in agriculture management in the US (Agegnehu et al., 2021).

Aside from its importance in agricultural management, liming has recently gained attention in its potential climate impact (Raymond et al., 2025). The application of crushed rocks to agriculture fields, referred to as enhanced rock weathering (ERW), has emerged as a promising carbon dioxide removal and climate mitigation strategy (Beerling et al., 2020). Enhanced carbonate weathering, particularly through large-scale agricultural liming, could offer a more immediate approach to atmospheric CO_2 mitigation due to its faster weathering rate (Gaillardet et al., 1999; Zeng et al., 2022; Liu et al., 2011). Furthermore, the application of lime has been shown to reduce the emission of nitrous oxide (N_2O) and methane (CH_4) emissions from soils (Khaliq et al., 2019; Shaaban et al., 2020), due to changes in the biotic and abiotic environment that are tied to soil pH (Zhang et al., 2022). However, since lime can act as either a source and a sink for atmospheric CO_2 depending on the weathering agent in the soils (Plummer and Wigley, 1976), and its carbon footprint can shift over time, often transitioning from a source to a sink depending on environmental and management conditions (Semhi et al., 2000), it will be important to first develop a better understanding of when and where lime has been applied in the past. A spatially-explicit dataset of historical lime applications across regions is critical for future studies to further explore its relevance both in agricultural management and potential climate mitigation.

West and McBride (2005) provided the first national estimate of agricultural lime applied in the continental US, reporting a peak of approximately 35 Mt yr^{-1} during the 1970s. However, their data included only a time-series of national total estimates, lacking spatial detail. To address this research gap, this study aims to

1. Compile a spatially explicit liming dataset (state-level for the period 1930–1950 and at the county-level for 1954–1987) for the US.

2. Use machine learning approaches to verify if agricultural and environmental factors can explain the spatial pattern for lime applications.

Quantifying the net climate mitigation impact of lime application is beyond the scope of this study and would require additional analysis in future work.

2 Data and Methods

2.1 Liming data

We compiled state-level liming data from 1930 to 1950 (Mehring et al., 1957) and county-level liming and agricultural data from 1954 to 1987 (U.S. Bureau of the Census, 1956, 1961, 1967, 1972, 1977, 1981, 1984, 1989) as tabulated within ICPSR dataset at the University of Michigan (Haines et al., 2018; https://www.icpsr.umich.edu/web/ICPSR/studies/35206, last access: 2 November 2026). Liming variables, including "lime (tons)" and "lime (acres)", were only available for the years 1954, 1959, 1964, 1969, 1974, 1978, 1982, and 1987. In each census year, there are some counties that did not report liming-related data. We will address the treatment of these missing values in the following section on spatiotemporal interpolation. Lime application data was not reported in Census records prior to 1954, and after 1987, it was aggregated as "area of fertilizer and lime application". Our dataset nevertheless covers a critical period when national agricultural lime application reached its peak during the 1970s (West and McBride, 2005). We convert all the units of liming variables to metric tons (t) and hectares (ha) in the calculations, visualizations, and final data output.

2.2 Environmental and agronomic variables

We compiled a comprehensive suite of environmental parameters, including agricultural metrics, climate conditions, soil properties, and lithological features, to further understand the potential controls of the spatial variation of agricultural liming (Table S1 in the Supplement). Agricultural data on specific crop production (e.g., corn, soybeans, wheat, cotton) and land use (e.g., cropland harvested, cropland pas-

tured, irrigated acreage) were also collected from the Census reports. County-level nutrient data from fertilizers and manure are extracted from Falcone (2021) (https://pubs.usgs.gov/publication/ofr20201153, last access: 2 November 2026). Averaged precipitation and temperature data (1978–1987) were sourced from the PRISM Climate Group, Oregon State University (https://prism.oregonstate.edu/, last access: 2 November 2026). Soil properties (i.e., cation exchange capacity and soil carbonate stocks as $CaCO_3$ equivalents) were obtained from re-gridded SSURGO data obtained from Walkinshaw et al. (2023) (https://casoilresource.lawr.ucdavis.edu/soil-properties/, last access: 2 November 2026). Lithological data, specifically the occurrence of carbonate sedimentary rocks, were sourced from Hartmann and Moosdorf (2012) (https://www.geo.uni-hamburg.de/en/geologie/forschung/aquatische-geochemie/glim.html, last access: 2 November 2026), as these rocks are assumed to weather more rapidly than silicates and thus influence soil acidity. County-level soil pH recommendations were derived from state-level agronomic extension guidelines by assigning each county the recommended pH based on its most commonly grown crop. The dominant crop in each county was identified using the 2022 CroplandCROS dataset (https://croplandcros.scinet.usda.gov, last access: 2 November 2026), and crop-specific pH recommendations were obtained from land-grant university extension publications for each state.

All the Raster-format datasets were spatially aggregated by averaging pixel values within the geographic boundaries of each county. This process assigns a single representative value to each county, ensuring that all raster-based variables are consistently aligned with the county-level analysis. We further average the agriculture (crops, fertilizers) and climate data across 1978–1987, corresponding to the last three census years (1978, 1982, and 1987) of lime application data. Soil, lithology, and pH recommendations are not temporally available in the yearly resolution. Lithology is not likely to have changed within decadal time scale, but soil properties and soil pH recommendations may have slightly changed over the decades. We acknowledge that this temporal mismatch presents a limitation of this analysis. However, to our knowledge there are no publicly available datasets for soil variables before the 21st century (Hengl et al., 2026), and there is no information on the historical soil pH recommendation in agriculture management, which prevents more robust information of their historical trend through time. Thus, the data we have is our best attempt to capture its spatial variability. Studies have also shown that the temporal trend of soil properties and crop types are much less than their spatial variation over the past decades (Thai et al., 2026; Ye et al., 2024). Therefore, for purpose of explaining spatial variation, we consider it reasonable to include these variables in the statistical analysis. For comparison, we also did the same analysis but removed these predictors that are not entirely collected in the same period (shown in Fig. S6 in the Supplement). We would like to highlight that further efforts in data products to resolve the change of soil properties and pH management will greatly benefit future research in this area.

To help explain the temporal variability of total lime application within CONUS across different years, we also extracted information on fertilizer application area and costs from the Census reports, as well as farm expenditures and income.

2.3 Spatial temporal interpolation

For visualization and analysis, the county-level data were joined with the 2012 U.S. Census Bureau TIGER/Line county-level shapefile (https://www.census.gov/cgi-bin/geo/shapefiles/index.php, last access: 2 November 2026). We opted for a modern version of a county-level shapefile since an earlier version was not available before the year 2007. The joining was executed by matching the unique 5-digit Geographic Identifier (GEOID) in the county-level shapefile, with the corresponding Federal Information Processing Series (FIPS) state-and-county codes embedded in the county-level census data. Due to missing land area for some counties in the original census data, the county-level land area was recalculated based on the more modern shapefile geometry, providing a more consistent basis for further rasterization of area-normalized values. We excluded all counties outside the contiguous United States (e.g., Alaska, Hawaii). A number of independent cities in the shapefile, including Baltimore, St. Louis, and several independent cities in Virginia, are absent from the census reports. These cities are administratively distinct from counties in the U.S. Census framework and are not included in county-level reporting. Consequently, no lime application data is available for them across any census year. Given that these independent cities are highly urbanized, with little to no agriculture, we reasonably assumed that no agricultural lime was applied in the areas. We treated two counties affected by historical name or administrative boundary changes separately before merging the data. Further details on the changes to county identifiers and the merging process are documented in the Supplement (Sect. S1).

In each census year, there were some counties that did not report data on lime application. The counties with missing data for each year (Fig. 1) were addressed using linear interpolation based on values from the preceding and following census years within the 1954–1987 time range. In cases where data were available only for the preceding year (e.g., the final year in the time series), missing values were extrapolated using the previous value. Table S2 shows the number of independent cities and missing counties that did not report lime application weight and limed area, and the associated missing land area and cropland area. The percentage of associated missing land area and cropland area range from 0 % to $\sim$ 20 %, except in 1974, which didn't report limed area. However, as shown in Fig. 1, most counties missing original lime application data are situated in areas with limited lim-

ing activity, particularly in the arid and desert regions of the western United States. Figure S1 shows a quantitative analysis of this uncertainty introduced by the missing counties in, demonstrating that the total lime application estimates are only slightly affected by the interpolation and data-filling for the missing counties each year (uncertainty are within 1 % in most years between pre- and post-interpolation values; Fig. S1).

We conducted the data processing mentioned above (temporal interpolation and spatial gap filling) for both lime applied weight (kt) and limed area (ha) and all the other agricultural metrics (i.e., cropland area, crop production, nutrient input) for each county. This resulted in a complete dataset with no missing value, enabling us to conduct further derivation and statistical analysis. We were then able to derive the lime application rate (lime applied weight / limed area) and lime-treated fraction (limed area / cropland area) and further analyze the main environmental controls on each variable. For the lime-treated fraction we made a simple assumption that within each county all lime is applied evenly and only on cropland (Oh and Raymond, 2006), since from the existing data resolution we could not further discern the small fraction that could be applied to pasture or rangeland in a sub-county level. We acknowledge that this simplification and its associated uncertainty present a limitation to this analysis and data product.

