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Temperature Trends and Accumulation of Chill Hours, Chill Units, and Chill Portions in South Carolina

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Abstract

There is considerable concern about the potential impact of climate change on agriculture, such as the accumulation of chilling hours needed to break the dormancy of many perennial plants, like fruit trees. Therefore, this study aimed to determine if there had been a significant change in air temperatures and chill hours, chill units, and chill portion accumulation in South Carolina over the last two decades. Two decades of daily maximum (T_{max}) and minimum (T_{min}) air temperature records were obtained from weather stations in thirty-one counties in South Carolina. Hourly temperature data, reconstructed from the daily data, were used to calculate the daily and annual chill hours, chill units, and chill portions accumulation using four different chill models for each location and year. The chill models included the $T(t) < 7.2^\circ C$ model, the $0^\circ C < T(t) < 7.2^\circ C$ model, the Utah model, and the Dynamic model. For each county, regression analyses were conducted to evaluate the historical trends. Despite year-to-year variability, the tendency was a statistically significant ($\alpha = 0.05$) increase in air temperature, averaging 0.089˚C per year for 20 out of 31 counties in South Carolina. The other 11 counties had no significant change in temperature. The average temperature increase in the 31 counties was 0.072˚C per year. The temperature increase resulted in a decrease in annual chill accumulation during the fall to spring, averaging 17.7 chill hours, 8.6 chill hours, 17.0 chill units, and 0.40 chill portions per year calculated with the $T(t) < 7.2^\circ C$, $0^\circ C < T(t) < 7.2^\circ C$, Utah, and Dynamic models, respectively. However, whether this decrease in chill values was statistically significant or not depended on the chill model used. This study did not investigate the cause of the observed historical trends in temperature and chill accumulation. Still, if the trends continue, they could significantly impact the future of the temperate fruit tree industry in the state.

Keywords

Chill Hours, Chill Units, Chill Portions, Temperature, Fruit Trees, Climate Change, Dormancy

1. Introduction

A recent climate report by the Intergovernmental Panel on Climate Change (IPCC, 2022) [1] expressed with very high confidence that temperature increases reaching 1.5˚C in the near term (2021 to 2040) due to global warming would cause increases in climate-related hazards and risks to ecosystems and humans. The report also expressed, with a high or very high level of confidence, that some of the impacts of the expected warming would include range shifts of terrestrial species and changes in timing (phenology), both globally and in North America. Agricultural production is intimately related to the long-term climate and the short-term weather conditions. Therefore, the expected increases in temperature in the near term could positively and negatively impact local agricultural production systems, depending on specific regional characteristics. For example, a positive impact on local agriculture could be the ability to produce new crops in the warmer climate. On the other hand, dealing with potential new invasive pests prospering in the warmer climate (*i.e.*, weeds, insects, etc.) would be an example of a negative impact.

One of the many potential concerns of a warming climate in agriculture is the potential impact of higher temperatures on the accumulation of chill hours, chill units, or chill portions needed to break the dormancy of many temperate fruit trees. This issue is already creating concerns among many researchers around the world. For example, Asse *et al.* (2018) [2] observed that spring phenological phases, such as budburst and flowering, have tended to occur earlier in some tree species because of temperature increases in the Alps. Further, they found that although winter warming might be beneficial in reducing the risk of late spring frost, they also warned that this effect was expected to become detrimental if the chilling requirement to break dormancy was not met. Prudencio *et al.* (2018) [3] observed decreased productivity in extra-late and ultra-late-flowering almond cultivars in a warm season when chilling requirements were not met. Darbyshire *et al.* (2017) [4], evaluating different apple phenology models in many locations, found that apple trees flowered later in sites with warmer winters. Delgado *et al.* (2021) [5], modeling the potential impact of future climate on apple trees in Spain, found that projected winter chill might decrease by 9 to 12 chill portions under an intermediate global warming scenario and by 9 to 24 chill portions under a pessimistic scenario. This reduction in chill portions is expected to affect the timing of dormancy break in the future significantly. However, Martínez-Lüscher *et al.* (2017) [6] found that apricot flowering time in the United Kingdom remained relatively unchanged despite significant temperature increases over several decades (1960 to 2014).

