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The Effects of Temperature and Season on Type 1 Diabetes Emergency Room Admissions in Georgia during January 2018 - December 2019

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Bachelor of Science and Art
Emory University
2021

Thesis Committee Chair: Dr. Stefanie Ebelt, Sc.D.

An abstract of
a thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
in partial fulfillment of the requirements for the degree of
Master of Public Health
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Abstract

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Climate change is a looming global threat, yet the relationship between temperature and chronic disease is under-researched. The aim of this study was to assess the relationship between monthly temperature and season and pediatric (<25 years of age) Type 1 Diabetes emergency room (ER) Admissions in the state of Georgia from January 2018 to December 2019. Monthly county-level age- and sex-stratified counts of Type 1 diabetes ER admissions were obtained through the Georgia Department of Public Health (DPH), Office of Health Indicators for Planning (OHIP). Weather information was collected for the 159 Georgia counties via Visual Crossings, a historical weather database. Population data were gathered from the US Census Bureau through R's TidyCensus package. Data were linked by month and county, and then aggregated into three agricultural zones across the state of Georgia. Poisson regression models were used to estimate the association of monthly Type 1 diabetes ER visits and monthly temperature (categorized into quartiles) or season (4-level) at lags of 0, 3, 6, or 9 months. Models controlled for sex, age groups, agricultural zone, and year, and included an offset by sex, age group, and agricultural zone population. Overall, while no findings were statistically significant, several general trends were found. Specifically, following various lag periods, children between ages 0 - 9 years old, and those living within agricultural zone 8B9A, located in central to coastal Georgia, had among the strongest estimated risks of visiting the emergency room for Type 1 Diabetes complications for both temperature and season. There is limited research evaluating the relationship between chronic illness, temperature, and climate change and it ought to be further explored.

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This project is dedicated to Yuki Raymond, the best editor I could ask for.

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Introduction and Background

Autoimmune diseases are those where the host's adaptive immune system attacks healthy cells (Janeway CA Jr et al., 2001). For individuals with Type 1 Diabetes (T1D), the immune system attacks the pancreas' β cells, which are responsible for producing insulin (DiMeglio et al., 2018). The destruction of the β cells is a gradual, unrelenting process. The period between the first attack on β cells to the clinical manifestation of symptoms can take months (CDC, 2022c). This period is known as partial remission or the "honeymoon period" (Majedah Abdul-Rasoul, 2006). On average this period lasts 9.2 months with a range between 1.9 to 32.9 months (Ozen et al., 2020; Pozzilli et al., 2005). At the end of the period, the body is unable to produce its own insulin, which is the hormone critical for processing glucose. Without insulin, glucose remains unused in the bloodstream, and the body breaks down muscles and fat for energy; this leads to the bloodstream becoming acidic and causing widespread damage across the body (CDC, 2022a).

The acidification of the bloodstream is referred to as Diabetic Ketoacidosis (DKA) (Cleveland Clinic, 2023; Mencher et al., 2019). It most often occurs when symptoms of uncontrolled blood glucose (excessive thirst, increased urination, sleepiness, weight loss) are dismissed in T1D (Cleveland Clinic, 2023; Mencher et al., 2019). While DKA can happen at any point in a diabetic's life, it is most often associated with the young and a delay in T1D diagnosis (Mencher et al., 2019). Up to 40% of newly diagnosed T1D patients initially presented with DKA to their local emergency room (ER) (Mencher et al., 2019). Still, DKA at any point in a diabetic's life is a serious medical emergency and is one of the most common reasons for T1D visiting the ER

(Doubova et al., 2018; Woo, 2007). In general, the top categories for a diabetic to visit the ER are cardiac complications (33.33%), neurological complications (18.06%), DKA (13.89%), infectious diseases (13.89%), hypertension (13.89%), and neuropathy (13.89%); these are all known compilations of diabetes (Woo, 2007).

Prior to the advent of manufactured insulin in the 1900s, T1D was a fatal condition. Fortunately, with treatment, today's diabetics can live healthy lives. Between 2001 and 2017, the number of T1D under 20 years old in the United States increased by 45%, making today's current overall prevalence 0.55% (Cowie, 2018; CDC, 2021). While individuals can be diagnosed at any age, it is most common for T1D to be identified around 13 or 14 years old (CDC, 2022b).

While originally believed to be an inevitable development for those with the genes, emerging literature suggests that precipitating events trigger T1D in genetically susceptible individuals (DiMeglio et al., 2018; Knip & Simell, 2012). Some viral infections have been found to incite or accelerate auto-destructive processes in susceptible individuals (Beyerlein et al., 2016; Christen et al., 2012; Filippi & von Herrath, 2008). Further, broader environmental factors have been implemented in pathogenesis as well. Neighboring European countries have varying incidence rates of T1D, and second-generation migrants to Sweden are more likely to develop T1D in comparison to first-generation (Dedrick et al., 2020; Hyttinen et al., 2003). Simultaneously, research has shown that genetically identical twins do not develop T1D at the same rate (Dedrick et al., 2020). Moreover, a 2020 paper from Japan found a seasonal correlation in T1D diagnosis, with more diabetics being diagnosed in March-May; however, this study did not look into potential drivers of this phenomenon (Nishioka et al., 2020). This strongly indicates an interplay of genetic and environmental factors in T1D pathogenesis. As a result, the scientific community believes that environmental influences contribute to the development of T1D in vulnerable individuals (Christen et al., 2012; Filippi & von Herrath, 2008).