2.4 Rasterization to pixel-level dataset

We transformed the county level liming data into a pixel-level, area-weighted liming intensity ($t\,ha^{-1}\,yr^{-1}$) by incorporating a temporal varying annual cropland area data product for the same region (Ye et al., 2024). In the cropland area dataset, the value of each pixel represents pixel's cropland density, ranging from 0–1. For each of the eight census years, we first calculated the cropland area within each county by summing the cropland-density values of all pixels located inside county boundaries. The total lime applied annually in each county was then divided by the cropland area calculated from Ye et al. (2024)'s pixel-based cropland product; this approach ensures that the sum of pixel-level lime application rates within each county remains consistent with the original county-level lime totals. We made a simplification here assuming that all the lime is applied evenly and only to cropland (Oh and Raymond, 2006), while the relatively small fraction that could be applied to pasture or rangeland is neglected. This assumption, though may come with uncertainty, is necessary to spatialize liming rates at sub-county resolution. The county level lime per cropland area was then rasterized into the same coordinate system and resolution (1 km) as the cropland area data product of Ye et al. (2024). Each pixel's lime application rate was then multiplied by its cropland-density value, which masks non-cropland pixels and proportionally scales values for partially cropland pixels. This approach ensures that the total amount of lime applied within each county remains unchanged, while downscaling the data to a sub-county (1 km) pixel resolution which is more accessible for users to conduct further analysis.

2.5 Statistical analysis

2.5.1 Pearson correlation and variable selection

To assess if environmental and agricultural variables can explain the spatial distribution of lime application, we used the average across three census years (1978, 1982, and 1987), representing the most recent decade with overlapping liming and environmental data. This period offers a more stable and representative snapshot of liming conditions. We began with a comprehensive set of agronomic, soil, and climatic variables (Table S1) and conducted a Pearson correlation analysis to evaluate linear relationships between each predictor and lime application (Fig. S5). To mitigate multicollinearity, we also examined pairwise correlations among predictors and removed variables from highly correlated pairs (Pearson's $r > 0.90$), including N fertilizer (kg) vs. P fertilizer (kg) ($r = 0.91$), and N manure (kg) vs. P manure (kg) ($r = 0.98$). Based on domain relevance and predictive strength, we retained one variable from each pair and removed the others. We calculated the Variance Inflation Factor (VIF) for all remaining predictors. Variables with high VIF values were selectively removed to reduce multicollinearity and improve model stability. Table S1 shows all the predictors considered in the analysis, together with their data sources, temporal coverage, units, transformations, VIF status, and final inclusion or exclusion status. The final list of features excluded is: P manure (kg), P fertilizer (kg), Silt (%), and Available Water Storage (cm). This process yielded a final set of 35 predictors with acceptable VIF values (range: 1.12 to 7.32), which were used for statistical and machine learning modeling (Table S3). This step ensured a more robust and interpretable analysis of environmental controls.

2.5.2 Random Forest Analysis

We employed a machine learning technique to account for complex relationships between lime applications and the predictor variables. Random Forest (RF) is a commonly used machine learning algorithm that can be used in both classification or regression by constructing an ensemble of decision trees to capture complex interactions and non-linear dependencies between predictor variables and the target variable (Breiman, 2001). This approach is particularly suited for modelling in an environmental or agricultural context characterized by high-dimensional, heterogeneous relationships (Shen et al., 2020; Burdett and Wellen, 2022; Siqueira et al., 2024; Jeong et al., 2016). Since liming is ultimately a human decision made by farmers, we can only determine the biophysical factors that might lead to higher probability of liming practice, while the actual occurrence of lime application still depends on individual management

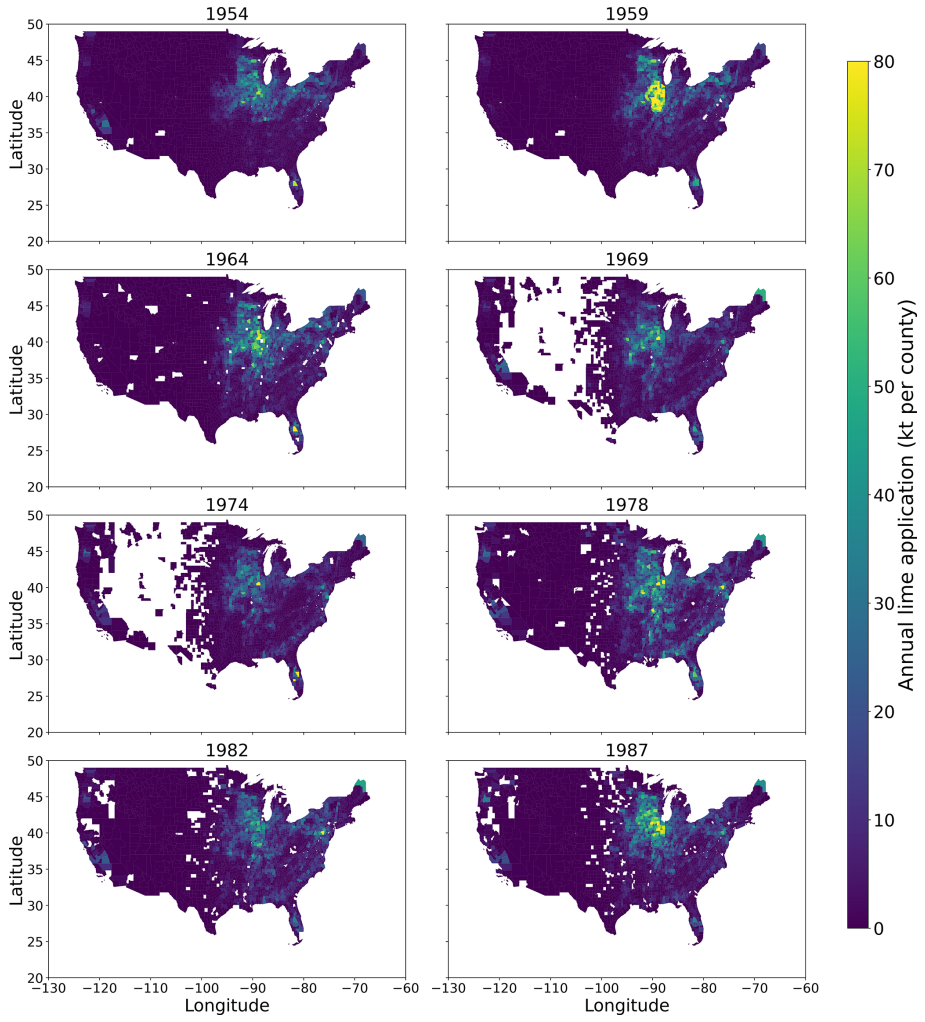

Figure 1. Lime application (kilotons, kt) by county in the continental US from 1954 to 1987. The white gaps indicate counties that originally reported missing data, before temporal interpolation and spatial filling were applied. The eight maps correspond to the census years between 1954 and 1987.

strategies. Thus, in the context of our study, the RF model is not intended to extrapolate temporal trends beyond the observed data range or to quantify specific causal drivers. Instead, it is used to assess whether the observed spatial patterns of lime application can be explained by environmental and agricultural factors with well-established agronomic relationships. We implemented the model in Python using the RandomForestRegressor class derived from bootstrapped datasets (Pedregosa et al., 2011). We performed a grid search across multiple combinations of hyperparameters using 5-fold cross-validation. Specifically, we tested: number of trees (n_estimators) = 100, 300, 500; maximum depth (max_depth) = 10, 20, and unlimited (None); minimum samples to split (min_samples_split) = 2 or 5; minimum samples per leaf (min_samples_leaf) = 1 or 2; and number of features considered at each split (max_features) = "sqrt" or 0.5. Despite testing this range of values, model performance was relatively stable, with test R^2 scores varying modestly across configurations. All models were implemented using scikit-learn (https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html, last access: 2 November 2026). To validate the model, we split our dataset (approximately 3000 counties in the contiguous USA) into 5 equal subsets, known as *folds*, based on the state of the county. We then performed 5-fold cross-validation, where each iteration trained the model on 4 of these folds and used the remaining fold as a testing set to evaluate model performance. Each fold served once as the testing set during the 5-fold cross-validation. This process ensures that the training data and testing set are from geographically independent regions (different states) and, in most cases, not of proximity. The best-performing model was selected based on the highest mean cross-validated R^2

and used for further interpretation, as our primary objective was to assess the relative importance of input features.