The development and selection of appropriate cultivars adaptable to local conditions, among other farming practices, should play a significant role in adapting to future climate conditions. For example, Rouse and Sherman (2003) [7] reported on low-chill peach cultivars adapted to the relatively warm climate prevalent in Florida, USA. Similarly, Delgado *et al.* (2021) [5] found considerable variability in the chilling requirements of ten apple cultivars (ranging from 59 to 90 chill portions), suggesting that it would be feasible to select appropriate apple cultivars according to current and expected local conditions. However, since planting fruit trees is a long-term investment, local farmers should have a reasonable estimate of the future climate before properly selecting and planting fruit trees.

Peach production, which is affected by chill unit accumulation, is an important economic activity in South Carolina. According to the USDA National Agriculture Statistics Service (NASS, 2022) [8], South Carolina's utilized peach production in 2021 was 72,630 tons, valued at US$106.151 million. By comparison, USA's utilized peach production was 61,890 tons, valued at US$624.366 million. Therefore, South Carolina's utilized peach production represented around 11% of the USA's production and 17% of the economic value. Rising temperatures in South Carolina could affect chill accumulation, potentially affecting peach production in the state. It is crucial to investigate the exposure of the peach industry to potential changes in the local climate. Therefore, the objective of this study was to determine if there had been a significant change in air temperatures and chill hours, chill units, and chill portion accumulation in South Carolina over the last two decades.

2. Methodology

2.1. Data Collection and Site Description

Data from a permanent network of electronic weather stations located in each county in South Carolina were used for this study. The data were obtained from the Web Service API made available by the Applied Climate Information System (ACIS) (http://data.rcc-acis.org/). An R script (R Core Team, 2021) [9] was developed to download the required data using HTTP requests following the guidelines described at http://www.rcc-acis.org/docs_webservices.html. The data included the daily maximum and minimum air temperature (T_{max} and T_{min}) and the weather station's geographic location (latitude and longitude). The daily T_{max} and T_{min} data were downloaded in CSV format using a station data request (StnData). The latitude and longitude were downloaded in JSON format using a station metadata request (StnMeta).

The above data were collected from thirty-one of the forty-six counties in South Carolina. These counties were selected because they had at least twenty years of temperature data that were available online. The thirty-one counties included in this study provided a good representation of the state's different regions, going from the mountainous upper-land areas in the northern part of the state to the lowlands of the coastal areas (**Figure 1**). The changes in elevations in the selected counties went from around 1000 m above sea level in Pickens County to the lowlands located in the state's coastal areas, such as Beaufort County, with elevations near sea level. The location of the counties represented a range of latitudes and elevations, which translated into considerable differences in temperatures among counties.