The role that environmental factors play in disease development is a growing concern with climate change. Anthropogenic climate change is projected to increase the planet's temperature substantially. The Intergovernmental Panel on Climate Change (IPCC) projects that by 2050, the planet will warm by 1.5 °C (IPCC, 2018). Increased temperatures have been shown to drive molecular stress in the human body. Indeed, those already living with T1D are more likely to experience adverse health consequences during heat waves (Vallianou et al., 2021). Further still, increased temperatures are shown to incite an immune response, such as through Heat Shock Proteins (Lindquist & Craig, 1988). These effects of heat are concerning given that physical and psychological stress has been implicated in the development of autoimmune diseases (Stojanovich & Marisavljevich, 2008). Consequently, it is of great importance to investigate the relationship between temperature eliciting immune responses in those where that exposure may lead to harmful health outcomes. As such, a first and vital step towards this understanding is to assess how temperature affects Type 1 Diabetics' ER admissions. The goal of this project was to assess the associations between temperature and season and Type 1 Diabetes ER admissions in the State of Georgia between January 2018 and December 2019.

Materials and Methods

Data Sources

ER visit data were obtained through the Georgia Department of Public Health (DPH), Office of Health Indicators for Planning (OHIP). This office collects health information from hospital discharge, ER visits, and other records to "provide valid and reliable local evidence about the health status of the population of Georgia" (GDPH, 2023). Overall, the agency organizes and deidentifies reported health indicators from Georgian counties. Information regarding a wide range of health statistics is publicly mapped and charted on their OASIS Mapping Tool website. Through OHIP, the number of ER visits for Type 1 Diabetes was obtained for the state of Georgia for 2018 – 2021 by discharge month and year and by county, sex, and five-year age groups. Type 1 Diabetes was defined according to the ICD-10-CM Code (E10 - Type 1 Diabetes Mellitus). The data were transferred from OHIP to Emory via email in an Excel file.

County weather information was collected via Visual Crossing, an informatics tool that provides detailed, historical temperature data (Visual Crossing, 2023). Given the patient data was restricted to monthly diagnoses, the weather data was likewise collected to reflect monthly temperature trends. As such, for each Georgian county, the daily maximum temperature (Celsius) was acquired from Visual Crossings and compiled into an Excel spreadsheet; this was used to generate the average monthly maximum temperature for each county.

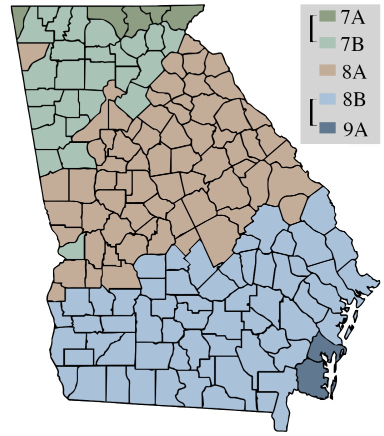

Figure 1: County Map of Georgia with Assigned Agricultural Zones

Moreover, counties were ultimately grouped together based on their USDA Agricultural Zones (USDA, 2023). If a county had multiple agricultural zones within its border, it was classified as belonging to the one which primarily dominated the landscape. Utilizing this method of classification, Georgia counties were categorized as belonging to one of five zones: 7A (n = 5 counties), 7B (n = 26 counties), 8A (n = 67 counties), 8B (n = 59 counties), and 9A (n = 2 counties) *(See Figure 1)* (USDA, 2023).

Season was determined in accordance with the National Oceanic and Atmospheric Administration's definition for the Northern Hemisphere: spring (March-May), summer (June - August), fall (September - November), winter (December - February) (NOAA, 2022).

Data Cleaning

All patients over 25 years old were excluded from statistical analysis, leaving researchers with 5,507 entries. Dates after 2019 were also excluded to limit the effect of the COVID-19 pandemic on the data analysis. Zones 7A and 9A had small sample sizes of 5 and 2 counties, respectively. Consequently, 7A and 9A were grouped with 7B and 8B to create agricultural groups 7A7B and 8B9A; agricultural group 8A was analyzed alone. This created three agricultural groups for the data analysis.

Given this grouping of the counties into agricultural zones, the temperature data also had to be reorganized. The average monthly high temperatures for each county were grouped in accordance with their new agricultural groupings. Thus, the temperature data researchers used for analysis reflected the monthly average maximum temperature for each agricultural zone in Georgia. Further, an additional temperature variable was developed, "Temperature_IQR", in which monthly temperatures by agricultural zones were categorized by quartile (Quartile 1, Quartile 2, Quartile 3, or Quartile 4) in order to support the assessment of non-linear temperature-response analyses. The temperature quartile ranges were Quartile 1 [2.8- 12.9 ℃], Quartile 2 [12.9 - 19.3 ℃], Quartile 3 [19.3 - 24.9 ℃], and Quartile 4 [24.9 - 27.4 ℃]. Lag terms were then computed to indicate values for three, six, and nine months prior to the current month. ER visit data entries were assigned "Season" of discharge and were also computed for three, six, and nine-month time lags.

In R, the TidyCensus package from the US Census Bureau was used to find the county-level population data for all Georgia counties. This included the population of individuals belonging to certain demographics, including age groups [0 - 4, 5 -9, 10 - 14, 15 - 19, 20 - 24] and gender [male or female]. Due to the small sample sizes of Type 1 Diabetes ER visits for the [0 - 4] age group, this age group was combined with the [5 - 9] age group to create the [0 - 9] age group. This restructuring of the data was also reflected in the county information pulled from the US Census Bureau. The county data were then aggregated based on associated agricultural groups.