Random Forest models further provide an assessment of variable importance using permutation importance, which quantifies the relative contribution of each predictor variable by measuring the decrease in model performance when the variable's values are randomly shuffled (Altmann et al., 2010). These scores were averaged across five folds to ensure a robust estimation of variable influence. In addition, partial dependence analyses offer insights into the marginal effect of each predictor on the target outcome, holding all other variables constant. This allows visualization of non-linear relationships and interaction effects between predictors and target outcome. The combination of linear (Pearson correlation) and non-linear (Random Forest model) approaches provides a more comprehensive view of the environmental factors influencing lime application, revealing the relevant factors that may explain spatial variability in lime application. We applied this statistical analysis to three response variables: (1) annual lime applied (metric tons per year, normalized by hectare of land area), (2) annual lime application rate (metric tons per hectare of limed area per year), and (3) annual lime-treated fraction (ratio of limed area to total cropland area per year) in each county. For the analysis of lime application rate and lime-treated fraction, we excluded counties with negligible agricultural activity to avoid undue influence from areas with little or no farming. Specifically, the analysis was restricted to counties in which cropland accounted for at least 10 % of total land area. This threshold was chosen to ensure that the results reflect variation in liming practices among counties with meaningful agricultural activity. We also tested other thresholds of minimum cropland (5 %, 15 %, 20 %) relative to the total land area (shown in the Supplement), which demonstrated very similar ranking of features.

3 Results

3.1 Spatial-temporal pattern of lime application

The growth in state-level estimates of lime use from 1930–1987 was disproportionately concentrated in the Midwest (Fig. 2). A rapid increase in application occurred between 1930 and 1950, likely corresponding to the onset of the Green Revolution in the 1940s, which introduced synthetic fertilizers and modern agricultural technologies (Smil, 2004). The increased use of nitrogen fertilizers likely led to enhanced soil acidification pressures and the need for pH management, making liming a necessary and more common practice. The increasing trend of lime application does not persist after 1950, and the total amount of lime applied exhibits considerable temporal variation (Fig. 2). In the early 1950s, most of the lime was applied in the Midwest states. In 1959 an abrupt increase of lime is shown in Illinois (close to 6 Mt lime yr^{-1}), which could potentially be due to a combination of soil management needs, and government programs or educational initiatives (such as the Illinois Voluntary Limestone Program, https://www.iaap-aggregates.org/agricultural-lime.html, last access: 2 November 2026). Starting from the 1960s, there is a gradual increase of lime application extending into the Southern US and particularly in the Southeastern coast, reaching a peak in 1978, which Georgia alone exceeded 1 Mt lime yr^{-1} statewide (Fig. 2). In the 1980s lime application slightly declined on the Southeastern coast but maintained a similar spatial pattern to the 1960s. Figures 3 and 4 show the county-level lime application mass from 1954 to 1987, highlighting lime application being initially concentrated around the Midwest in the 1950s, a gradual decline in the later 1960s to early 1970s, an increase and expansion to the South and Southeast in the late 1970s, and a slight decline in the 1980s.

The temporal-spatial pattern of county-level limed area (Fig. 5) approximately resembles that of limed applied mass, with counties that exhibit higher limed areas also concentrated in the Midwest regions. Limed areas were high in the Midwest by the 1950s and gradually extended southward into the eastern and southern coasts starting from the 1970s. However, compared to limed weight, the limed area in the Southeastern coast shows a more significant signal, suggesting that an equivalent amount of lime is applied over a larger area in the Southeast. Compared to the states with the highest lime weight applied being all in the Midwestern regions, the states that have the highest limed area include both Midwestern and Southeastern states (Fig. S2). The relationship between limed weight and limed area across regions reflects the variation of lime application rates across regions, which may be influenced by local soil and climate properties (Fig. S3).

The lime application rate for each county (Fig. 6), calculated as the ratio of applied mass to area of lime application, shows a sharp transition between the western and eastern parts of the US. Most of the lime was applied only in the eastern half of the US, while only a few coastal regions received lime in the western half of the US. Lime application rates were relatively lower during the 1950s but reached a similar level from the 1960s to the 1980s. Figure S4 shows that the midwestern states of the US had the highest lime application rate (> 4 t ha^{-1} yr^{-1}). Notably, Michigan and Minnesota, though not ranked as the top 10 states of total amount applied (Fig. 2), have a high lime application rate ranking (8th and 10th respectively). In comparison with the Midwest, the Eastern, Southeastern, and Southern regions of the US, have lower lime application rates (~ 2 t ha^{-1} yr^{-1}).

The lime-treated fraction, calculated as the ratio of limed land area to total cropland area each year, reveals a distinct Midwest–Southeast contrast in the eastern half of the US (Fig. 7). The Southeast generally shows a higher lime-treated fraction compared to the Midwest. In the 1950s, most regions had a low value (< 10 % of cropland limed per year), with only Florida and a few areas along the eastern seaboard exhibiting higher values (~ 20 %). A marked increase in this

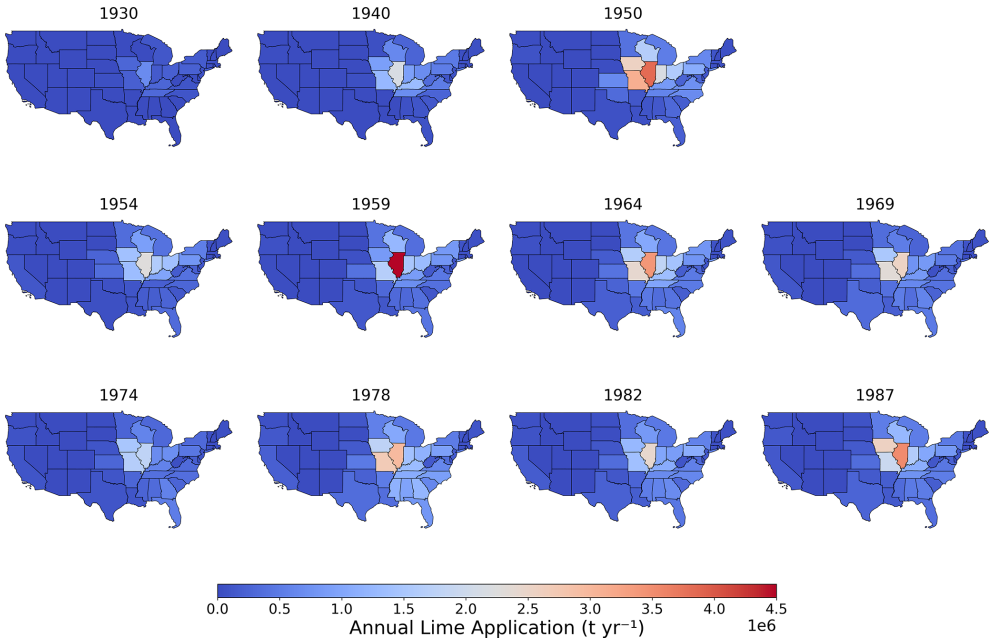

Figure 2. Annual lime application (metric tons per year, $t\,yr^{-1}$) per state in the contiguous US from 1930 to 1987. The data from 1930 to 1950 is from the state-level data from the USDA report, while the data between 1954–1987 is summed from the county-level data from the Census reports. The data represents the condition during each specific year, not including the period in between.

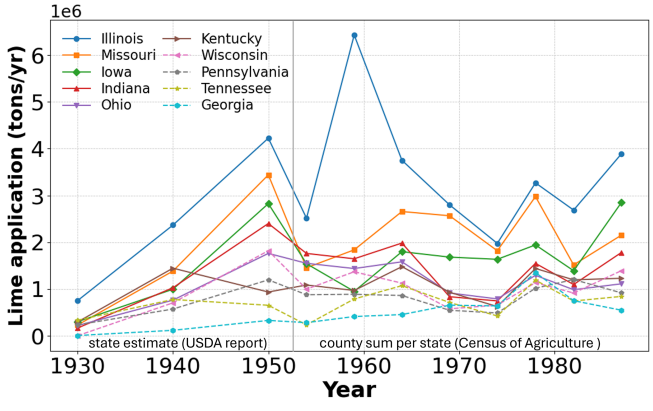

Figure 3. Temporal variations in lime applied (metric tons per year, $t\,yr^{-1}$) per state in the contiguous US from 1930 to 1987. The data from 1930 to 1950 is from the state-level data from the USDA report, while the data between 1954–1987 is summed from the county-level data from the Census reports. The figure shows the top 10 states ranked by state-level total lime application during 1954–1987, with Illinois applying the most lime, followed by Missouri, Iowa, Indiana, Ohio, Kentucky, Wisconsin, Pennsylvania, Tennessee, and Georgia.

ratio occurred throughout the Southeast beginning in the 1960s, peaking at $\sim 30\,\%$ in the late 1970s. In contrast, the Midwest consistently maintained much lower values, with only $\sim 5\,\%$ of cropland limed annually. If assuming an uniform application across cropland, this corresponds to an average liming interval of once every 20 years in the Midwest (Oh and Raymond, 2006), versus once every 5 years in the Southeast. However, the actual liming frequency is difficult to estimate, as lime is often used episodically, when soil acidity becomes sufficiently severe, which crop growth becomes limited. This contrasting spatial pattern in both Fig. 6 (lime application rate) and Fig. 7 (lime-treated fraction) highlights the spatial differences in lime management, which are largely influenced by underlying soil pH distributions driven by climate and soil properties. We acknowledge that the large spatial heterogeneity in lime use is influenced by finer-scale factors and historical cropland expansion that cannot be fully resolved with the current county-level dataset. We also acknowledge our assumption that all lime is applied evenly to cropland presents uncertainties and limitation to our analysis of lime-treated fraction and pixel-level liming intensity data (Fig. 8). As a result, the observed patterns should be interpreted as regional signals rather than precise representations of field-scale liming decisions. Figure 8 shows the spatial-temporal pattern of lime application per cropland area ($t\,ha^{-1}\,yr^{-1}$) application, transformed into pixel-level, area-weighted liming intensity.

