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RESEARCH ARTICLE

Farming Becomes More Precarious With Age: Injury in Maine Agricultural Communities, 2008–2022, via Time Series Analysis

Laura E. Jones[1] | Erika Scott[2] | Nicole Krupa[1] | Cristina S. Hansen-Ruiz[2] | Paul Jenkins[1]

[1]Center for Biostatistics, Bassett Research Institute, Bassett Medical Center, Cooperstown, New York, USA | [2]Northeast Center for Occupational Health and Safety in Agriculture, Forestry, and Fishing, Bassett Medical Center, Cooperstown, New York, USA

Correspondence: Laura E. Jones (laura.jones@bassett.org)

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ABSTRACT

Background: Fatal occupational injury rates among agricultural workers are within the top 10 most dangerous civilian jobs. However, tracking and documenting non-fatal agricultural injuries in Maine, as in other states, has proved challenging. In 2021, we developed a machine learning-based strategy to extract injury cases from free-text pre-hospital care records (PCRs), which together with final human coding, produces injury time-series records coded by type, severity, location, date, and subject industry. In this paper we explore and summarize novel time-series records for agriculture obtained from PCR from Maine.

Methods: From a fully labeled Maine dataset ($N = 57{,}960$) comprising coded injuries, we selected only agricultural events, yielding 1604 injuries from 2008 to 2022. We summarize by year, month and age category, and establish seasonality before decomposing time series data, divided into three roughly equal 4-year sub-periods, into seasonal, trend and random components using a classical additive model. We investigate associations between age category and injury rate via mixed effects regression, then perform time series regression on differenced monthly injury time series and temperature records to determine if, seasonality aside, temperature extrema are responsible for increased injuries. Finally, we visualize and summarize trend and random components for each study sub-period.

Results: Injury rates show strong seasonality with a peak in July–August, and a trough in January or February. Subject age drifts slowly upwards during our study period, and there is a significant and positive association between age category and injury rate for all but the most elderly farm workers. Injury rates in the age categories of 40–81 years increase dramatically between 2016 and the 2019–2022 period, as does the moving average of the injury rates, and the variability of the random component of the time series.

Conclusions: There is a significant positive association between increasing age category and injury rate across all periods. While our injury data has strong seasonality, we find no significant associations between monthly temperature extremes and injury rates. Moving average trends for injury rates in the two periods comprising 2008–2016 show little change in trend, but injury rate trend shifts upward in 2019–2022, almost doubling in mean value.

Abbreviations: ACF, autocorrelation function; CDC, Centers for Disease Control and Prevention; CV, coefficient of variation; FRHSS, Farm and Ranch Health and Safety Surveys; IRB, Institutional Review Board; LOESS, locally estimated scatterplot smoothing; NIOSH, National Institute for Occupational Safety and Health; OISPA, Occupational Injury Surveillance of Production Agriculture; PCR, pre-hospital care record; SOII, survey of occupational injuries and illnesses; STL, seasonal trend decomposition.

1 | Introduction

Agricultural workers currently suffer 19.5 deaths per 100,000 workers in the United States, rates five times greater than typical workers in other occupational sectors [1, 2], yet these fatalities represent the "tip of an injury iceberg" [3]—with far more uncounted nonfatal injuries affecting farmers and farm workers. Capturing and documenting nonfatal agricultural injuries and illnesses remains challenging [4–6] as regulatory exemptions in the Occupational Health and Safety Act contribute directly to inaccurate injury reporting in this sector [7]. Common data sources such as the Survey of Occupational Injuries and Illnesses (SOII) exclude self-employed agricultural workers and workers at farms with less than 11 employees; [7, 8] thus under-reporting may be particularly true of smaller northeast US farming operations, many of which are family-run.

To accurately document nonfatal agricultural injuries, we utilize a novel data source, emergency response pre-hospital care records (PCRs), to capture injury burden in this sector [9, 10]. In 2021 we developed a free-text analysis workflow that involved pre-processing of PCRs for keyword stems [11], then employed a naïve-Bayes-based classifier to identify and exclude records of no interest, thereby greatly reducing the number of records sent to human coders for final coding [12]. We have run this workflow on 15 years of PCRs from Maine, yielding a time series of 1604 injuries coded to agriculture from January 2008 to April 2023.

Agricultural injury counts and rates in the United States exhibit a strong seasonality, with most occurring between April and September, a period corresponding with peak farming activities such as planting, field work and harvesting [13, 14]. The busy period typically sees an influx of temporary seasonal workers, yielding a larger pool of at-risk individuals. While temporary seasonal workers make up a critical workforce, regions with smaller farms, such as Maine, tend to have many farms that rely on a sole operator or a few family members to operate. These farm owners are an aging workforce [15]. Seasonality in agricultural injuries can display a strong bimodal trajectory with a double peak, one in the spring during planting, and a second larger peak in the late summer or early fall during harvest [16], with leading causes of injury being machinery—associated with transportation, tilling or harvest — falls, and animal encounters. Exposure to summer heat during peak work periods can result in purely heat-related injuries such as heat stroke and syncope, and heat exhaustion, but also increases the likelihood of impaired-vigilance-associated traumatic injury in farmworkers, particularly during work-intensive activities in July and August [17]. With climate change, summers are becoming hotter and weather more variable and extreme. Due to the physically arduous nature of their work, performed outside with prolonged sun exposure, often under substandard working conditions, farmworkers are especially vulnerable to heatwaves, which are increasing in frequency and intensity [18]. Injury risk factors for agricultural workers include intensive manual labor; piece-rate payment schemes that encourage workers to maximize pay by pushing beyond their own physical limitations; lack of control over workplace environment and safety, including access to water and shade, and often, poor living conditions [18–21].

Injury time series data decompositions, along with data visualizations, are more recently used to identify seasonality in acute and traumatic injury and to capture and understand time-related trends and patterns [14, 22]. Both retrospective and contemporaneous (on-line) injury time series analyses are powerful tools for documenting the evolution of injury trajectories in close to real-time, alerting researchers and policy makers to emerging injury trends in vulnerable populations. Our aim here is to explore, visualize, and summarize novel agricultural injury time series data obtained from PCRs from the US state of Maine, for the period from 2008 to 2022, with special attention on subject age and injury seasonality.

2 | Materials and Methods

2.1 | Population at Risk and Study Population

We determined population at risk of injury for agricultural and farming communities in Maine at four time points within or bracketing our study period: 2007, 2012, 2017, and 2022 (Supporting Information: Table S1). Discussion of how population at risk was computed is found in Supporting Information: Appendix 1, and a similar process is also described by Earle-Richardson et al. [23]. As we didn't obtain population-at-risk numbers for each individual study year, study years 2008–2009 used population-at-risk values determined for 2007; study years 2010–2014 used values for 2012; study years 2015, 2016, and 2019 used values determined for 2017, and study years 2020 to April 2023 used population-at-risk values for 2022. We were not able to obtain detailed information on population-at-risk by season or by quarter. Study population subjects were categorized by age as follows: age no more than 20 years, age 21–40 years, age 41–60 years, age 61–80 years, and age 81 and above.