Following this data cleaning, Poisson regression models were used to estimate the effect of average monthly maximum temperature, season, and primary Type 1 Diabetes ER admissions in the state of Georgia. In these models, the outcome data were specified as monthly ER visits by sex, age group, and agricultural zone; the exposure of interest was monthly- agricultural zone-specific maximum temperature or season at a lag of 0, 3, 6, or 9 months. Models additionally controlled for sex, age group, agricultural zone, and year, and included an offset by sex, age group, and agricultural zone population. For instance, a data entry for a [10 - 14] male in agricultural group 8A in 2018 was offset by the 2018 total population of [10 - 14] males in agricultural group 8A as reported by the US Census Bureau. Below is the basic R model code for overall associations:

Model Code Equation for Poisson Regression Model (example based on temperature at lag 0):

```
Poisson Model For Temperature's NoLag  <- glm (ER Visit ~ Temperature Lag 0 + Sex
+ Age Groups + Agricultural Groups + Year,  offset = log(Population Offset), family =
poisson(link = "log"),  data = Cleaned Dataset)
summary(Poisson Model For Temperature's NoLag )
exp(coef(Poisson Model For Temperature's NoLag ))
round( cbind(RR=exp(coef(Poisson Model For Temperature's NoLag )),
          exp(confint(Poisson Model For Temperature's NoLag ))), 2)
tab_model(Poisson Model For Temperature's NoLag )
```

Analyses were also stratified by age group and by agricultural zone, as follows:

Model Code Equation for Stratified Poisson Regression Models (example based on temperature at lag 0 and age group 0 - 9):

```
Filtered dataset <- filter(Cleaned Dataset, Age Groups == "0 - 9")
Poisson Model For Temperature's NoLag  <- glm (ER Visit ~ Temperature Lag 0 +Sex +
Age Groups + Agricultural Groups + Year,  offset = log(Population Offset), family =
poisson(link = "log"),  data = Filtered Dataset)
summary(Poisson Model For Temperature's NoLag )
exp(coef(Poisson Model For Temperature's NoLag ))
round( cbind(RR=exp(coef(Poisson Model For Temperature's NoLag )),
        exp(confint(Poisson Model For Temperature's NoLag ))), 2)
tab_model(Poisson Model For Temperature's NoLag )
```

Results

There were 3713 ER visits for Type 1 Diabetes in the State of Georgia between January 2018 and December 2019. 487 visits were for patients in the age group [0 - 9], 926 visits for the age group [10 - 14], 1148 visits for the age group [15 - 19], and 1152 visits for the age group [20 - 24]. There were 2186 visits by female patients and 1527 visits by male patients. 1136 visits were by patients residing in the 7A7B agricultural group, 1745 visits by patients residing in the 8A group, and 832 visits by patients residing in the 8B9A group.

Overall associations of temperature and season and T1D ER visits are displayed in Table 1. This table depicts overall temperature and season results across all age groups, sexes, and agricultural zones. Table 2 presents associations of temperature and season, stratified by age group. Table 3 likewise presents associations of temperature and season by each agricultural zone. Temperature [Quartile 1], and Season [Winter] were used as reference groups in all analyses. The results in each table are presented as incidence rate ratios (IRR), relative to the respective reference group.

Table 1: Overall Associations of Monthly Temperature and Season on T1D ER Visits

(Offset by Sex of Age group within an Agricultural zone)

TEMPURATURE (1C)

	No Lag			**3 Month Lag**			**6 Month Lag**			**9 Month Lag**		
Predictors	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*
Temperature [Quartile 1]	1.00			1.00			1.00			1.00		
Temperature [Quartile 2]	0.96	0.87 - 1.05	0.366	0.99	0.89 - 1.11	0.889	1.02	0.91 - 1.13	0.752	1.04	0.94 - 1.16	0.433
Temperature [Quartile 3]	0.98	0.89 - 1.08	0.724	1.05	0.94 - 1.17	0.349	1.01	0.91 - 1.12	0.881	0.98	0.87 - 1.11	0.788
Temperature [Quartile 4]	0.97	0.88 - 1.06	0.479	1.06	0.96 - 1.17	0.234	1.02	0.91 - 1.15	0.738	0.96	0.84 - 1.09	0.488

SEASON (1C)

	No Lag			**3 Month Lag**			**6 Month Lag**			**9 Month Lag**		
Predictors	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*
Season [Winter]	1.00			1.00			1.00			1.00		
Season [Fall]	1.01	0.92 - 1.10	0.838	0.94	0.86 - 1.03	0.185	1.01	0.90 - 1.14	0.860	1.01	0.89 - 1.14	0.881
Season [Spring]	0.97	0.88 - 1.06	0.492	0.97	0.88 - 1.07	0.575	1.04	0.95 - 1.14	0.398	0.99	0.87 - 1.13	0.911
Season [Summer]	0.95	0.87 - 1.04	0.281	0.96	0.87 - 1.06	0.406	1.02	0.91 - 1.13	0.776	1.02	0.91 - 1.15	0.707

Table 1 Results

In Table 1, across all time lags, for both temperature and season, the incidence rate ratios varied no more than ± 0.06. The peak incidence rate ratio for temperature was 1.06, and the minimum was 0.96. The greatest relative increase in rate ratio for temperature was observed in [Quartile 4] between the 0 and 3-month time lag with +0.09; the largest relative decrease was also seen in [Quartile 4], between the 6 and 9-month time lag with -0.06.

Across its lags, [Quartile 3] tended to have marginally stronger average rate ratios in comparison to the other quartiles; [Quartile 3] had an average IRR of 1.005, whereas the other quartiles were ≤ 1.0025. However, this relationship varies across different lags. Specifically, the [Quartile 3] IRR was greatest in the 3-month lag (1.05) compared to the other lags. Given [Quartile 3] represents the warmest temperatures, this may indicate an exposure-response to high temperatures 3 months after exposure.

Moreover, across the lags, the strongest incidence rate ratios occurred at the 3-month exposure. Moreover, within the 3-month exposure, the highest temperature quartile, Quartile 4, had the greatest sum increase in an incidence rate ratio of +0.09. Quartile 2 and Quartile 3 sum increase in incidence rate ratio was +0.03 and +0.07, respectively.