2.2. Estimation of Hourly Temperatures

Hourly temperature data were only available online for a few South Carolina

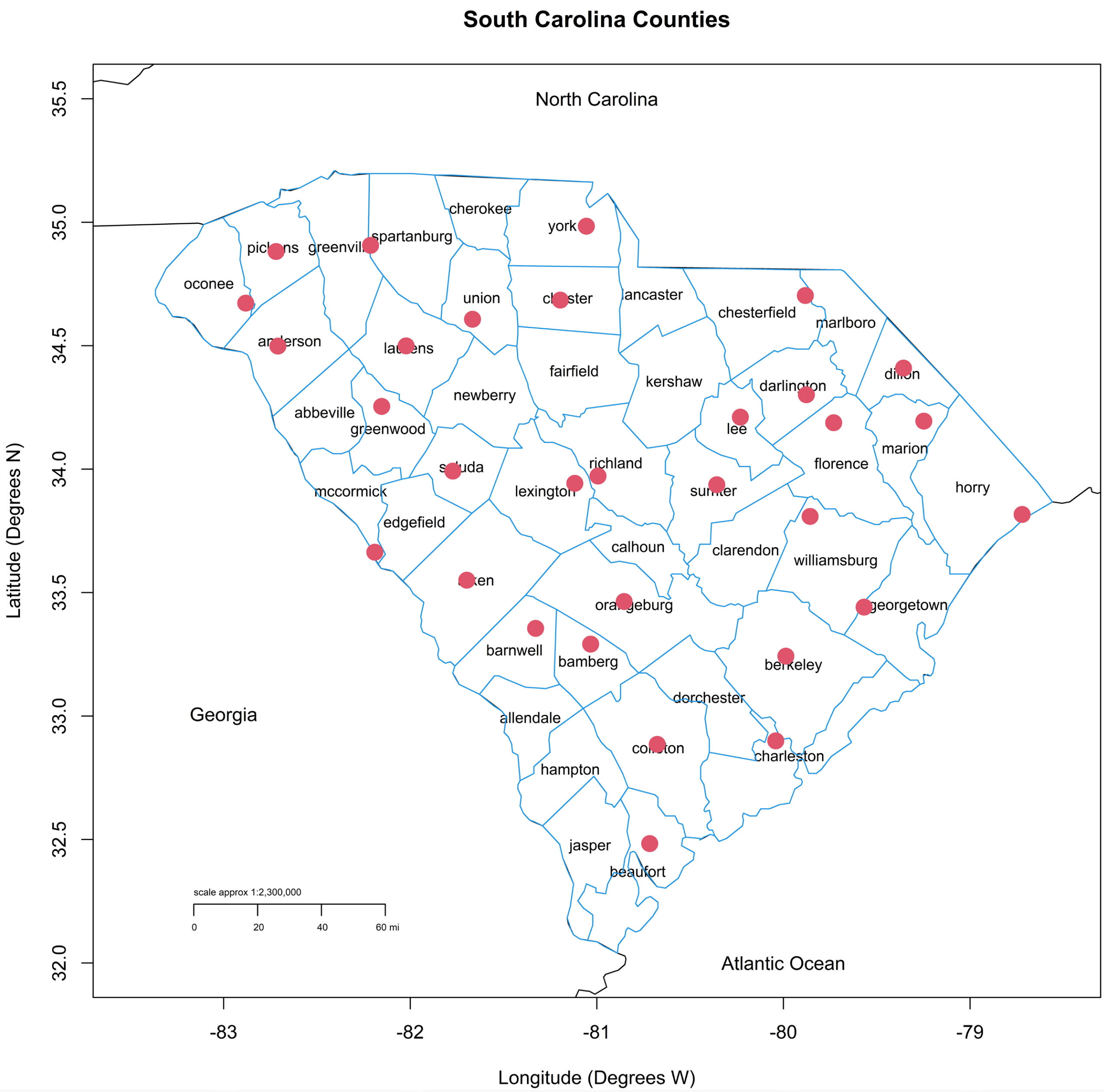

Figure 1. Locations of temperature measuring sites in South Carolina.

stations. These stations reporting hourly data were typically airport weather stations located away from agricultural settings. Therefore, the hourly temperatures [T(t)] needed to calculate chill hours, chill units, and chill portions were estimated from the daily T_{max} and T_{min} air temperatures using the procedure proposed by Linvill (1990) [10] and later implemented by Linsley-Noakes *et al.*, (1995) [11], and Delgado *et al.*, (2021) [5].

2.3. Calculation of Hourly and Daily Chill Values

The hourly chill hours were calculated from the hourly temperatures using the T(t) < 7.2˚C model (Linvill, 1990 [10]; Miranda *et al.*, 2013 [12]; Payero and Sekaran, 2021 [13]) and the 0˚C < T(t) < 7.2˚C model (Zang and Taylor, 2011 [14]). The chill units were calculated using the Utah model (Richardson *et al.*, 1974 [15]; Alburquerque *et al.*, 2008 [16]). Chill portions were computed using the Dynamic model (Fishman *et al.*, 1987 [17]; Fishman *et al.*, 1987 [18]; Zhang and Taylor, 2011 [14]; Miranda *et al.*, 2013 [12]; Melke, 2015 [19]). For the T(t) < 7.2˚C and the 0˚C < T(t) < 7.2˚C model, the hourly chill hours were calculated following the specified temperature ranges. The Utah model's hourly chill units were calculated according to the temperature ranges in **Table 1**.