2.2 | Data Acquisition, Processing, and Classification Workflow

We created a labeled dataset from processed and classified PCR records from the state of Maine for years 2008 to April 2023.

The application for PCR data required that we meet data handling security standards of the Maine Bureau of Emergency Medical Services. Cleaning and processing is described in detail by Hirabayashi et al. [11], and the machine learning workflow used to label it is described by Scott et al. [12]. Cleaning involved removing duplicate records identified by matches on four features: subject sex, admission date, ZIP code, and date of birth. Before omitting duplicates and irrelevant samples, our dataset comprised 3,720,304 records, and after omissions, 2,364,895 records remained. Of these 57,960 were tagged with an occupational injury status as described here [12] (see Supporting Information: Table S2 for details). Our dataset for time series analysis comprises only records that were tagged as *confirmed acute or traumatic agricultural injuries* (Class 1); *confirmed acute or traumatic, suspected agricultural* (Class 2) *and suspected acute or traumatic, confirmed agricultural injuries* (Class 3). Box 1 shows a distribution of injury types over the study period. These samples comprise 1,604 injuries occurring

BOX 1. | Injuries per class by year

Year	Injury class 1	Injury class 2	Injury class 3
2008	32	38	10
2009	56	53	15
2010	55	66	11
2011	33	34	17
2012	40	54	21
2013	54	49	19
2014	39	56	12
2015	30	48	14
2016	36	47	13
2019	61	98	15
2020	56	80	14
2021	60	105	6
2022	43	83	10
2023*	7	13	1

*Partial year (Jan–Apr).

between study years 2008 and 2016, and study years 2019 to April 2023. See Supporting Information: Table S2 for a summary of preprocessing, total labeled records and total cases (case classes/injury types 1, 2, and 3) by year. Note that Class 0 thus consists of injuries that are neither confirmed nor suspected as agricultural. We were unable to acquire records for 2017, and those from 2018 were omitted due to coding conflicts. Missing units for the remaining sample are approximately 2.7%, and affect age determinations.

2.3 | Features

Selected features include injury case class (described above), industry (agriculture), injury month and year (2008–2016, 2019–2022), subject sex and subject age, categorized into five levels: "ages 20 and under" (Level A), "ages 21–40" (Level B), "ages 41–60" (Level C), "ages 61–80" (Level D), and "ages 81 and over" (Level E) as described above. Injury rates were computed from the above as follows: for counts by month, we grouped counts of all injury classes (1, 2, and 3) by year and month and summed each grouping, then computed mean count and standard error by month over the entire study period and over the three equal periods described above. We computed rates by scaling individual injuries by population at risk.

2.4 | Visualization

We summarized injury counts and mean rates by month for the entire study period and also in three roughly equal periods, 2008–2011; 2012–2016, and 2019–2023. Counts and rates were visualized as bar charts by month to reveal seasonality and we compared successive periods to show any overall increases or decreases in injury counts/rates not ascribable to seasonality. Monthly means and standard errors were scaled to a population of 10,000 at risk. Given evidence that our farming communities are generally aging and declining in size over the study period, we summarized subject age distribution graphically by year and in tabular format. We further quantified the significance of any differences in age distribution over time by bivariate regression and analysis of variance (ANOVA). Finally, we visualized changes in injury rates by age category over the three study periods, and quantified their significance via bivariate regression and ANOVA.

2.5 | Time-Series Analysis

2.5.1 | *Processing and Seasonality*

Given the 2 year gap (2017–2018) in our data, we separate our time series into three equal units, a period from 2008 to 2011, and from 2012 to 2016 before the gap, and the period from 2019 to 2023. We first convert the monthly rate data from each unit into a time-series, and compute the autocorrelation function (ACF) of each time series to verify the period of seasonality. The autocorrelation of a time series measures the relationship between the time series and a lagged version of itself over a set of different lag times. A time series with seasonality will have repeating components, yielding regular spikes and repeating patterns at certain lags.

As additional evidence of the seasonality of our injury data, we plot injury rates by month against monthly minimum, mean, and maximum temperatures for our three 4-year study periods (please see Supporting Information: Figure S1). Because our injuries are grouped by month due to their temporal irregularity, a cross-correlation and examination of lags does not yield anything of note. Applying two differences—a seasonal difference and a first difference—is necessary when the data has both a seasonal pattern and an underlying trend that both cause non-stationarity.

We thus difference each time series twice to remove seasonality (Lag 12) and trend (Lag 1) and achieve stationarity, and then perform simple linear regressions between differenced injury rate and monthly temperature trajectories by period to determine if there are associations between temperature extremes (without seasonality) and injury rates. Differenced time-series are checked prior to regression for stationarity using the Box-Ljung test, and we check model residuals for significant autocorrelation using the ACF function and the Breusch–Godfrey test for the presence of serial correlation (evidence of model misspecification).

2.5.2 | *Decomposition and Visualization*

Seasonal and other fluctuations are roughly similar over time for each time series, so for decompositions, an additive model is sufficient, and based on the ACF, we set the data to a seasonal period of 12 (months) per year. To examine overall trends in the data without the seasonality, we decompose each time series into three additive parts using Loess Seasonal Trend decomposition (STL), which is particularly useful for nonlinear trends [24, 25]. Each time series is decomposed into seasonality, trend, and a remainder comprising all signal that isn't described by seasonality or trend. The LOESS (locally estimated scatterplot smoothing) filter uses local nonparametric regression to estimate the seasonal component and any linear or nonlinear trend in the data, fitting smooth curves to weighted subsets of points near each point in the dataset, with points closer to the target point receiving more weight. The method performs best on complete annual cycles, so we omit 2023 from the decomposition as there are only 5 months of data. Once the seasonal signature and trend are subtracted from the time series, the remaining signal is assumed to be random. We then visualize the original time series alongside seasonality, trend, and random (remainder) components in plots. For each of the three periods, we summarize mean, median, IQR, and extrema, then compute coefficient of variation (CV) for the trend (moving average) and remainder components. Distributions of trend and remainder data are also visualized as box plots by period.

Data wrangling and time series manipulation were performed in the R programming language (R4.4.1) using tidyverse, the ts (time series) package, decompose function and forecast packages [26, 27]. Time series regressions were performed on differenced data using tsml. Visualizations were made using the R ggplot2 package.

This study was approved by the Institutional Review Board of the author's institution.

3 | Results

3.1 | Population at Risk

Population at risk is difficult to assess in American farming communities, especially those dominated by smaller and family farms, as working family members, including spouses and children, as well as unpaid workers must be estimated and included. Our population-at-risk information contains four points over a period of 16 years (Supporting Information: Table S1). According to our assessments for this period, the population-at-risk peaks in 2012 at roughly 32,331 persons, and by 2022 dropped to approximately 25,619 persons, a decline of about 21%.