For the season, the peak incidence rate ratio was 1.04, and the minimum was 0.94. The greatest relative increase in rate ratio for the season was observed in both [Spring] and [Fall] at the 3 and 6-month time lag with +0.07; the largest relative decrease was seen in [Fall], between the 0 and

3-month time lag of -0.07. Overall, for temperature, the 3-month time lag had a weak increase in rate ratios; the season's greatest increase occurred at the 6-month lag. Across its lags, all of the seasons had a smaller rate ratio than the reference group. This would indicate an absence of an exposure response to the season.

However, across all the lags, the strongest incidence rate ratios occurred at the 6-month exposure. Moreover, within the 3-month exposure, the highest seasons, Fall and Spring had the greatest sum increase in an incidence rate ratio of +0.07. Summer's sum increase in incidence rate ratio was +0.06.

In Table 1, no results had a significant p-value.

Table 2: Associations of Temperature and Season with T1D ER Visits, by Age Group

(Offset by Sex of Age group within an Agricultural zone)

TEMPURATURE AND AGE GROUPS (1C)

	No Lag			3 Month Lag			6 Month Lag			9 Month Lag		
Predictors	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*
Temp [Q1] * Age Group [0 - 9]	1.00			1.00			1.00			1.00		
Temp [Q2] * Age Group [0 - 9]	0.97	0.75 - 1.26	0.832	0.94	0.66 - 1.32	0.712	0.97	0.72 - 1.32	0.849	1.16	0.88 - 1.54	0.305
Temp [Q3] * Age Group [0 - 9]	0.96	0.74 - 1.24	0.761	1.08	0.81 - 1.43	0.606	0.98	0.73 - 1.31	0.876	1.01	0.72 - 1.41	0.964
Temp [Q4] * Age Group [0 - 9]	0.96	0.75 - 1.22	0.740	1.04	0.80 - 1.37	0.762	1.07	0.78 - 1.48	0.682	1.06	0.73 - 1.53	0.757
Temp [Q1] * Age Group [10 - 14]	1.00			1.00			1.00			1.00		
Temp [Q2] * Age Group [10 - 14]	0.95	0.78 - 1.15	0.585	0.97	0.78 - 1.22	0.820	1.04	0.83 - 1.29	0.759	1.10	0.89 - 1.36	0.392
Temp [Q3] * Age Group [10 - 14]	0.90	0.74 - 1.10	0.311	1.05	0.84 - 1.32	0.647	1.03	0.83 - 1.28	0.811	1.00	0.78 - 1.28	0.987
Temp [Q4] * Age Group [10 - 14]	0.92	0.77 - 1.10	0.370	1.05	0.86 - 1.29	0.644	1.09	0.86 - 1.38	0.473	1.00	0.78 - 1.29	0.984
Temp [Q1] * Age Group [15- 19]	1.00			1.00			1.00			1.00		
Temp [Q2] * Age Group [15- 19]	0.96	0.81 - 1.15	0.669	0.96	0.78 - 1.18	0.677	1.11	0.92 - 1.35	0.268	0.91	0.75 - 1.10	0.313
Temp [Q3] * Age Group [15- 19]	1.11	0.93 - 1.32	0.253	1.00	0.82 - 1.22	0.982	1.07	0.88 - 1.29	0.496	0.92	0.73 - 1.15	0.470
Temp [Q4] * Age Group [15- 19]	1.00	0.85 - 1.19	0.973	1.10	0.92 - 1.32	0.286	0.94	0.76 - 1.17	0.589	0.95	0.75 - 1.20	0.681
Temp [Q1] * Age Group [20 - 24]	1.00			1.00			1.00			1.00		
Temp [Q2] * Age Group [20 - 24]	0.96	0.81 - 1.15	0.682	1.06	0.87 - 1.29	0.580	0.94	0.78 - 1.14	0.543	1.07	0.88 - 1.30	0.508
Temp [Q3] * Age Group [20 - 24]	0.95	0.80 - 1.13	0.562	1.10	0.91 - 1.35	0.325	0.94	0.78 - 1.14	0.549	1.00	0.80 - 1.25	0.968
Temp [Q4] * Age Group [20 - 24]	0.98	0.83 - 1.16	0.826	1.04	0.87 - 1.25	0.659	1.01	0.83 - 1.25	0.892	0.88	0.70 - 1.11	0.279

SEASON AND AGE GROUPS (1C)