3.2 Statistical analysis of environmental factors

We analyzed environmental factors that could potentially explain lime-application patterns in terms of three separate outcome variables, averaged three census years from 1978 to 1987: (a) lime applied per county, normalized by county land area (b) lime application rate, and (c) lime-treated fraction.

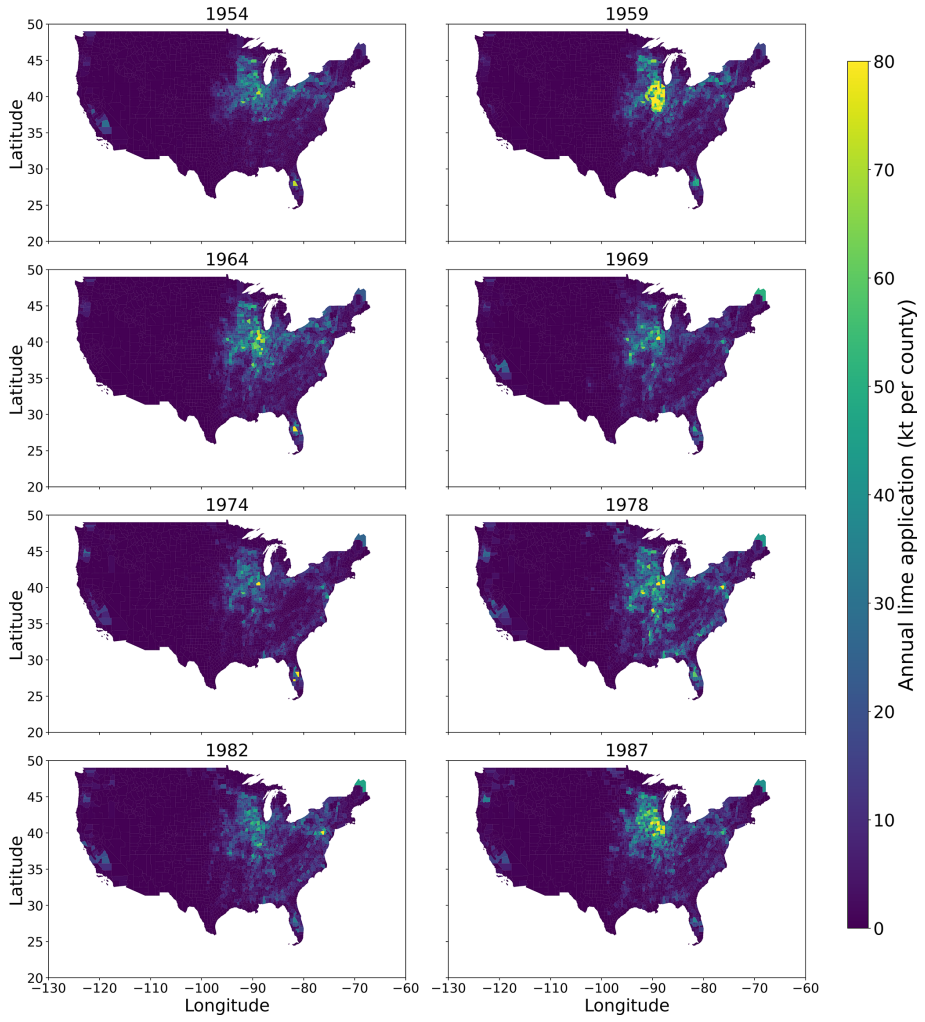

Figure 4. Annual lime application (kilotons, kt) per county in the contiguous US for the eight census years from 1954 to 1987, as reported by the Census Bureau. The maps display the lime application across counties with missing data temporarily interpolated and spatially filled, as described in the Methods section. The data only represents the condition during each specific census year, not including the period in between.

After removing the highly correlated predictors from the initial environmental parameters (Fig. S5, Tables S1 and S3), our Random Forest models demonstrated R^2 values averaging from 0.66 to 0.73 on state-level cross validation data (20 % of data) (Fig. 9), showing substantial predictive skill when applied to geographically independent regions. We also compared running our statistical model without pH recommendation and soil variables, which the data collection period does not exactly match the same temporal period as our liming data. The performance R^2 values drop from a range of 0.66–0.73 to 0.46–0.66 (shown in Fig. S6), demonstrating these omitted variables still provide further predictive power in modelling spatial variation. For the remainder of the discussion, we will focus on the model that includes pH recommendation and soil variables, which we believe can still provide useful insights to explain spatial variability.

For the average annual lime applied per county (normalized by county land area), the variables that show the highest permutation importance in the Random Forest model were corn grain production, mean precipitation, soil pH, N fertilizer, most of which showed strong positive associations except soil pH showing negative association (Fig. 9a). These were followed by total cropland, soybean production and pH recommendations. Partial dependence plots (Fig. S7) indicate that counties with greater crop production, higher precipitation, lower soil pH, elevated fertilizer inputs, and higher pH targets tend to apply more lime. With respect to the lime application rate, the variables with the highest permutation importance were mean precipitation, positively correlated with the response, followed by mean temperature, soil pH, and sand percentage, all showing negative correlations. Additional predictors included wind erodibility index (negative correlation), carbonate mineral stocks (negative correlation),

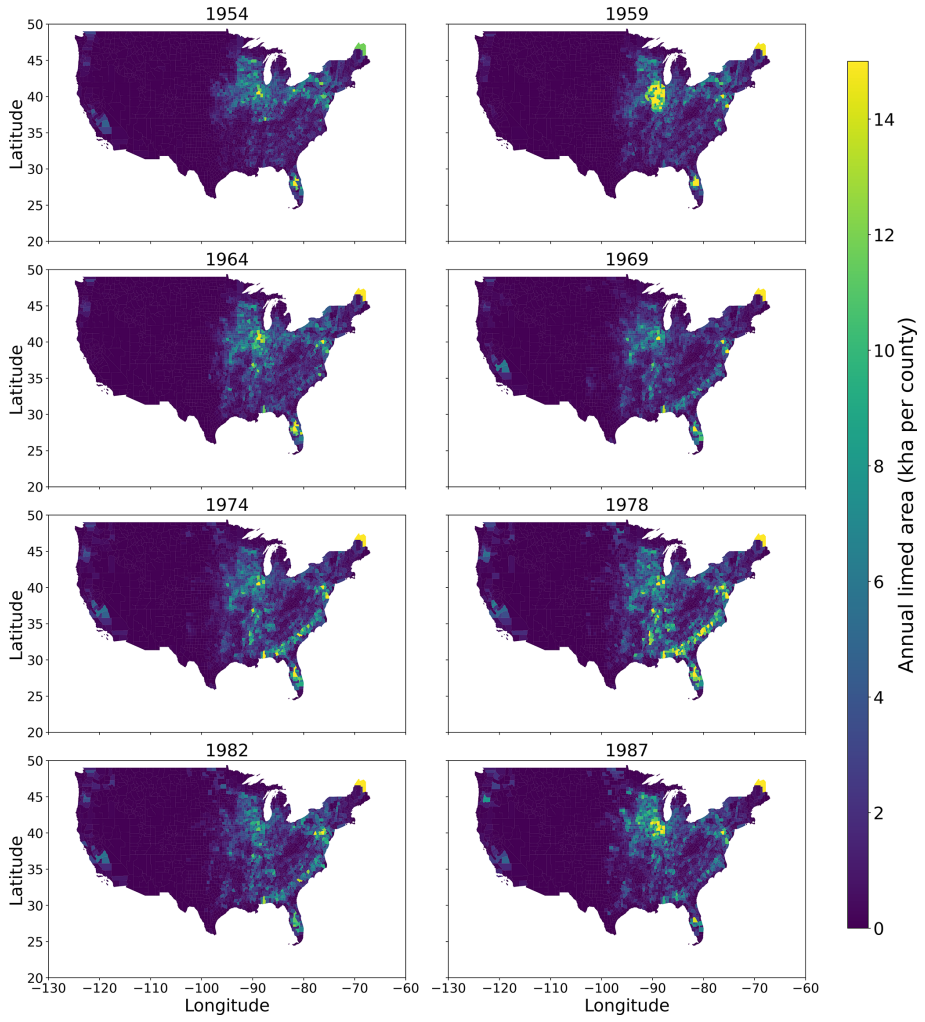

Figure 5. Annual limed area (kilohectares, kha) per county in the contiguous US for eight census years from 1954 to 1987, as reported by the Census Bureau. The maps display lime application across counties, with missing data temporarily interpolated and spatially filled, as described in the Methods section.