3.2 | Study Population

Our study population is 70% male, 28.5% female and 1.8% unspecified sex. The median subject age is 57, and age category distribution trends older with 43.5% of injury subjects over age 60, and 73% age 41 and above. Sex distributions by age category (proportions by sex) are fairly even. Based on our injury data, we infer that the average age of the farming community has increased over this period as well. In 2008, our reference year, the average age of an injury subject was 47 years old, but by 2012 the mean age of an injury subject was 56 years old (2012 was the first year to be significantly over reference, see Supporting Information: Table S3).

3.3 | Injury Rates and Seasonality

We show mean injury rates per 10,000 at risk by month for each of the three sub-periods (2008–2011, 2012–2016, and 2019–2023) in bar plot form in Figure 1. Average seasonality across the entire dataset is illustrated by the monthly mean rates (Table 1) Rates peak in the summer months at over five injury cases per 10,000, and then drop to roughly two injuries per 10,000 in the winter. More granular data suggests an increasing trend over time, however, (Figure 1). All three periods show a strong seasonality, with peaks in injuries occurring in the summer months of June and July, and minima in the winter months of January and February. From 2008 to 2016 (Figure 1a,b), monthly injury dynamics are similar, yet for 2019–2022, rates show a sharp increase for each month, with the largest increases in the summer peak injury season (Figure 1 and Table 1). However, there are no significant associations between monthly injury rates and monthly temperature extrema from time-series regression of differenced monthly injury rates and temperature data for minimum or maximum monthly temperatures (see Supporting Information: Figure 1 and Table S4).

3.4 | Subject Age and Injury Rates

Subject age drifts upwards slowly during our study period, though differences between each successive year are likely not statistically significant (Figure 2 and Supporting Information: Table 2). The first significant difference in age relative to baseline (2008) is in 2012. However, injury rates are significantly associated with age and age category, and this result appears to deepen over the three time-windows considered.

Injury rate distribution by age category and time period are shown in Figure 3 as a tri-plot with a panel for each equal length study period and displayed in tabular format in Table 2. The first period considered (2008–2011) shows highest injury rates in the 41–60-year old group (Cohort “C”; mean 10.7, 95% CI: 7.6–13.9), followed by the 61–80-year old group (Cohort “D”; mean 7.9, 95%CI: 5.4–10.4); see Figure 3a. By 2012–2016 (Figure 3b), injury rates in Cohorts C and D are similar (mean 10.9, 95%CI: 9.4–12.5 for Group C, and 10.8; 95%CI: 8.9–12.8 for Group D), suggesting relatively increased injury rates in the older of the two cohorts. In 2019–2023, all cohorts are elevated, but increased injury rates in Cohort D (mean 19.7, 95% CI: 11.7–27.7) by far exceed increases in other age-groups (Figure 3c).

Results from mixed effects regression of monthly rates against age category (reference level Cohort A, “under 20 years”), with ‘year’ as a random effect suggests that all age categories show significantly elevated injury rates above reference except for the most elderly group (Cohort “E”, ages 81 and above, Table 3). In simple regression models with year as a fixed effect (not shown) there is also a significant association with increasing time, though we tested for effect modification by time and an interaction term is not significant.

3.5 | Time Series Analysis: Injury Rates and Time

We perform time series decomposition on the data as three time series, comprising injuries from 2008 to 2011, 2012 to 2016 and the third comprising injuries after the time gap (2017–2018), thus from 2019 to 2022. Time series decomposition requires an assessment of seasonality, and autocorrelation function (ACF) plots show significant sinusoidal dynamics for both time series segments, with significant (above the blue line) positive correlations at 12 months for all three periods. This confirms the

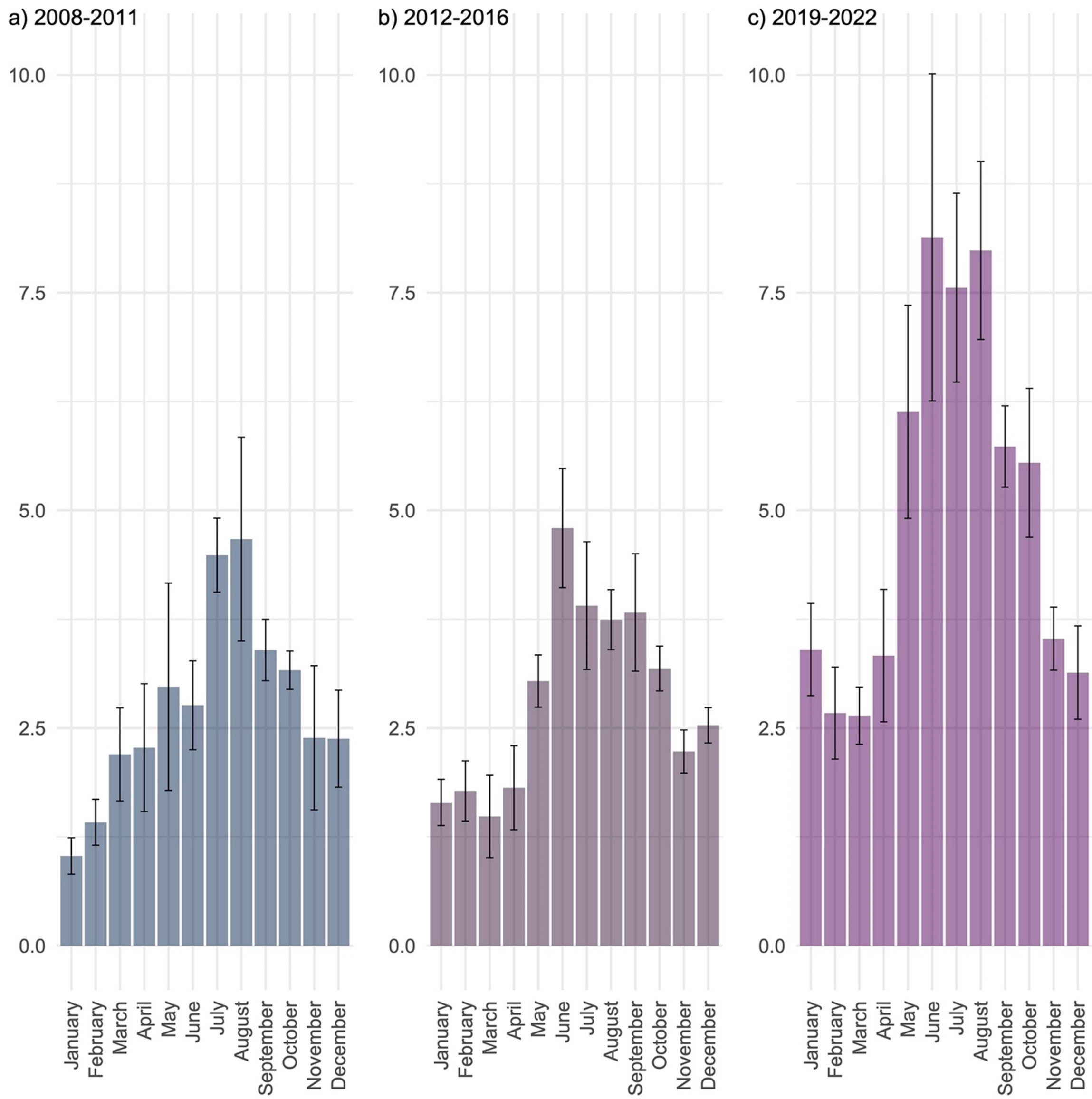

FIGURE 1 | Mean agricultural injury rates per 10,000 workers at risk over three periods of roughly similar length during our study period: (a), years January 2008–December 2011; (b) January 2012–December 2016, and (c) years January 2019–December 2022. Note that rates for January through April are skewed by the inclusion of the partial 2023 counts, so we omit them here. Rates of agricultural injuries are similar for the first two periods, especially during seasonal highs, and then increase dramatically during the final study period. See Table 1 for counts and rates in tabular format.