	No Lag			3 Month Lag			6 Month Lag			9 Month Lag		
Predictors	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*
Winter * Age Group [0 - 9]	1.00			1.00			1.00			1.00		
Fall * Age Group [0 - 9]	1.06	0.84 - 1.36	0.610	0.88	0.69 - 1.12	0.311	1.11	0.80 - 1.54	0.528	0.99	0.71 - 1.4	0.963
Spring * Age Group [0- 9]	0.98	0.75 - 1.28	0.874	0.96	0.73 - 1.25	0.776	1.11	0.86 - 1.44	0.434	0.89	0.62 - 1.26	0.510
Summer * Age Group [0 - 9]	0.94	0.72 - 1.22	0.630	0.93	0.71 - 1.19	0.552	1.08	0.80 - 1.45	0.633	0.98	0.71 - 1.36	0.908
Winter * Age Group [10 - 14]	1.00			1.00			1.00			1.00		
Fall * Age Group [10 - 14]	0.96	0.80 - 1.15	0.657	0.95	0.79 - 1.14	0.550	1.03	0.81 - 1.32	0.792	1.08	0.84 - 1.38	0.555
Spring * Age Group [10 - 14]	0.96	0.80 - 1.16	0.689	1.06	0.86 - 1.30	0.578	1.04	0.86 - 1.26	0.679	0.97	0.74 - 1.27	0.817
Summer * Age Group [10 - 14]	0.91	0.76 - 1.09	0.302	0.99	0.81 - 1.20	0.882	1.11	0.89 - 1.37	0.349	1.00	0.79 - 1.28	0.987
Winter * Age Group [15- 19]	1.00			1.00			1.00			1.00		
Fall * Age Group [15- 19]	1.10	0.94 - 1.29	0.240	0.86	0.73 - 1.01	0.063	1.08	0.86 - 1.34	0.499	0.87	0.70 - 1.10	0.254
Spring * Age Group [15- 19]	0.99	0.83 - 1.18	0.924	0.85	0.70 - 1.01	0.072	1.12	0.95 - 1.32	0.180	0.96	0.76 - 1.22	0.739
Summer * Age Group [15- 19]	0.95	0.80 - 1.12	0.542	0.93	0.78 - 1.10	0.405	0.95	0.78 - 1.16	0.639	1.01	0.81 - 1.26	0.934
Winter * Age Group [20 - 24]	1.00			1.00			1.00			1.00		
Fall * Age Group [20 - 24]	0.94	0.80 - 1.10	0.416	1.06	0.90 - 1.24	0.500	0.90	0.73 - 1.11	0.333	1.09	0.88 - 1.36	0.424
Spring * Age Group [20 - 24]	0.94	0.80 - 1.12	0.495	1.04	0.87 - 1.25	0.659	0.94	0.80 - 1.12	0.490	1.08	0.85 - 1.35	0.533
Summer * Age Group [20 - 24]	0.99	0.84 - 1.16	0.884	1.00	0.84 - 1.18	0.982	0.98	0.80 - 1.18	0.805	1.07	0.86 - 1.33	0.530

<u>Table 2 Results</u>

Temperature

Table 2 looked at the interaction of age groups on temperature and seasons. For temperature, the incidence rate ratios varied no more than ± 0.16.

The Age Group [0- 9] had a maximum incidence rate ratio of 1.16 and a minimum of 0.94. Its greatest relative increase was seen in [Quartile 2] between 6 and 9 months of +0.19; the largest relative decrease in rate ratio was seen in [Quartile 3] between 3 and 6 months of -0.10. Within Age Group [0- 9], across its lags, [Quartile 4] tended to have stronger average rate ratios in comparison to the other quartiles; [Quartile 4] had an average IRR of 1.03, whereas the other quartiles were ≤ 1.01. However, this relationship varies across different lags. Specifically, the [Quartile 4] IRR was greatest in the 6-month lag (1.07) in comparison to the other lags. Given [Quartile 4] represents the warmest temperatures, this may indicate an exposure-response to high temperatures 6 months after exposure.

The Age Group [10 -14] had a maximum incidence rate ratio of 1.10 and a minimum of 0.90. Its greatest relative increase was seen in [Quartile 3] between 0 and 3 months of +0.15; the largest relative decrease in rate ratio was seen in [Quartile 4] between 6 and 9 months of -0.09. Within Age Group [10- 14], across its lags, [Quartile 2] and [Quartile 4], had stronger average rate ratios in comparison to the other quartiles; both had an average IRR of 1.02, whereas the other quartiles were 1.00. However, this relationship varies across different lags. Specifically, the [Quartile 2] IRR was greatest in the 9-month lag (1.10) in comparison to the other lags (1.00). This may indicate an exposure-response to mild to moderate temperatures 9 months after exposure.

The Age Group [15 -19] had a maximum incidence rate ratio of 1.11 and a minimum of 0.91. Its greatest relative increase was seen in [Quartile 2] between 3 and 6 months of +0.15; the largest relative decrease in rate ratio was also seen in [Quartile 2] between 6 and 9 months of -0.20. Within the Age Group [15- 19], across its lags, [Quartile 3] had stronger average rate ratios in comparison to the other quartiles; [Quartile 3] had an average IRR of 1.025, whereas the other quartiles were ≤ 1.00. However, this relationship varies across different lags. In particular, the [Quartile 3] IRR was greatest in the no lag (1.11) in comparison to the other lags (<1.00). This may indicate an exposure response to moderate temperatures directly after exposure.

The Age Group [20 -24] had a maximum incidence rate ratio of 1.10 and a minimum of 0.88. Its greatest relative increase was seen in [Quartile 3] between 0 and 3 months of +0.15; the largest relative decrease in rate ratio was also seen in [Quartile 3] between 3 and 6 months of -0.16. No results had a significant p-value. Within the Age Group [20- 24], across its lags, [Quartile 2] had a marginally stronger average rate ratio in comparison to the other quartiles; [Quartile 2] had an average IRR of 1.0075, whereas the other quartiles were ≤ 1.00. However, this relationship varies across different lags. Specifically, [Quartile 2] IRR was greatest in the 9-month lag (1.07) in comparison to the other lags (<1.00). This may indicate an exposure-response to mild to moderate temperatures 9 months after exposure.

Across the age groups, the strongest incidence rate ratios occurred at the 3-month exposure. Moreover, within the 3-month exposure, the highest temperature quartile, Quartile 4, had the greatest sum increase in an incidence rate ratio of +0.37. Quartile 2 and Quartile 3 sum increase in incidence rate ratio was +0.09 and +0.31, respectively. Moreover, for age groups 0 - 9 and 10 - 14, the effect persists into the 6-month lag.