and soil organic matter (positive correlation) (Fig. 9b). Partial dependence analyses reveal increased lime application rates in wetter and colder regions with lower soil pH, sand percentage, wind erodibility, carbonate mineral stocks, and higher soil organic matter (Fig. S8). For lime-treated fraction, soil pH shows the highest permutation importance, exhibiting a strong negative correlation. Other important predictors included mean precipitation and sand percentage (positive correlations), and carbonate mineral stocks (negative correlations), cropland harvested percentage (positive correlations) (Fig. 9c). Partial dependence analysis shows that counties with lower soil pH, greater rainfall, higher sand content, lower carbonate minerals, and higher harvested cropland percentage exhibited a higher lime-treated fraction among croplands (Fig. S9). It is worth noting that though the relative ranking of these features may change slightly with different hyperparameter settings in the RF model, the important features in the model reveal important information of the underlying relationships. For Fig. 9b and c, we also conducted sensitivity analysis using different thresholds of minimum cropland percentage (5 %–20 %) in the county land area, which all show similar results of permutation importance ranking (Figs. S10, S11). Overall, we confirmed that our estimates of intensively limed areas correspond with areas of lower pH, productive cropland with high fertilizer application etc. The average annual lime applied (normalized by county land area) in each county can largely be explained by agricultural management practices, including crop production, fertilizer application, and soil pH recommendations, as well as climate. The average application rate and lime-treated fraction can also be explained by regional climatic conditions, soil properties, and cropland usage (harvested/pastured cropland percentage).

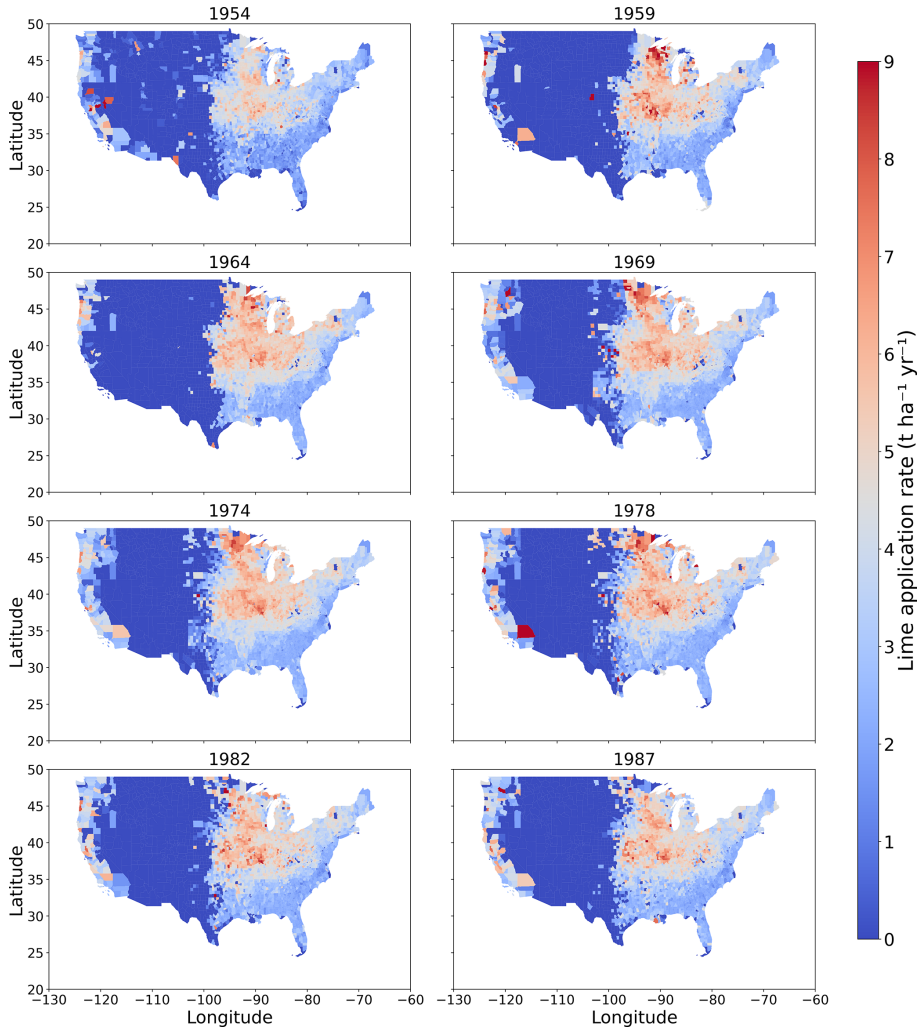

Figure 6. Lime application rate ($t\,ha^{-1}\,yr^{-1}$) for each county in the contiguous US from 1954 to 1987. Rates were calculated as the total lime applied in each county (t) divided by the limed area (ha) for each census year. The eight maps represent the eight census years that reported data during this period.

4 Discussion

4.1 Spatial and temporal change of county-level lime application

From our results we showed that most agricultural lime was applied in the Midwest region of the continental US during the years 1930–1987. This pattern likely reflects higher precipitation and lower soil pH in the east compared to western US (Hoffmeister, 1947; Wieczorek, 2019). Precipitation leaches base cations (calcium, magnesium) and depletes buffering agents such as $CaCO_3$, causing soil pH to drop nonlinearly as rainfall increases (Slessarev et al., 2016). Consistent with this observation, we found that the average soil pH (from SSURGO) has a strong negative correlation with average precipitation (from PRISM) (Pearson's $r = -0.80$; Fig. S5).

An extensive amount of lime is applied in the Corn Belt in the American Midwest, which has more than 70 million hectares in corn and soybean rotation and is one of the most intensively managed agricultural regions globally (Green et al., 2018). Corn grain production emerged as the strongest predictor of average annual lime applied per county (normalized by county land area) in the permutation-based model (Fig. 9a), followed by mean precipitation, soil pH, soybean production, nitrogen fertilizer, and total cropland. We further show that there is a gradual expansion of the lime application area (Fig. 5), which correlates with a southward extension, of corn and soybean production area (Figs. S12, S13), and a slight decline in cotton and tobacco production (Figs. S14, S15) was shown. There is also an increase in lime application on the Southeastern coast starting from the 1960s and 1970s, matching the increase of agriculture in the region.

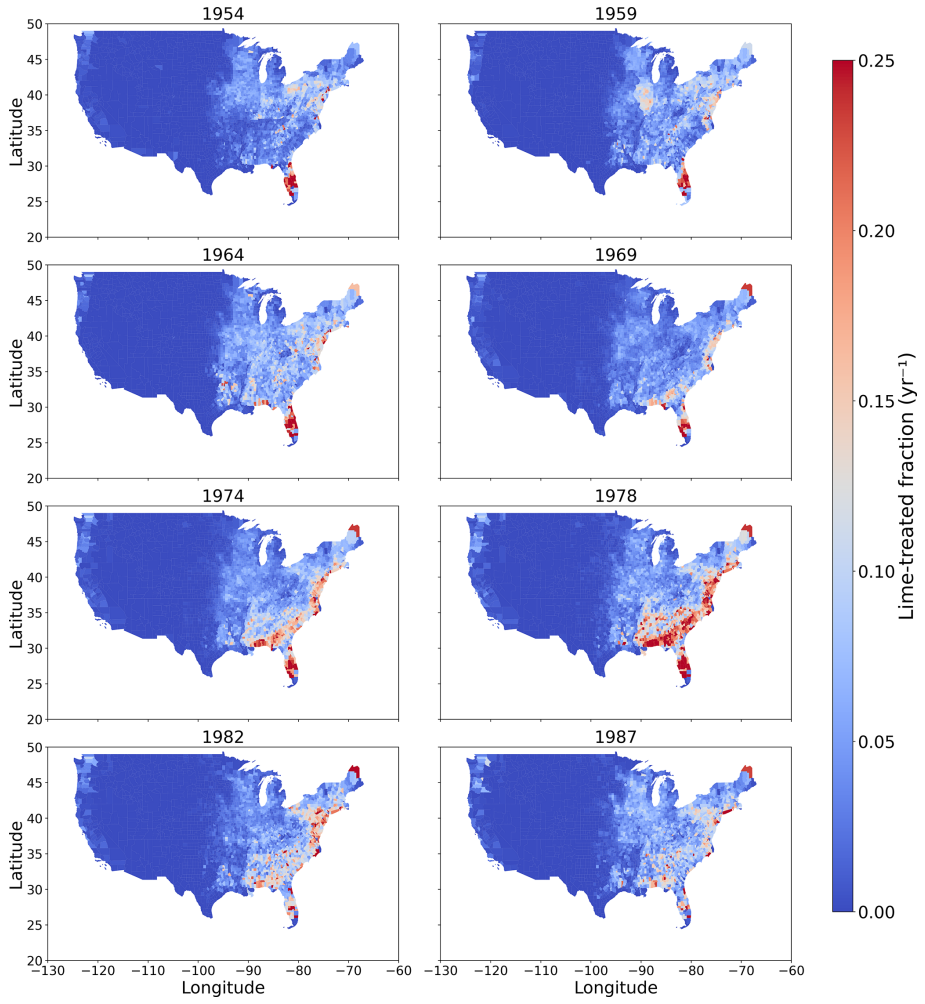

Figure 7. Lime-treated fraction (yr^{-1}) for each county in the contiguous US from 1954 to 1987, calculated as the ratio of limed area to total cropland area. The eight maps represent the eight census years, showing the fraction of cropland treated with lime annually.