strong annual (12 month) seasonal signature in agricultural injury rates that we observed qualitatively across the entire study period. Since the raw time series show no sign of exponential increase, our decompositions assume an additive model and a seasonal period of 12 months: that is, the components displayed—trend, seasonal, random—are added to form the "observed" (Figure 4a–c). There is a strong seasonality in injury rates with a roughly annual (12 month) cycle from February to January.

For 2008–2011 (Figure 4a), the decomposed trendline shows clear breaking points, that is, distinct shifts in trend with a peak around January 2010–March 2010, then a decline. The median value of the trend line for 2008–2011 is 2.6/10,000 at risk (mean 2.8/10,000; standard deviation 0.68). The seasonal component is small in amplitude, roughly in the range [−1.5, +2.0] injuries per month. The trendline from the decomposition of the 2012–2016 time series (Figure 4b) is similar, with a median of 2.9 (mean 2.8, standard deviation 0.27), and a seasonal component of roughly ±2 injuries per month (Table 4).

The period from January 2019 to December 2022 shows distinct nonlinear shifts in trend, at with a peak in summer 2021. The median value of the trend line for the period from January 2019–December 2022 is 4.8/10,000 (mean 4.9, standard deviation 0.52), almost twice as high as the prior period. The amplitude of the seasonal component is also more substantial for this 4 year period, approximately twice the size of the prior period at ±3 injuries.

Our summary analysis of trend data suggests that a distinct and significant shift upwards in the trend, or moving average of injury rates, occurred in the period 2019–2022 (Figure 5) relative to prior periods. In addition, variance increases for the remainder, the 'random' component of our time series, with the

TABLE 1 | Mean injury counts and rates per 10,000 at risk by month for agriculture in the state of Maine averaged over the full study period (2008–2016 and 2019–April 2023) from pre-hospital care records (PCRs). Agricultural injuries show strong seasonality, with mean injury counts/rates increasing from February to August, and then falling from September to January. See Figure 1 for visualization.

Month	Injury count	(95% CI)	Rate/ 10,000	(95% CI)
January	5.6	4.0–7.2	1.9	1.3–2.5
February	5.8	4.6–7.0	2.0	1.5–2.5
March	6.1	4.6–7.6	2.0	1.6–2.6
April	7.0	4.9–9.1	2.4	1.7–3.1
May	11.6	8.4–14.9	4.0	2.7–5.2
June	15.2	11.0–19.3	5.2	3.5–6.9
July	15.4	12.3–18.5	5.2	4.0–6.4
August	15.7	12.1–19.2	5.3	4.0–6.7
September	12.7	10.5–14.9	4.3	3.5–5.1
October	11.5	9.7–13.2	3.9	3.1–4.7
November	7.9	6.2–9.6	2.7	2.1–3.3
December	8.0	6.6–9.4	2.8	2.2–3.2

Abbreviation: CI, confidence interval.

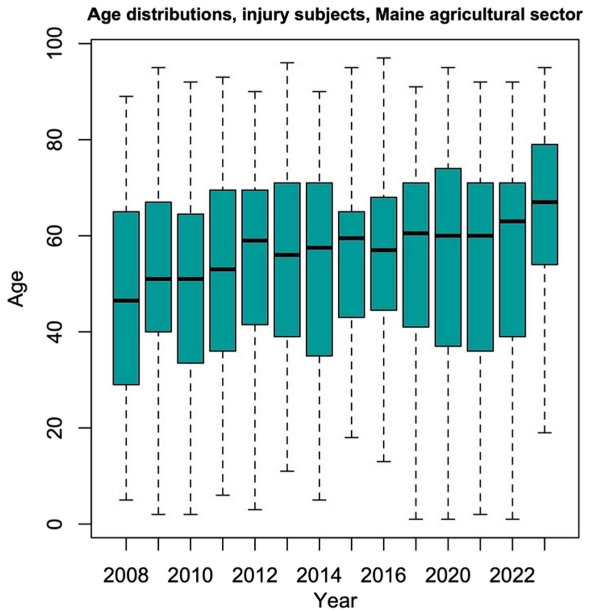

FIGURE 2 | Age distribution of injury subjects, Maine agricultural sector.

coefficient of variation (CV) doubling in 2019–2023 relative to prior periods (Figure 5 and Table 4).

4 | Discussion

Our analysis of novel time-series records of agricultural injuries from the state of Maine, obtained from PCR records, years 2008–2023, reveals farming communities in demographic jeopardy. Over the course of our study period, the mean age of injured workers has slowly but steadily increased. As the average age of farmers continues to increase, this suggests that the entire sector is aging and not sustainably replenished by younger workers [15]. This is more obvious when injuries are aggregated by year and age-group: workers in older age categories, especially ages 61–80 years, suffer increasingly higher rates of injury when comparing the 4 year periods 2008–2011, 2012–2016, and 2019–2022.

The trend analysis, notable for its sudden doubling in mean in 2019, seems at first mysterious, suggesting perhaps a general increase in all emergency responses with time. Yet examination of cleaned, deduped PCR records over time from years 2008–2022 shows emergency call frequency roughly holding steady over the study period (Supporting Information: Table S2; slope of increase in deduped and cleaned records with time is $O(10^{-5})$; $p = 0.08$).

Meanwhile our injury counts hold steady for much of the study period, increasing sharply by 2019. Note that the size of the working farm population at risk dropped by approximately 21% from a peak of 32,331 in 2010–25,691 in 2022 (Supporting Information: Appendix 1). Bracketing the period of greatest injury increase between 2017 and 2022, total production and sales actually increased 40% [29, 30]. Together this suggests a declining pool of aging workers, racking up proportionally more injuries. This may be attributed to an increasing and strenuous work burden shouldered by a farming population in attrition, perhaps past a critical threshold. Further, the COVID-19 pandemic had significant impacts on the rural workforce, with businesses such as small farms being disproportionately affected by labor shortages [31]. It is possible that along with existing demographic changes to the farm workforce, trying to keep up with production with fewer workers during and following the pandemic contributed to increased injury rates.