The hourly chill portions using the Dynamic model were calculated using the Dynamic_Model() function from the R package chillR (Luedeling and Fernandez, 2022 [20]). The daily chill values (hours, units, or portions) for each chill model were calculated by adding the hourly chill values for each 24-hour period (starting from sunrise). The annual chill values were calculated for each year and county by adding the daily chill values between Oct. 1st and Apr. 20th.

2.4. Statistical Analyses

Statistical analyses for this study were conducted using R (R Core Team, 2021 [9]). Linear regression analyses were used to determine whether the changes in mean temperature ($T_{mean} = [T_{max} + T_{min}]/2$) and annual chill values observed over the previous two decades were statistically significant ($\alpha = 0.05$). A regression analysis was conducted using year as the independent variable and T_{mean} as the dependent variable for each county. Regression analyses were performed for each county and chill model using year as the independent variable and annual chill value as the dependent variable. A positive slope of the line indicated that the variable tended to increase over time, and a negative slope showed the opposite trend. The p-value of the slope showed if the increasing or decreasing trend was statistically significant (different from zero at $\alpha = 0.05$).

Table 1. Definitions of the Utah model.

Temperature (˚C)	<1.4	1.5 - 2.4	2.5 - 9.1	9.2 - 12.4	12.5 - 15.9	16 - 18	>18
Chill Units	0.0	0.5	1.0	0.5	0.0	−0.5	−1.0

3. Results and Discussion

3.1. Historical Trends in Temperature

An example of the regression analyses conducted to evaluate the historical trend in temperature (T_{mean}) for four counties in South Carolina is shown in Figure 2. For Barnwell and Beaufort counties, the slope of the lines was positive, indicating that the temperature tended to increase over the previous two decades at 0.101˚C and 0.117˚C per year, respectively. The slope of the relationship for both counties had a p-value < 0.05, meaning that the observed increase in temperature was statistically significant. Marion and Spartanburg counties, on the other hand, had a p-value > 0.05, which indicates that the observed temperature changes were not statistically significant for these counties.

The weather station coordinates, temperature, and regression results for the temperature trend by county are shown in Table 2. These results indicate that except for Marion County, the regression analyses for all the other counties resulted in a positive slope, signifying that the general tendency had been for the temperature to increase over the previous two decades. However, the increase in