However, lime application and limed areas along the Southeastern coast both show a decline in the 1980s, which coincides with a decrease in crop production, particularly corn and soybean (Figs. S12–S18). The relative ratio of total cropland in this region did not show a clear decline (Fig. S19). However, the percentage of cropland harvested (Fig. S20) shows a strong decrease in 1987, while the percentage of cropland that is neither harvested nor pastured (Fig. S21) shows a clear increase, potentially indicating gradual abandonment of cropland for other uses. Our statistical model also shows that percentage of cropland that is neither harvested nor pastured has a negative correlation with the lime application rate (Fig. 9b), while the percentage of cropland shows a positive correlation with lime-treated fraction (Fig. 9c), demonstrating the potential influence of land use change in shaping the spatial variation of lime application. The decrease in crop production in this region could be an onset of urbanization and conservation programs (Napton et al., 2010). Additionally, the growth of the regional lumber industry during this period may have further slightly reduced agriculture, contributing to the observed decline in lime application (Prestemon and Abt, 2002).

Since lime is mainly applied to correct soil pH, and not to boost the yield of specific crop type, the relative higher importance of corn and soybeans shown in our analysis as compared to other crop types (e.g., cotton, tobacco, wheat, hay) (Figs. S14–S18), is mainly related to the intensity of associated farming practices. Corn and soybeans constitute a significantly larger portion of the US's harvested grains (Zulauf et al., 2023) and are often grown with much higher intensity relative to other crop types (Annan et al., 2024). The intensive agriculture, including frequent fertilizer inputs, acidifies the soil, necessitating lime application. Additionally, soybeans are also a nitrogen fixing species, which can promote nitrification and increase soil acidification (Nyatsanga and Pierre, 1973). Although other crops like alfalfa may be more pH-sensitive, their production is less fertilizer intensive and may result in a weaker apparent relationship

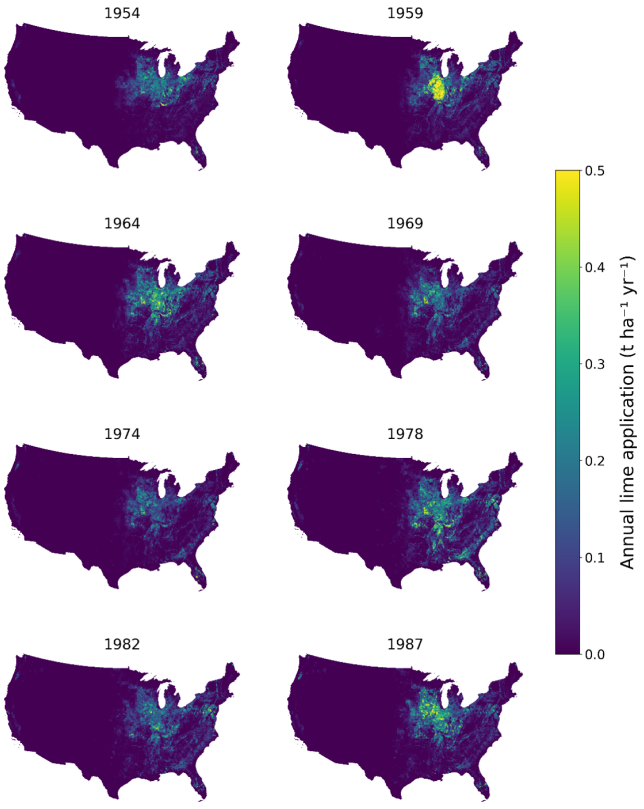

Figure 8. Area-weighted liming intensity ($t\,ha^{-1}\,yr^{-1}$) in 1 km pixel resolution over the contiguous US from 1954 to 1987. Rates were calculated as the annual lime applied (t) divided by the cropland area (ha) from Ye et al. (2024). For each county lime is assumed to be applied evenly on cropland. The eight maps represent the eight census years that reported data during this period. The pixel-level dataset is in 1 km resolution.

with lime application (Mallarino et al., 2011). As for non-alfalfa hay systems, relatively low profit margins may deter investment in fertilizer and lime applications. Furthermore, counties in the Midwest that predominantly grow corn and soybeans tend to have a higher proportion of cropland relative to total land area (Fig. S19), which adds to the association between production of these crops and the amount of lime applied relative to total county area. Taken together, our results suggest that while broad patterns such as the association between lime use and corn-soybean agriculture are evident, the factors that influence lime application could be complex, regionally dynamic, and shaped by interacting environmental, agronomic, and economic factors. The complex relationship between different factors prevents us from isolating one or two causal drivers of liming. The lack of sub-county–level lime use data and the absence of crop-specific lime recommendations are limitations of our study. Thus, results from the machine-learning spatial analysis should be interpreted only as an explanatory perspective on large-scale spatial patterns and relationships of lime application, rather than as field-scale drivers of liming decisions.

4.2 Spatial distribution of lime application rate and treated fraction

We show a spatial pattern of higher liming application rates ($> 4\,t\,ha^{-1}\,yr^{-1}$) and longer liming intervals (~ 20 years) in the Midwest and lower application rates with shorter intervals (~ 5 years) near the Southeastern coastal regions (Figs. 6–7). Permutation importance analysis (Fig. 9b) shows that mean precipitation is the most important predictor of lime application rate, followed by mean temperature, soil pH, sand content, wind erodibility index, carbonate mineral stock, and soil organic matter. In contrast, the lime-treated fraction in each county is most strongly explained by soil pH, followed by mean precipitation, sand content, and carbonate mineral stock (Fig. 9c). Together, these findings verify that the lime application practices shown in our data can potentially be explained by a complex interplay between acidification drivers and soil buffering responses.

The required lime application rate and lime-treated fraction are heavily dependent on the soil acidification rate and pH buffering capacity (Xu et al., 2022; Kanzaki et al., 2024). Higher precipitation leads to faster leaching of base cations, while regions of warmer temperatures lead to faster decomposition and organic acid release, with both processes leading to faster soil acidification (Ulrich, 1986). However, precipitation appears to be a necessary condition for acidification to manifest at scale, while temperature acts both as a direct driver and an indirect proxy for soil characteristics. Specifically, warmer regions tend to have more weathered soils with low buffering capacity, while cooler regions, particularly in the Midwest, often retain glacially derived carbonates and clay minerals that confer greater buffering potential. This helps explain the somewhat counterintuitive negative correlation between temperature and application rate: although warmer regions acidify faster, their low-buffering soils allow for smaller lime doses per application, whereas cooler, more buffered soils require larger doses when they are eventually limed. This pattern is further supported by the partial dependence plots (Fig. S8), which reveal a distinct threshold-like response: lime application rate increases steeply with precipitation beyond approximately 750–800 $mm\,yr^{-1}$, and declines sharply with temperature above 12–13 °C. These non-linear relationships imply that precipitation is a key threshold variable enabling acidification, while temperature's response reflects both its role in driving acid production and its spatial correlation with regional differences in soil buffering capacity.