Prior studies have shown that it is typically youth and the elderly that bear the greater burden of farm injuries, whereas our peak injury group includes prime working age adults from 41 to 60 years of age, as well as older farmers aged from 61 to 80 years. Alabama farmers between 20 and 44 years of age were found to have a cumulative injury incidence risk of 11.5%, compared to 6.9% for the 45–64 year old cohort, and 5.8% for farmers aged 65 and above, though this study may suffer from its smaller sample size ($n = 718$) [16]. Injury-predictive features here included younger age, farm ownership, full-time farming, alcohol consumption and prior injury status. A more recent (2009) study showed that older farm workers aged 55+ had higher fatality rates (45.8 vs. 25.4/100,000 at risk per year) relative to the overall farming population, but lower injury rates [32]. However, injuries occurring in farm families and small farms, and thus subject age, may be underreported. For adult members of farming families aged 20–54, family members and relatives comprised 72% of injuries reported in a national surveillance instrument (NIOSH OISPA 2001, 2004; comprising 15,259 and 16,239 farms, respectively). Among older age groups, however, 88% of injuries were to farming family members and relatives [32].

The primary summer to late summer injury seasonality we observe here appears roughly consistent with other studies [6, 13, 14, 16], but there are small regional differences in peaks as winters are colder and longer in New England, and spring arrives relatively late. A recent study of data from the 2018–2020

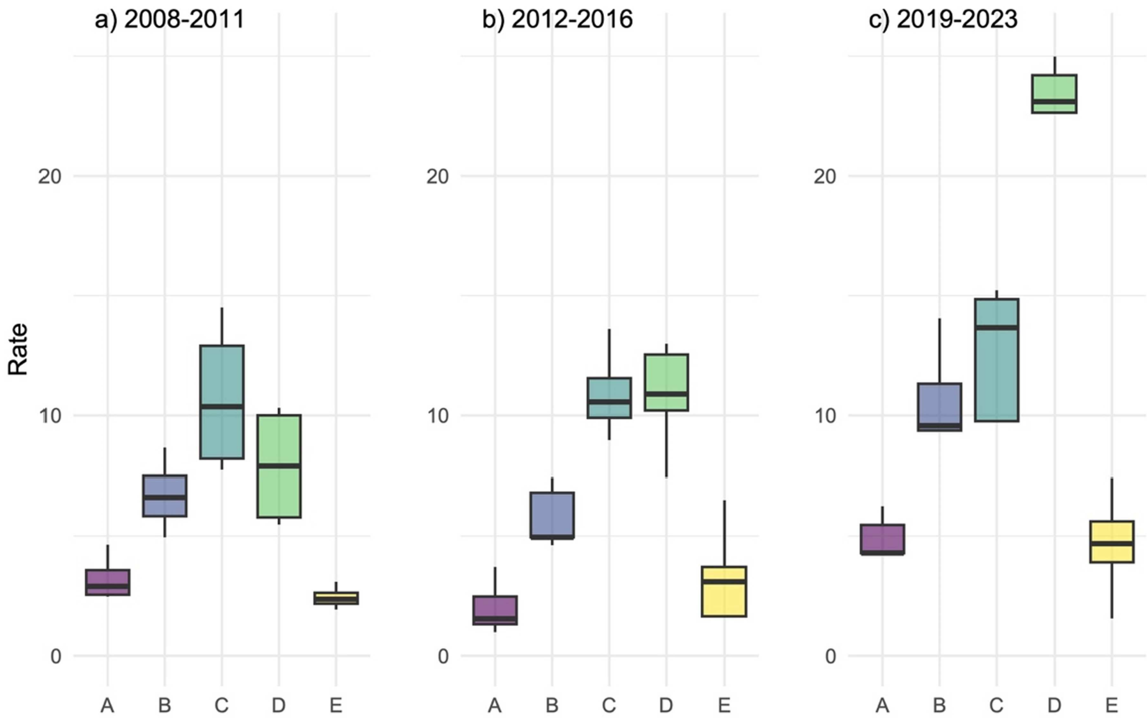

FIGURE 3 | Injury rates per 10,000 by age category. (a) Study period from 2008 to 2011; (b) study period from 2012 to 2016, and (c) study period 2019–April 2023. Age groups are identified by letter: A is youth 20 years of age and under; B is 21–40 years of age; C is 41–60 years of age; D is 61–80 years of age, and E represents injury rates in subjects ages 81 and over.

TABLE 2 | Mean injury rates by age category for each time series period.

Period	Age category	Mean injury rate per 10,000 at risk	95% CI
January 2008–December 2011	A: 20 years or less	3.2	2.3–4.2
	B: 21–40 years	6.7	5.2–8.3
	C: 41–60 years	10.7	7.6–13.9
	D: 61–80 years	7.9	5.4–10.4
	E: 81 or older	2.4	2.0–2.9
January 2012–December 2016	A: 20 years or less	2.0	1.1–3.0
	B: 21–40 years	5.8	4.6–6.9
	C: 41–60 years	10.9	9.4–12.5
	D: 61–80 years	10.8	8.9–12.8
	E: 81 or older	3.3	1.6–5.1
January 2019–April 2023	A: 20 years or less	4.1	2.2–6.1
	B: 21–40 years_	9.0	4.7–13.4
	C: 41–60 years	11.1	6.2–16.0
	D: 61–80 years	19.7	11.7–27.7
	E: 81 or older	4.6	2.7–6.5

Abbreviation: CI, confidence interval.

Farm and Ranch Health and Safety Surveys (FRHSS) in seven midwestern states suggested that for this region, most injuries occurred in the spring (34.2%) followed by summer months (24.7%), but that male operators had higher odds of injury in the summer (adjusted OR 2.41) [13]. Here stress and exhaustion are also a factor in injury as surveyed workers who reported higher stress levels experienced significantly higher odds of injury, with highest relative rates in the fall harvest time [13], and it may be especially acute for older workers. In a small two-part study on the work habits, health, and injury rates of older (55–70 years) Illinois farmers, Lizer and Petrea (2008) found that self-reported stress, including financial stress, was associated with injury among farmers in the 55–59 year age cohort. They further note that other occupational sectors do require physically strenuous labor of subjects older than 65 years of age [33].

TABLE 3 | Associations between injury rate (per 10,000 at risk), age category, and year from mixed effects linear regression of monthly injury rates against age category, with year as a random effect. Reference level for age category is A, "injury subject is 20 years of age or less."

Coefficient	Level	Mean	95%CI	*p*-Value	ANOVA
(Intercept)	Reference A	3.3	1.3–5.1	0.0003	F: 32.9 $p < 0.0001$
Age category	B	4.4	2.1–6.6	0.0007	
	C	8.3	6.1–10.5	< 0.0001	
	D	10.6	8.3–12.8	< 0.0001	
	E	0.36	−1.86, 2.6	0.77	

Abbreviations: ANOVA, analysis of variance; CI, confidence interval.