Season

As seen in Table 2, the incidence rate ratios for Season varied no more than ± 0.15. The Age Group [0 - 9] had a maximum incidence rate ratio of 1.11 and a minimum of 0.88. Its greatest relative increase was seen in [Fall] between 3 and 6 months of +0.23; the largest relative decrease in rate ratio was seen in [Spring] between 6 and 9 months of -0.22. Within the Age Group [0- 9], across its lags, [Fall] had a marginally stronger average rate ratio in comparison to the other quartiles; [Fall] had an average IRR of 1.01, whereas the other seasons were ≤ 1.00. However, this relationship varies across different lags. Specifically, [Fall]'s IRR was greatest in the 6-month lag (1.11) in comparison to the other lags (<1.08). This may indicate an exposure-response to mild to moderate temperatures 6 months after exposure.

The Age Group [10 -14] had a maximum incidence rate ratio of 1.11 and a minimum of 0.91. Its greatest relative increase was seen in [Summer] between 3 and 6 months of +0.12; the largest relative decrease in rate ratio was also seen in [Summer] between 6 and 9 months of -0.11. Within the Age Group [10- 14], across its lags, [Fall] had a marginally stronger average rate ratio in comparison to the other quartiles; [Fall] had an average IRR of 1.01, whereas the other quartiles were ≤ 1.0075. However, this relationship varies across different lags. [Falls]'s IRR was greatest in the 9-month lag (1.08) in comparison to the other lags (<1.00). This may indicate an exposure-response to mild to moderate temperatures 9 months after exposure.

The Age Group [15 -19] had a maximum incidence rate ratio of 1.12 and a minimum of 0.85. Its greatest relative increase was seen in [Spring] between 3 and 6 months of +0.27; the largest relative decrease in rate ratio was seen in [Fall] between 0 and 3 months of -0.24. Within the Age

Group [15- 19], across its lags, all of the quartiles had a smaller rate ratio than the reference group. This would indicate an absence of an exposure-response to temperatures in the [15 - 19] age group.

The Age Group [20 -24] had a maximum incidence rate ratio of 1.09 and a minimum of 0.90. Its greatest relative increase was seen in [Fall] between 6 and 9 months of +0.19; the largest relative decrease in rate ratio was also seen in [Fall] between 3 and 6 months of -0.16. No results had a significant p-value. Within the Age Group [20 - 24], across its lags, [Summer] had a marginally stronger average rate ratio in comparison to the other quartiles; [Summer] had an average IRR of 1.01, whereas the other quartiles were ≤ 1.00. However, this relationship varies across different lags. Specifically, [Summer]'s IRR was greatest in the 9-month lag (1.07). This may indicate an exposure-response to mild to moderate temperatures 9 months after exposure.

Across the age groups, the strongest incidence rate ratios occurred at the 6-month exposure. Within the 6-month exposure, Fall had the greatest sum increase in an incidence rate ratio of +0.37. Spring and Summer's sum increase in incidence rate ratio was +0.30 and +0.27, respectively.

In Table 2, no results had a significant p-value.

Table 3: Associations of Temperature and Season and T1D ER Visits, by Agricultural Zone

(Offset by Sex of Age group within an Agricultural zone)

TEMPURATURE AND AGRICULTURAL GROUPS (1C)

	No Lag			3 Month Lag			6 Month Lag			9 Month Lag		
Predictors	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*
Temp [Q1] * Agi Group [7A7B]	1.00			1.00			1.00			1.00		
Temp [Q2] * Agi Group [7A7B]	0.95	0.81 - 1.11	0.515	1.02	0.85 - 1.23	0.800	0.92	0.77 - 1.10	0.365	1.05	0.85 - 1.29	0.667
Temp [Q3] * Agi Group [7A7B]	0.98	0.84 - 1.15	0.801	1.09	0.93 - 1.28	0.300	0.94	0.80 - 1.10	0.413	0.94	0.77 - 1.15	0.560
Temp [Q4] * Agi Group [7A7B	1.05	0.89 - 1.24	0.563	1.03	0.87 - 1.23	0.706	0.96	0.69 - 1.31	0.825	0.90	0.66 - 1.20	0.482
Temp [Q1] * Agi Group [8A]	1.00			1.00			1.00			1.00		
Temp [Q2] * Agi Group [8A]	0.93	0.80 - 1.08	0.315	0.91	0.76 - 1.09	0.297	1.15	0.96 - 1.37	0.130	1.03	0.88 - 1.20	0.708
Temp [Q3] * Agi Group [8A]	0.94	0.81 - 1.10	0.439	1.02	0.85 - 1.23	0.794	1.11	0.93 - 1.33	0.267	0.99	0.81 - 1.20	0.896
Temp [Q4] * Agi Group [8A]	0.91	0.80 - 1.05	0.209	1.04	0.89 - 1.21	0.648	1.12	0.95 - 1.34	0.194	0.96	0.81 - 1.15	0.683
Temp [Q1] * Agi Group [8B9A]	1.00			1.00			1.00			1.00		
Temp [Q2] * Agi Group [8B9A]	1.01	0.82 - 1.26	0.908	1.10	0.86 - 1.42	0.460	0.98	0.77 - 1.26	0.876	1.03	0.82 - 1.31	0.810
Temp [Q3] * Agi Group [8B9A]	1.06	0.85 - 1.32	0.613	1.07	0.82 - 1.38	0.632	1.03	0.80 - 1.33	0.805	1.02	0.77 - 1.34	0.908
Temp [Q4] * Agi Group [8B9A]	1.00	0.82 - 1.22	0.972	1.09	0.88 - 1.37	0.426	1.00	0.79 - 1.28	0.996	0.97	0.75 - 1.27	0.840

SEASON AND AGRICULTURAL GROUPS (1C)