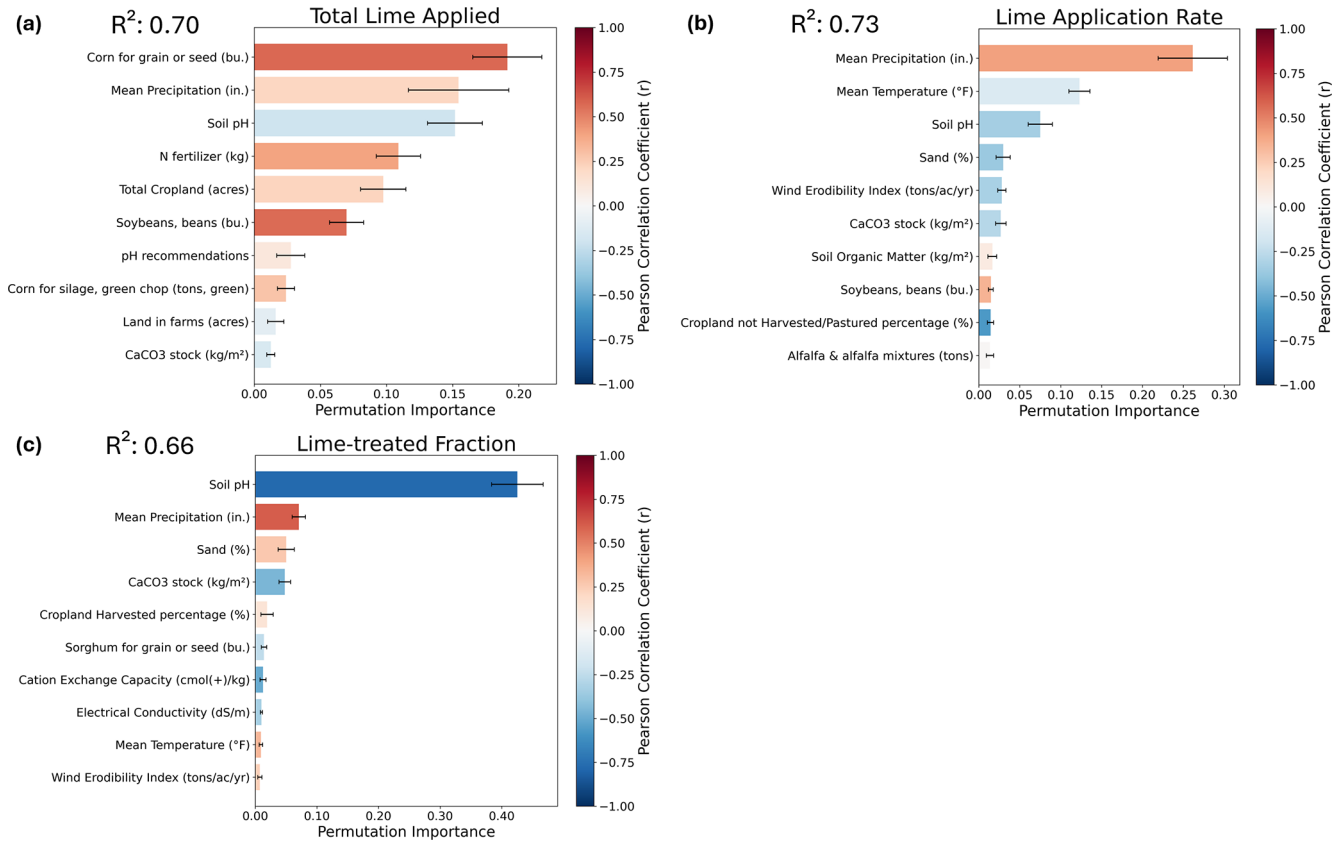

Figure 9. Statistical and machine learning analysis of average annual **(a)** lime applied per county per year, normalized by county land area ($t\,ha^{-1}\,yr^{-1}$), **(b)** lime application rate ($t\,ha^{-1}\,yr^{-1}$), and **(c)** lime-treated fraction (yr^{-1}) per county across the three census years from 1978 to 1987. For **(b)** and **(c)** we ran the analysis only on the counties that have greater than 10 % cropland by area, to minimize the influence of counties that have minimal agriculture. The bar length represents the permutation importance of all variables in the random forest model, with the error bar showing the standard error for the permutation importance across the 5-folds of cross validation training. Only the top ten variables with the highest permutation importance are shown here. The colors represent the Pearson correlation coefficients with the target variable.

4.3 Regional variation in buffering capacity and liming strategy

Resisting the higher acidification rates associated with warmer, wetter conditions in the Southeastern USA likely entail a higher lime-treated fraction among croplands. However, these regions typically do not require higher application rates per event, as their soils exhibit relatively low pH buffering capacity. The pH buffering capacity of soils varies systematically between the Midwest and the Southeast, which can also explain the spatial variations in lime application rate and treated fraction. Soil buffering capacity is influenced by naturally occurring carbonate minerals ($CaCO_3$ and $CaMg(CO_3)_2$), which can directly neutralize acidity when it dissolves. The influence of carbonate minerals is particularly relevant in some Midwestern soils, where residual carbonate from glacial parent materials helps maintain higher soil pH values. In contrast, Southeastern soil typically lacks carbonate minerals, making them more vulnerable to acidification (Fig. S22). In addition to carbonates, cation exchange capacity (CEC) helps to resist swings in pH by capturing or releasing adsorbed base cations and protons (Weil and Brady, 2017). CEC also varies systematically between the Southeastern and Midwestern USA. Several factors contribute to the lower CEC observed in highly weathered Southeastern regions (Fig. S23), which are dominated by low activity clay minerals, coarser particle sizes, elevated concentrations of detrital quartz (Woodruff et al., 2009), and lower organic matter content (Solly et al., 2020). Conversely, soils in the upper Midwest are derived from glacial parent materials and loess (Börker et al., 2018), which are often characterized by higher organic matter contents, smaller soil particle sizes, and higher activity clay minerals (Figs. S24, S25), providing more CEC and better pH buffering capacity. These finer-textured soils are also generally less erodible by wind, consistent with the observed negative correlation between wind erodibility and lime application rate.

Although CEC and carbonate content are key conceptual components of buffering capacity, they did not emerge as

top predictors in the permutation importance analysis. This is likely due to collinearity with soil pH, which reflects the integrated outcome of both acidification pressure and buffering history. In this sense, soil pH serves as a practical proxy for underlying soil properties that govern liming frequency. The spatial correlation is particularly relevant in the Southeastern US, where low soil pH tends to co-occur with both low CEC and minimal carbonate content, rendering pH a strong indicator of inherently low buffering capacity. A similar rationale applies temperature's high variable importance in predicting lime application rate, which as discussed earlier, is likely to reflect its spatial co-correlation with the degree of soil weathering and associated buffering capacity.

In summary, both climatic drivers (temperature and precipitation), soil mineralogy (including soil pH, carbonate presence, wind erodibility, soil organic matter, and particle size distribution), and slight influence of cropland usage (harvested/pastured cropland percentage) together can explain the spatial variation of lime application rate and lime-treated fraction. The Midwestern region requires less frequent but larger amounts of lime application to maintain soil pH, while the Southeastern region requires more frequent but smaller amounts of lime application to effectively maintain optimal pH levels (Ross et al., 1964).

4.4 Temporal variability of total agricultural lime application

We further hypothesize that economics may have played an important role in shaping the temporal variability of lime use. As shown in Fig. S26, the late 1960s and early 1970s witnessed a surge in fertilizer expenditures and a drop in fertilizer cost, likely driven by technological advances, leading farmers to prioritize fertilizer over liming. This behavior may have contributed to the notable decline in lime application during this period. The immediate yield gains from increased fertilizer use could have overshadowed the longer-term implications of reduced liming, particularly given that soil acidification tends to accumulate gradually over multi-year or decadal timescales. In 1974, fertilizer prices rebounded sharply in conjunction with the global fuel crisis (Brunelle et al., 2015), aligning with the most pronounced dip in lime application rate observed that year. In the late 1970s to early 1980s, farm incomes peaked, and input costs stabilized (Fig. S27), creating conditions conducive to greater focus on long-term soil health. Consequently, this period saw a resurgence in lime application. It is also likely that this period marked growing recognition of the soil acidification problem, as several studies on liming and soil pH management were published during this time (Nyborg and Hoyt, 1978; Bache, 1980). By the late 1980s, declining crop sales and lower input costs suggest a period of adjustment and input optimization, potentially explaining the modest reduction in total lime applied (Fig. S26).

4.5 Comparison of total lime application estimate with West and McBride (2005)

Figure 10 shows a comparison between the total lime application in our dataset and the national estimate of lime application in West and McBride (2005), which to our knowledge is the first national estimate of agriculture lime applied in the US. Our study and West and McBride (2005) both show that lime application increases very slowly starting from the 1910s but started to rapidly increase in $\sim$1930 and reach a high range of values, exceeding 20 Mt yr^{-1} around 1950. However, there are some discrepancies from 1950 through 1980. West and McBride (2005) estimated the total lime applied to continue to increase, particularly during the 1970s, which exceeded 30 Mt yr^{-1}, while our dataset shows the total lime applied to be more consistent in the range of 15–25 Mt yr^{-1}. Oh and Raymond (2006) conducted a regional study based on the county-level liming dataset from the Census reports and first noticed disagreements in the trends of the regional sum of the county-level data and the national estimate from West and McBride (2005). However, Oh and Raymond (2006)'s study was done over a small region of the US, and a spatially explicit dataset of lime application across the US was not yet available at that time to address the uncertainty in the total lime estimates.