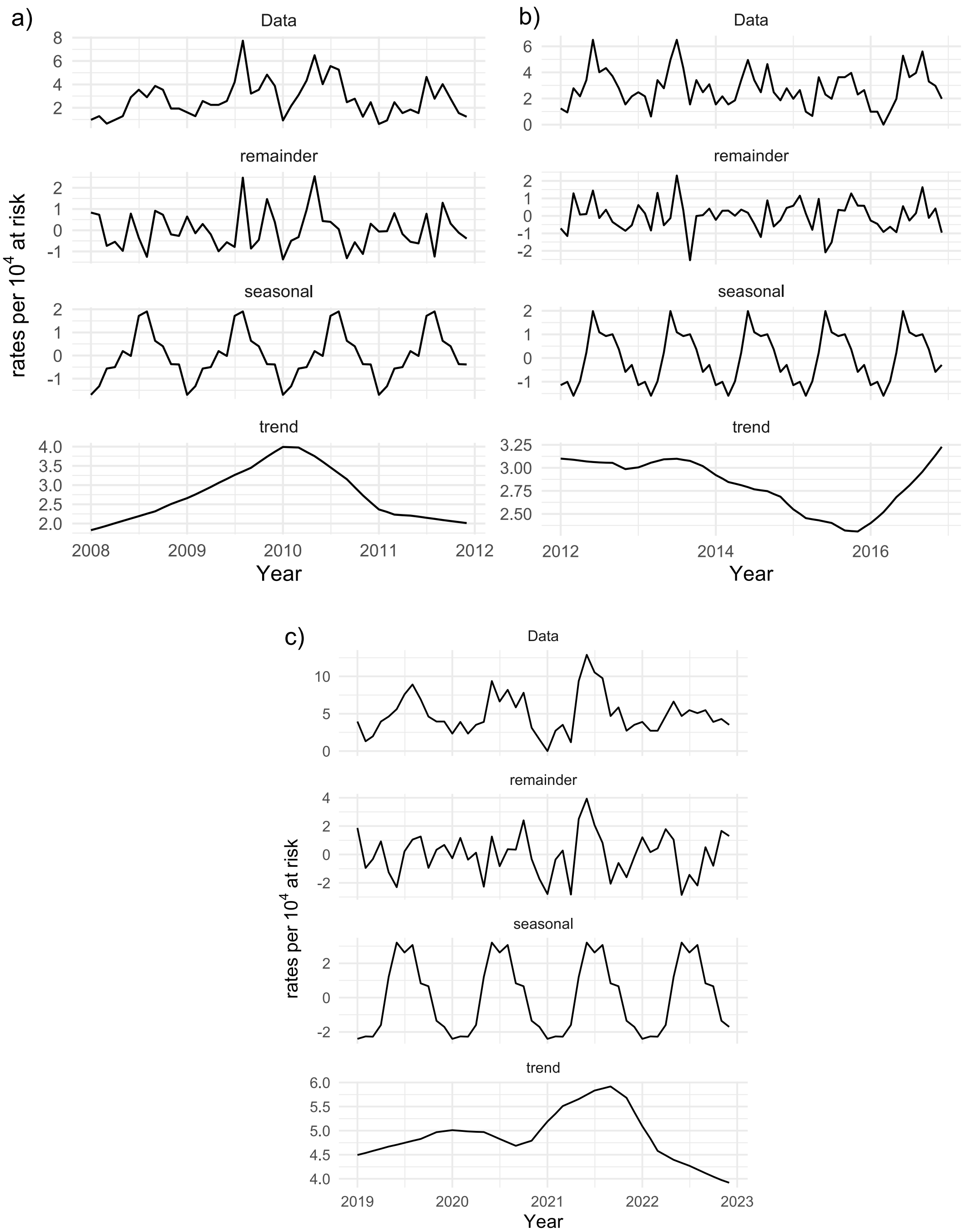

FIGURE 4 | Decomposition of Maine injury rates time series for 2008–2011 (top left, a), 2012–2016 (top right, b), and 2019–2023 (bottom, c).

TABLE 4 | Analysis of decomposed injury time series trend and remainder data. Trend data will reflect any upward or downward drift in the moving average of injury rates across each period. "Remainder" data comprise potentially random event dynamics after trend and seasonality are removed, and should be roughly centered about zero. The coefficient of variation (CV) is a measure of variability.

		Monthly Injury rates per 10,000 agricultural workers at risk					
Period	**Component**	**Minimum**	**Median**	**Mean**	**IQR**	**Maximum**	**|CV|**
2008–2011	Trend	1.8	2.6	2.8	1.15	4.0	0.25
	Remainder	−1.4	−0.2	0.01	1.2	2.6	84.3
2012–2016	Trend	2.3	2.9	2.8	0.5	3.2	0.1
	Remainder	−2.5	0.05	−0.01	1.0	2.3	94.5
2019–2022	Trend	3.9	4.8	4.9	0.5	5.9	0.1
	Remainder	−2.9	0.2	0.01	2.0	3.9	137.4

Abbreviation: IQR, interquartile range.

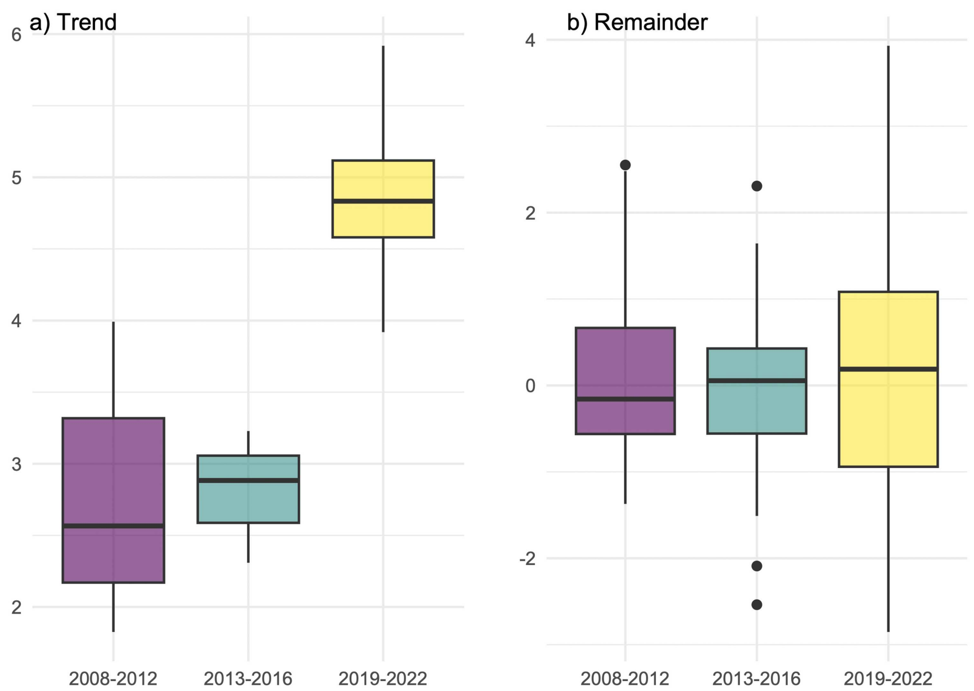

FIGURE 5 | Boxplots visualizing summary statistics for analysis of decomposed injury time series trend and remainder data by study period. (a) Visualization of differences in trend by study period of interest. Note significant shift between first two periods and 2019–2022; $\Pr(>F) < 2.2\times10^{-22}$ from ANOVA. (b) Visualization of differences in "remainder" by study period. Note the differences in variance, especially for 2019–2022.; $\Pr(>F) = 9.4\times10^{-5}$, Levene's test for homogeneity of variances [28] (Null hypothesis is homogeneity). ANOVA, analysis of variance.