	No Lag			3 Month Lag			6 Month Lag			9 Month Lag		
Predictors	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*	*Incidence Rate Ratios*	*Confidence Intervals*	*p*
Winter * Agi Group [7A7B]	1.00			1.00			1.00			1.00		
Fall * Agi Group [7A7B]	1.01	0.86 - 1.19	0.867	1.00	0.85 - 1.18	0.990	0.97	0.78 - 1.20	0.779	0.98	0.78 - 1.24	0.897
Spring * Agi Group [7A7B]	1.01	0.85 - 1.20	0.888	0.96	0.80 - 1.16	0.682	0.98	0.83 - 1.16	0.805	1.03	0.82 - 1.29	0.818
Summer * Agi Group [7A7B]	1.02	0.86 - 1.20	0.847	0.98	0.82 - 1.17	0.832	0.95	0.78 - 1.15	0.579	1.00	0.81 - 1.26	0.966
Winter * Agi Group [8A]	1.00			1.00			1.00			1.00		
Fall * Agi Group [8A]	0.99	0.88 - 1.13	0.917	0.90	0.79 - 1.03	0.118	1.07	0.89 - 1.27	0.486	1.02	0.85 - 1.22	0.860
Spring * Agi Group [8A]	0.93	0.81 - 1.06	0.275	0.98	0.85 - 1.14	0.822	1.08	0.94 - 1.24	0.261	0.94	0.78 - 1.15	0.563
Summer * Agi Group [8A]	0.89	0.78 - 1.02	0.108	0.95	0.83 - 1.09	0.444	1.07	0.91 - 1.26	0.391	1.01	0.85 - 1.20	0.950
Winter * Agi Group [8B9A]	1.00			1.00			1.00			1.00		
Fall * Agi Group [8B9A]	1.03	0.85 - 1.25	0.746	0.94	0.78 - 1.14	0.539	0.97	0.75 - 1.25	0.806	1.03	0.79 - 1.34	0.836
Spring * Agi Group [8B9A]	0.99	0.82 - 1.21	0.941	0.96	0.77 - 1.18	0.694	1.05	0.87 - 1.28	0.598	1.04	0.79 - 1.36	0.794
Summer * Agi Group [8B9A]	0.97	0.80 - 1.19	0.785	0.96	0.79 - 1.17	0.696	1.00	0.80 - 1.25	0.979	1.10	0.85 - 1.42	0.470

<u>*Table 3 Results*</u>

Temperature

For temperature, the incidence rate ratios varied no more than ± 0.15. The Agricultural Group [7A7B] had a maximum incidence rate ratio of 1.09 and a minimum of 0.90. Its greatest relative increase was seen in [Quartile 2] between 6 and 9 months of +0.13; the largest relative decrease in rate ratio was seen in [Quartile 3] between 3 and 6 months of -0.15. Within the Agricultural Group [7A7B], across its lags, all of the quartiles had a smaller rate ratio than the reference group. This would indicate an absence of an exposure-response to temperatures in the [7A7B] Agricultural Group.

The Agricultural Group [8A] had a maximum incidence rate ratio of 1.15 and a minimum of 0.91. Its greatest relative increase was seen in [Quartile 2] between 3 and 6 months of +0.24; the largest relative decrease in rate ratio was seen in [Quartile 4] between 6 and 9 months of -0.16. Within Agricultural Group [8A], across its lags, [Quartile 3] had a marginally stronger average rate ratio in comparison to the other quartiles; [Quartile 3] had an average IRR of 1.015, whereas the other quartiles were ≤ 1.0075. However, this relationship varies across different lags. Specifically, [Quartile 3]'s IRR was greatest in the 6-month lag (1.11). This may indicate an exposure-response to mild to moderate temperatures 6 months after exposure.

The Agricultural Group [8B9A] had a maximum incidence rate ratio of 1.10 and a minimum of 0.97. Its greatest relative increase was seen in [Quartile 2] and [Quartile 4], both between 0 and 3 months of +0.09; the largest relative decrease in rate ratio was seen in [Quartile 2] between 3 and 6 months of -0.12. Within Agricultural Group [8B9A], across its lags, [Quartile 3] had a stronger average rate ratio in comparison to the other quartiles; [Quartile 3] had an average IRR of 1.045, whereas the other quartiles were ≤ 1.03. However, this relationship varies across different lags. Specifically, [Quartile 3]'s IRR was greatest in the 3-month lag (1.07). This may indicate an exposure response to mild to moderate temperatures 3 months after exposure.

Across the agricultural groups, the strongest incidence rate ratios occurred at the 3-month exposure. Moreover, within the 3-month exposure, the highest temperature quartiles were Quartiles 3 and 4, which both had the sum increase in an incidence rate ratio of +0.20. Quartile 2's sum increase in incidence rate ratio was +0.14.

Season

Regarding Season, as seen in Table 3, the incidence rate ratios for Season varied no more than ± 0.11. The Agricultural Group [7A7B] had a maximum incidence rate ratio of 1.03 and a minimum of 0.95. Its greatest relative increase was seen in [Spring] and [Summer], both between 6 and 9 months of +0.05; the largest relative decrease in rate ratio was seen in [Spring] between 0 and 3 months of -0.05. Within the Agricultural Group [7A7B], across its lags, all of the quartiles had a smaller rate ratio than the reference group. This would indicate an absence of an exposure-response to seasons in the [7A7B] Agricultural Group.

The Agricultural Group [8A] had a maximum incidence rate ratio of 1.08 and a minimum of 0.89. Its greatest relative increase was seen in [Fall] between 3 and 6 months of +0.17; the largest relative decrease in rate ratio was seen in [Spring] between 6 and 9 months of -0.14. Within the Agricultural Group [8A], across its lags, all of the quartiles had a smaller rate ratio than the reference group. This would indicate an absence of an exposure-response to seasons in the [8A] Agricultural Group.