Here we revisited the discrepancy between the national estimate of lime application and that of West and McBride (2005). We suggest that the difference is primarily due to uncertainties in the methodology of West and McBride (2005), which relies on data from the Mineral Yearbook (U.S. Bureau of Mines, 1927–1996; U.S. Geological Survey, 1906–1927, 1997–2002). The Mineral Yearbook classifies crushed stones by their intended use, with agricultural limestone being a sub-category of "agricultural uses". We noticed roughly half of crushed stones are classified under an "unspecified end-use" category. West and McBride (2005) estimated total agricultural lime by combining explicitly labeled agricultural limestone with an inferred fraction (approximately 2 %–3 %) from the unspecified category, assuming proportional distribution across all categories.

We further extended the methodology of West and McBride (2005) until 2022 (orange line) (data extracted from https://www.usgs.gov/centers/national-minerals-information-center/crushed-stone-statistics-and-information, last access: 2 November 2026). We aggregated the number of crushed stones specified as "agricultural limestone" with an estimated percentage of agricultural lime within the "unspecified" end-use category. We show that the fraction of data in the unspecified end-use category (blue line; assumed to be used for agriculture) is similar in magnitude as those specified to be used for agriculture (purple line). This suggests that $\sim$50 % of the estimate in West and McBride (2005) is sensitive to how "unspecified" use is interpreted, which leads to high uncertainty and potential biases in total estimate.

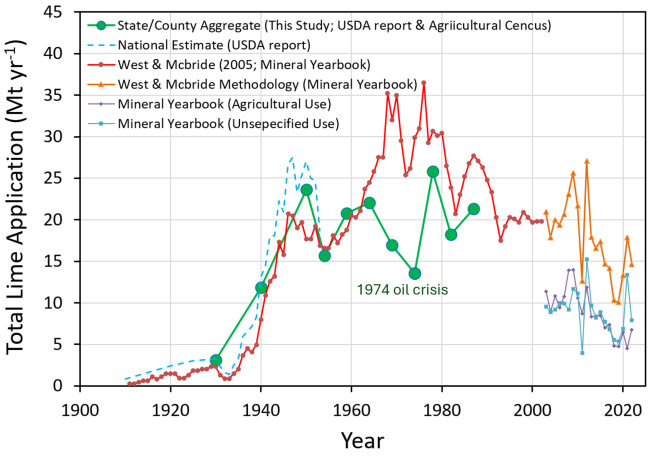

Figure 10. Comparison of national estimates of the total weight of lime applied (tons) over time. Our study's compilation (state-level aggregate (1930–1950) from the USDA report and county-level aggregate (1954–1987) from the Agriculture Census) are shown as green dots. The green dashed line represents the national estimate reported annually in the USDA report (1910–1950). The red line represents national estimates from West and McBride (2005). The orange dots indicate the extended total lime applied calculation based on the Mineral Yearbook using methods from West and McBride (2005). The purple line represents the fraction of lime applied for agricultural use, and the blue line reflects the unspecified end-use fraction, scaled by the ratio of agricultural use to total specified end-use, representing the potential lime used for agriculture.

Given that agricultural limestone is such a small fraction of the total unspecified crushed rocks (2 %–3 %), small variations in this percentage would lead to a large impact on the total estimated agricultural lime. Therefore, we believe that our compiled dataset potentially offers a more robust representation of the total amount of lime applied in the US. The range of 15–25 Mt yr^{-1} derived from the agricultural census records presents an alternative estimate of total lime application, compared with the 25–35 Mt yr^{-1} suggested in West and McBride (2005).

Based on our extended analysis using the methodology of West and McBride (2005), we show that total annual lime application over the past two decades varied between 10–25 Mt yr^{-1} but declined from its peak in the 1970s. A potential explanation for this is that cropland area expansion and harvested percentage area reached their maximum in the 1970s (Figs. S19–S20), which largely explains the observed peak in lime application during that period. Once cropland expansion stabilized and soil in many regions were sufficiently ameliorated, lime use declined. We acknowledge that due to the uncertainty in the methodology of West and McBride (2005), it is not entirely certain whether the total lime application decreased after our dataset ended in 1987. However, the total nutrient inputs via fertilizers have not seen any significant increase in nitrogen and phosphorus inputs since 1980 (Fig. S28). Although liming and fertilizer application do not always follow the same trajectory, a significant portion of lime is used to reduce soil acidity resulting from fertilizer use. Therefore, trends in fertilizer applications provide some evidence that total agricultural lime application likely did not increase after our dataset ended in 1987. As such, we believe the temporal range of our dataset already captures the period during which lime application reached its full extent in the United States. A simple comparison between pH recommendations and averaged soil pH data (Fig. S29) shows that, in many regions of the Southeastern US, soil pH is below the pH recommendation for achieving optimal crop yields. As such soil acidity could potentially be further corrected through more lime application. However, the lack of temporally explicit and crop-specific data prevents further quantification of this phenomenon. Further work is required to assess if policy should encourage additional lime applications.

5 Data availability

The dataset presented in this study is publicly available on Zenodo at https://doi.org/10.5281/zenodo.15758274 (Tsao et al., 2026).

This dataset provides spatially explicit records of agricultural lime application across the contiguous United States, combining state-level estimates (1930–1950) and county-level estimates (1954–1987) derived from historical agricultural census reports. The dataset includes: (1) State-level data from 1930 to 1950, (2) County-level data from 1954 to 1987, (3) Pixel-level data in 1 km resolution of area-weighted liming intensity from 1954–1987.

The dataset is organized into three components:

1. State-level lime application (1930–1950).

   The file StateLevel1930-1950.csv contains state-level lime application data from 1930 to 1950, reported in metric tons. These values were compiled from historical US agricultural census and summary reports.

2. County-level lime application (1954–1987).

   The file CountyLevel1954-1987.zip contains a shapefile with county-level lime application data for the period 1954 to 1987. Each record represents a county-year observation and includes the following variables:

   year: Year of observation

   GEOID_shp: County GEOID associated with the modern US county shapefile

   FIPS_cens: County FIPS code in the historical census reports (Cities/modern counties that are not included in the historical census reports will show missing values)

   LimeTons: Total lime applied (t)

TonsStatus: Whether LimeTons was observed or imputed

LimeArea: Area limed (ha)

AreaStatus: Whether LimeArea was observed or imputed

CropArea: Total cropland area (ha)

CropStatus: Whether CropArea was observed or imputed

LimeRate: Lime application rate, defined as lime applied per unit limed area ($t\,ha^{-1}\,yr^{-1}$)

LimeIntsty: Liming intensity, defined as lime applied per unit cropland area ($t\,ha^{-1}\,yr^{-1}$)

LimeFreq: Lime-treated fraction, defined as limed area divided by cropland area for the year (yr^{-1})

3. Pixel-level lime application (1954–1987).

   The file PixelLevel_1km_t_ha_1954_1987.zip contains pixel-level estimates of area-weighted liming intensity at 1 km spatial resolution, expressed in metric tons per hectare per year ($t\,ha^{-1}\,yr^{-1}$). The archive includes eight raster files corresponding to the eight agricultural census years between 1954 and 1987.

6 Code availability

The code used for data processing, interpolation, and machine learning analysis is all publicly available on Zenodo at https://doi.org/10.5281/zenodo.23774097 (Tsao, 2026).

7 Conclusion

In this study, we compiled and presented the first spatially explicit data set of agricultural lime application in the US from 1930–1987 (https://doi.org/10.5281/zenodo.15758274, Tsao et al., 2026). We showed that the Midwest region has the most amount of lime applied, while the South and Southeastern coastal region of the US has gradually increased lime application. We also showed that the Midwest has a higher lime application rate than the Southeast and Eastern US, while the lime-treated fraction is higher in the Southeast and Eastern regions than in the Midwest. Using machine learning algorithms, we showed that on the county level, the total amount of lime applied can be explained by the spatial variation of agricultural management practices (soybean and corn production, fertilizers, soil pH recommendation) alongside natural factors such as soil pH and climate. Lime application rate and lime-treated fraction can further be explained by natural regional climate (e.g., precipitation, temperature) and soil characteristics (e.g., soil pH, carbonate minerals, particle size distribution, soil texture, organic matter). We also showed that the temporal variability in total lime application may be influenced by economic factors, including competing input decisions such as fertilizer use, as well as fluctuations in fuel prices and farm income and expenditure.

Our study synthesizes historical lime application practices from 1930–1987 across both temporal and spatial dimensions. As liming has significant importance in modern day agriculture practices and recently gains attention for its potential role in climate mitigation, understanding historical spatial pattern of lime applications offers a critical observational baseline for future research efforts. We would like to highlight that the liming data being not available in the Census report after 1987 greatly limit the capacity of this research. Similar to recent work which argued for better data collection efforts to support a more sustainable food system (Rissing et al., 2023), we believe that a restart of the collection effort of lime application variables by the USDA would greatly enhance the community's knowledge of current agricultural liming practices. Future research could potentially build on these spatially explicit data of lime applications by accounting the variations in soil types and climate conditions. Comparing these trends against historical climate-relevant data (e.g. soil carbon stock, river alkalinity) during this period will enable a comprehensive assessment of further agricultural or climate-mitigation questions.

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