Additional information (extracted from PCRs and coded by human coders) associated with this agricultural injury dataset is described in a second paper [34]. This latter study examines OIICS-coded injuries from Maine agricultural workers, obtained via mining PCRs, and visualized and summarized to help readers better understand changes in agricultural injury source, event, nature and body part injured over the 15 year study period.

4.1 | Limitations

Because our data are temporally sparse (about 1600 injuries over the course of 15 years), we grouped by month. A more granular time-spacing, such as by week, would have been preferable for time series analysis, but a by-week time series would have resulted in many weekly zero values. We do not scale individual subject age groups by age-grouped population at risk, because this information is not available or easily estimated. The dataset is small, spread over more than a decade, and includes a 2-year gap; results should thus be considered exploratory and descriptive. Finally, we do not have seasonal population records, so our rates are not adjusted for a potential increase in workers during the busy summer farming season. However, the decomposition of the time series into seasonal, trend and random components removes seasonality from the trend and random component analysis.

5 | Conclusions

Our exploration of agricultural injury rates in the state of Maine depicts a farming community that on average is aging during our study period and becoming more injury-prone, with age groups from 61 to 80 being the most likely to be injured, followed by prime working age subjects aged 41–60. There is a significant positive association between increasing age category and injury rate across all periods. While our injury data has strong seasonality, we find no significant associations between monthly temperature extremes and injury rates. However, it is possible that considering denser, more granular daily or weekly injury data from a larger sample, that is, including additional New England states, might reveal a pattern of heat- or cold-associated injuries. Moving average trends for injury rates without seasonality in the two periods comprising 2008–2016 show only small increases over this period, but nearly double for the final study period from 2019 to 2022. It is as if the injury trendline has been shifted upwards by a factor of two for this period, relative to prior periods. Together with the nearly doubled variability in the random (remainder) component of the time series for this period, this suggests a significant, possibly unelucidated change, an evolution both in working population age and the strenuousness of the work environment.

Author Contributions

Laura E. Jones: conceptualization, data curation and cleaning, analytical plan, software, analysis, writing (original draft), manuscript development and revision. **Erika Scott:** funding, project management, manuscript development and revision. **Nicole Krupa:** data selection, curation and cleaning. **Cristina S. Hansen-Ruiz:** project management, manuscript development and revision. **Paul Jenkins:** manuscript development and revision. All authors read and approved the final manuscript.

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The data analyzed here are available in raw form from the Maine Bureau of Emergency Medical Services, but restrictions apply and they are used under license for the current study. Those interested in applying may contact the Maine EMS Bureau. We thank the Maine EMS Bureau for the ability to request and utilize these data to enhance safety and health for the agricultural community. The workflow and code developed by the authors is available by a written request to the corresponding author. The study was supported by the CDC-NIOSH (Grant number 2U54OH007542).

Ethics Statement

This study was approved by the Institutional Review Board of the Mary Imogene Bassett Hospital (Bassett Medical Center).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Please see acknowledgements for details on data availability.

References

1. U.S. Bureau of Labor Statistics, "Civilian Occupations With High Fatal Work Injury Rates, 2022," 2023.

2. S. Li, M. M. S. Raza, and S. Issa, "Agricultural Injury Surveillance in the United States and Canada: A Systematic Literature Review," *Journal of Agromedicine* 29, no. 2 (2024): 122–135, https://doi.org/10.1080/1059924x.2024.2304699.

3. C. Peek-Asa, T. Young, A. Swanton, C. Missikpode, and M. Ramirez, "Surveillance of Agricultural Injuries and Fatalities," 2025. Great Plains Center for Agricultural Health, https://gpcah.public-health.uiowa.edu/center-projects/surveillance-of-agricultural-injuries-and-fatalities/.

4. J. P. Leigh, J. Du, and S. A. McCurdy, "An Estimate of the U.S. Government's Undercount of Nonfatal Occupational Injuries and Illnesses in Agriculture," *Annals of Epidemiology* 24, no. 4 (2014): 254–259, https://doi.org/10.1016/j.annepidem.2014.01.006.

5. J. P. Leigh, J. P. Marcin, and T. R. Miller, "An Estimate of the U.S. Government's Undercount of Nonfatal Occupational Injuries," *Journal of Occupational and Environmental Medicine* 46, no. 1 (2004): 10–18, https://doi.org/10.1097/01.jom.0000105909.66435.53.

6. S. Gorucu, J. Michael, and K. Chege, "Nonfatal Agricultural Injuries Treated in Emergency Departments: 2015-2019," *Journal of Agromedicine* 27, no. 1 (2022): 41–50, https://doi.org/10.1080/1059924x.2021.1913271.

7. OSHA, "Occupational Safety and Health Act of 1970. U S Public Law 91-596," 1970.

8. T. W. Kelsey, "The Agrarian Myth and Policy Responses to Farm Safety," *American Journal of Public Health* 84, no. 7 (1994): 1171–1177.

9. E. E. Scott, N. L. Krupa, M. Horsman, and P. L. Jenkins, "Estimation of Agricultural and Logging Injury Incidence in Maine Using Electronic Administrative Data Sets," *Journal of Agromedicine* 20, no. 2 (2015): 195–204, https://doi.org/10.1080/1059924x.2015.1009668.

10. E. E. Scott, L. Hirabayashi, N. L. Krupa, J. A. Sorensen, and P. L. Jenkins, "Developing Surveillance Methodology for Agricultural and Logging Injury in New Hampshire Using Electronic Administrative Data Sets," *Journal of Occupational & Environmental Medicine* 57, no. 8 (2015): 866–872, https://doi.org/10.1097/jom.0000000000000482.

11. L. Hirabayashi, E. Scott, P. Jenkins, and N. Krupa, "Occupational Injury Surveillance Methods Using Free Text Data and Machine Learning: Creating a Gold Standard Data Set," in *Sage Research Methods Cases: Medicine and Health* (SAGE Publications Ltd, 2020), https://doi.org/10.4135/9781529720488.

12. E. Scott, L. Hirabayashi, A. Levenstein, N. Krupa, and P. Jenkins, "The Development of a Machine Learning Algorithm to Identify Occupational Injuries in Agriculture Using Pre-Hospital Care Reports," *Health Information Science and Systems* 9, no. 1 (2021): 31, https://doi.org/10.1007/s13755-021-00161-9.