The Agricultural Group [8B9A] had a maximum incidence rate ratio of 1.10 and a minimum of 0.94. Its greatest relative increase was seen in [Summer] between 6 and 9 months of +0.10; the largest relative decrease in rate ratio was seen in [Fall] between 0 and 3 months of -0.09. No results had a significant p-value. Within Agricultural Group [8B9A], across its lags, [Spring] had a marginally stronger average rate ratio in comparison to the other quartiles; [Spring] had an average IRR of 1.01, whereas the other quartiles were ≤ 1.0075. However, this relationship varies across different lags. Specifically, [Spring]'s IRR was greatest in the 6-month lag (1.05). This may indicate an exposure-response to mild to moderate temperatures 6 months after exposure.

For season, the greatest overall peak in incidence rate ratios occurred at the 6-month exposure. Within the 6-month exposure, Spring had the greatest sum increase in an incidence rate ratio of +0.21. Fall and Summer's sum increase in incidence rate ratio was +0.17 and +0.13, respectively.

In Table 3, no results had a significant p-value.

Discussion

This study examined if monthly temperature or season was associated with Type 1 Diabetes ER admissions in the State of Georgia between January 2018 and December 2019. Across all analyses, there was no significant difference in IRRs from Poisson regression models estimating the effects of temperature compared to those focusing on season. Moreover, the results from this study showed no significant association between temperature or season and Type 1 Diabetes ER admissions in the State of Georgia between January 2018 and December 2019.

However, some general trends in incidence rate ratios were observed. It should be noted that with these trends in IRR, all had wide and overlapping confidence intervals, impairing and limiting the ability to identify differences between different lags and across age or agricultural groups.

In the overall model (Table 1), the strongest association was for temperature occurring 3 months prior to the month of ER visits, with temperature in the 4th quartile showing the strongest IRR relative to the 1st quartile. However, for the season, the strongest association was for spring occurring 6 months prior to the month of ER visits, with spring showing the strongest IRR relative to winter. This would suggest that individuals are more likely to visit the emergency room for Type 1 Diabetes complications in the periods following hot to warm conditions.

Across Table 2 and Table 3, the sum greatest peak in temperatures' incidence rate ratio occurred 3 months after exposure to Quartile 4 (24.9 - 27.4°C). The greatest potential association for exposure-response by age group occurred in those between ages 0 - 9 (1.030, specifically 6 months after exposure to extreme temperatures (1.07), Quartile 4 (24.9 - 27.4 °C). Further, the greatest potential association for exposure-response by the agricultural group occurred in those living in 8B9A (1.045), specifically 3 months after exposure to extreme temperatures (1.07), Quartile 3 (19.3 - 24.9 °C). This would suggest that while the periods following extreme temperatures are hazardous to the general population's health, individuals between 0 - 9 years old and those in zone 8B9A are more at risk of visiting the emergency room for Type 1 Diabetes complications following warm to hot temperatures.

For season, across Table 2 and Table 3, the sum greatest peak in incidence rate ratio occurred 6 months after exposure to Fall. Across the age groups, no singular group appeared to be at an increased risk in comparison to one another for season. However, the greatest potential association for exposure-response by the agricultural group occurred in those living in 8B9A (1.01), specifically 6 months after exposure to warmer seasons (1.05), Spring. This would suggest that while the periods following warmer temperatures are hazardous to the general population's health, individuals in zone 8B9A are more at risk of visiting the emergency room for Type 1 Diabetes complications following warm temperatures.

Given the lack of significant results and wide, overlapping confidence intervals, these results are limited and cannot be broadly extrapolated. Yet, while the results couldn't be teased apart in this study, it hints at an interaction between age, agricultural groups, and temperature or season. Relationships are different across various stratifications and the results cannot be generally summarized. Still, it appears that following various periods of mild/warm temperatures or tolerable seasons, individuals between ages 0 - 9 and those living within agricultural group 8B9A have weak trends for visiting the Emergency Room regarding Type 1 Diabetes complications. The findings regarding these general trends are in line with existing scientific literature. Nishioka et al. found a seasonal correlation in T1D diagnosis, with more diabetics being diagnosed in March-May (2020). The results of this paper also indicate a seasonal or temperature correlation with Type 1 Diabetes ER Admissions, but this varies based on location and age demographic.

Still, while these general trends can be noted, they are not significant. Several limitations in this study curtail these findings. Firstly, the data analysis ultimately just looked at two years (2018 and 2019) to limit the influence of the COVID-19 pandemic on this analysis. While this time frame included 3,713 T1D ER admissions, future studies ought to include a wider time frame. Additionally, the data provided by GDPH OHIP only recorded patient ER admission by month. This severely limited the ability of this study to be able to understand how acute weather extremes may influence T1D ER admissions in the state of Georgia. Further, some of the study populations had a restricted sample size. For instance, in the original 0 - 4 age group, many of the agricultural zones had less than 15 ER visits for that population across the entire time period. This forced the researcher to have to combine populations and thus limit the specific analysis for those smaller groups. Finally, this study would be perhaps best enhanced if it utilized dates of initial T1D diagnosis rather than ER admissions. This would allow researchers to better understand the relationship between extreme temperatures, Type 1 Diabetes pathogenesis, and how this would evolve in the face of global warming.

Conclusion

The results from this study show no significant association between temperature or season and Type 1 Diabetes ER admissions in the State of Georgia between January 2018 and December 2019. However, some nonsignificant general trends in incidence rate ratios were observed. This topic ought to be further explored, making the aforementioned improvements, to best understand the effects of climate on health. Climate change is an impending disaster that will greatly change the environment in which we live and subsequently affect human health. This includes chronic diseases, such as Type 1 Diabetes. There is limited research evaluating the relationship between chronic illness and climate change and it ought to be further explored.

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