13. R. Ahmed, Y. Du, G. Haynatzki, S. Tucker, A. K. Ramos, and R. H. Rautiainen, "Seasonal Patterns of Injury Characteristics Among Farmers and Ranchers in the U.S. Central States," *Journal of Agromedicine* 29, no. 4 (2024): 653–664, https://doi.org/10.1080/1059924X.2024.2387645.

14. E. W. Lundstrom, S. A. Hendricks, S. M. Marsh, C. P. Groth, G. S. Smith, and R. Bhandari, "Temporal Trends in Occupational Injuries Treated in US Emergency Departments, 2012-2019," *Injury Epidemiology* 10, no. 1 (2023): 13, https://doi.org/10.1186/s40621-023-00423-y.

15. USDA, "Census of Agriculture," accessed April 18, 2025, https://www.nass.usda.gov/Publications/AgCensus/2022/#full_report.

16. C. Zhou and J. M. Roseman, "Agricultural Injuries Among a Population-Based Sample of Farm Operators in Alabama," *American Journal of Industrial Medicine* 25, no. 3 (1994): 385–402, https://doi.org/10.1002/ajim.4700250307.

17. J. T. Spector, J. Krenz, M. Calkins, et al., "Associations Between Heat Exposure, Vigilance, and Balance Performance in Summer Tree Fruit Harvesters," *Applied Ergonomics* 67 (2018): 1–8, https://doi.org/10.1016/j.apergo.2017.09.002.

18. M. El Khayat, D. A. Halwani, L. Hneiny, I. Alameddine, M. A. Haidar, and R. R. Habib, "Impacts of Climate Change and Heat Stress on Farmworkers' Health: A Scoping Review," *Frontiers in Public Health* 10 (2022): 782811, https://doi.org/10.3389/fpubh.2022.782811.

19. J. T. Spector, J. Krenz, and K. N. Blank, "Risk Factors for Heat-Related Illness in Washington Crop Workers," *Journal of Agromedicine*

20, no. 3 (2015): 349–359, https://doi.org/10.1080/1059924X.2015.1047107.

20. N. L. Fleischer, H. M. Tiesman, J. Sumitani, et al., “Public Health Impact of Heat-Related Illness Among Migrant Farmworkers,” *American Journal of Preventive Medicine* 44, no. 3 (2013): 199–206, https://doi.org/10.1016/j.amepre.2012.10.020.

21. D. Öztaş, B. Kurt, A. Koç, and M. Akbaba, “Living Conditions, Access to Healthcare Services, and Occupational Health and Safety Conditions of Migrant Seasonal Agricultural Workers in the Çukurova Region,” *Journal of Agromedicine* 23, no. 3 (2018): 262–269, https://doi.org/10.1080/1059924X.2018.1470048.

22. H. Gomes, V. Parasram, J. Collins, and C. Socias-Morales, “Time Series, Seasonality and Trend Evaluation of 7 Years (2015-2021) of OSHA Severe Injury Data,” *Journal of Safety Research* 86 (2023): 30–38, https://doi.org/10.1016/j.jsr.2023.06.005.

23. G. B. Earle-Richardson, P. L. Jenkins, E. E. Scott, and J. J. May, “Improving Agricultural Injury Surveillance: A Comparison of Incidence and Type of Injury Event Among Three Data Sources,” *American Journal of Industrial Medicine* 54, no. 8 (2011): 586–596, https://doi.org/10.1002/ajim.20960.

24. W. G. Jacoby, “Loess,” *Electoral Studies* 19, no. 4 (2000): 577–613.

25. K. Hartmann, J. Krois, and A. Rudolph, “Seasonal and Trend Decomposition Using Loess (STL),” in *Statistics and Geodata Analysis Using R (SOGA-R)* (Department of Earth Sciences, Freie Universitaet Berlin, 2023).

26. M. Kendall and A. Stuart, *The Advanced Theory of Statistics*, Vol. 3 (1983), 410–414.

27. Forecast: Forecasting Functions For Time Series and Linear Models, (2024): https://pkg.robjhyndman.com/forecast/.

28. Y. Zhou, Y. Zhu, and W. K. Wong, “Statistical Tests for Homogeneity of Variance for Clinical Trials and Recommendations,” *Contemporary Clinical Trials Communications* 33 (2023): 101119, https://doi.org/10.1016/j.conctc.2023.101119.

29. A. Farnham, “How are Maine Farms Faring? Highlights from the 2022 Census of Agriculture,” in *Policy & Research, Food & Farm System* (Maine Farmland Trust, 2024), https://www.mainefarmlandtrust.org/blogs/how-are-maine-farms-faring-highlights-from-the-2022-census-of-agriculture.

30. Service, U. N. A. S, “Summary by Size of Farm”, 2022 Census of Agriculture, Maine, Table 71, 2022, accessed February 5, 2025, https://www.nass.usda.gov/Publications/AgCensus/2022/Full_Report/Volume_1,_Chapter_1_State_Level/Maine/st23_1_071_071.pdf.

31. M. M. Brooks, J. T. Mueller, and B. C. Thiede, “Rural-Urban Differences in the Labor-Force Impacts of COVID-19 in the United States,” *Socius: Sociological Research for a Dynamic World* 7 (2021: 23780231211022094, https://doi.org/10.1177/23780231211022094.

32. J. R. Myers, L. A. Layne, and S. M. Marsh, “Injuries and Fatalities to U.S. Farmers and Farm Workers 55 Years and Older,” *American Journal of Industrial Medicine* 52, no. 3 (2009): 185–194, https://doi.org/10.1002/ajim.20661.

33. S. K. Lizer and R. E. Petrea, “Health and Safety Needs of Older Farmers: Part II. Agricultural Injuries,” *AAOHN Journal* 56, no. 1 (2008): 9–14, https://doi.org/10.3928/08910162-20080101-05.

34. L. E. Jones, M. Kern, C. S. Hansen-Ruiz, N. Krupa, P. Jenkins, and E. Scott, “Detailed Classification of Agricultural Injuries Mined From Maine PCR Records (2008-2022) Reveals Significant Differences in Injury Source, Event, and Nature by Age Group and Sex,” *Journal of Agromedicine* 11 (2025): 1–13.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Figure S1: Example plots of Maine temperature maxima (red), mean (black) and minima (blue) against Maine injury records for 2008–December 2011 (left); 2012–December 2016 (right) and 2019– December 2022 (bottom). **Table S1:** Determination of population at risk for injury, Maine agricultural and farm workers 2008-2023. **Table S2:** EMS records processed and labeled to create time series dataset, which comprises Ag Injury Cases from the ‘Labeled Data’ column. Labeled Data includes case classes 0, 1, 2, or 3; Ag injury cases comprise only case classes 1, 2, or 3. **Table S3:** Mean age by year, agricultural injury victims, reference year is 2008. **Table S4:** Association between injury rate (per 10,000 at risk) and average monthly temperature extrema, from log-linear time-series regression of differenced monthly injury rates against differenced monthly temperature maxima and minima (Figure S1).