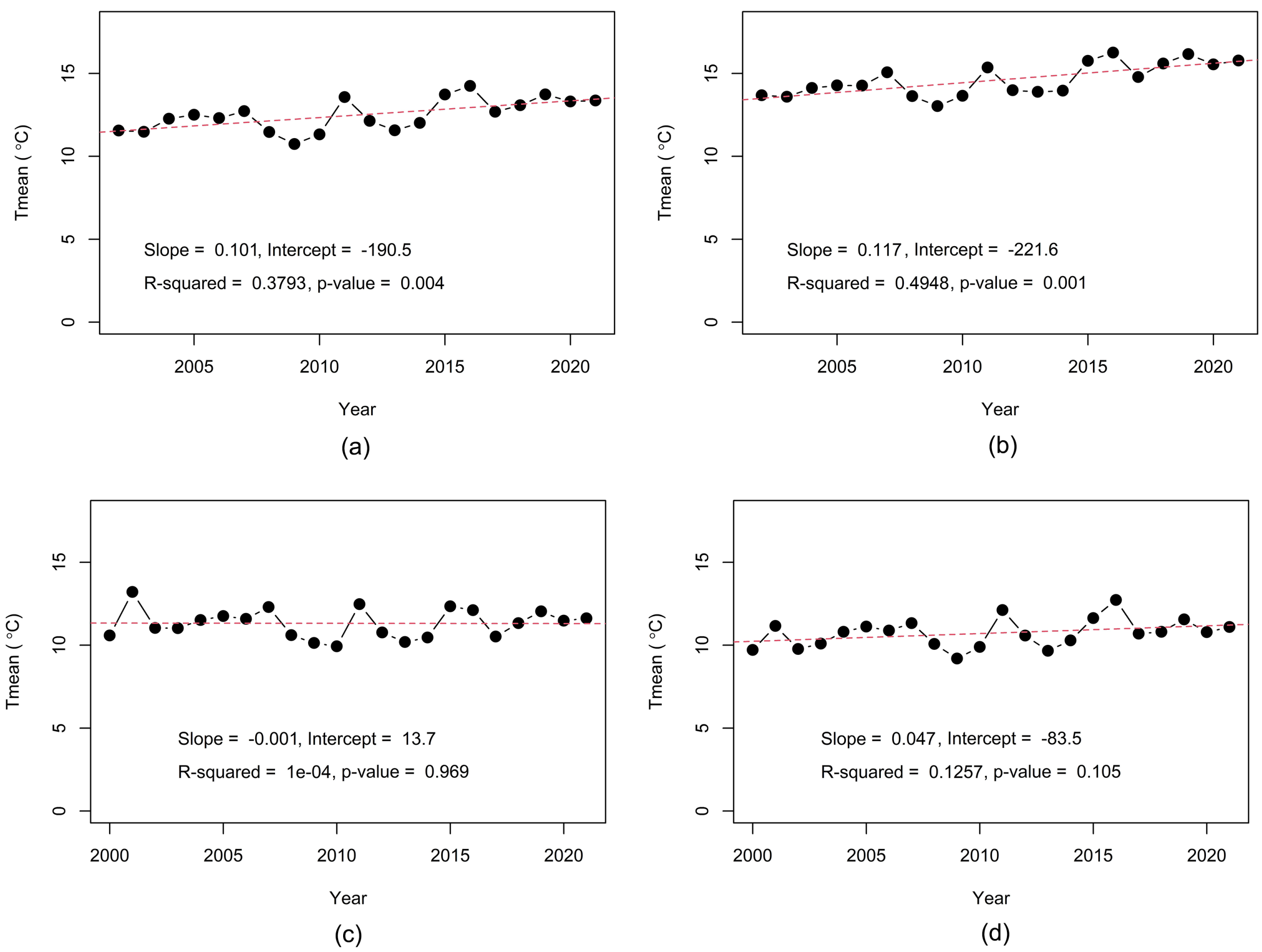

Figure 2. Regression analysis of mean air temperature (T_{mean}) and year for four counties in South Carolina. The dashed red line is the regression line. (a) Barnwell county; (b) Beaufort county; (c) Marion county; (d) Spartanburg county.

Table 2. Average air temperature data and regression analysis results of mean air temperature (T_{mean}) and year for each county in South Carolina from 2002 to 2022 (S = significant, NS = not significant at $\alpha = 0.05$).

County	Coordinates		Temperature			Regression results				
	Lon	Lat	T_{max}	T_{min}	T_{mean}	Intercept	Slope	R^2	p-value	S or NS
Aiken	−81.70	33.55	19.25	5.79	12.52	−369.64	0.190	0.35	0.043	S
Anderson	−82.71	34.50	17.06	4.79	10.93	−152.16	0.081	0.29	0.009	S
Bamberg	−81.03	33.29	19.06	6.18	12.62	−110.36	0.061	0.09	0.167	NS
Barnwell	−81.33	33.36	18.78	6.19	12.49	−190.50	0.101	0.38	0.004	S
Beaufort	−80.72	32.48	20.44	8.79	14.62	−221.60	0.117	0.49	0.001	S
Berkeley	−79.99	33.24	19.71	6.92	13.31	−188.67	0.100	0.34	0.004	S
Charleston	−80.04	32.90	20.31	8.10	14.20	−151.15	0.082	0.32	0.006	S
Chester	−81.20	34.68	16.71	3.03	9.87	−180.31	0.095	0.36	0.003	S
Chesterfield	−79.88	34.70	17.32	3.92	10.62	−148.22	0.079	0.22	0.029	S
Colleton	−80.68	32.89	19.72	5.94	12.83	−110.33	0.061	0.19	0.043	S
Darlington	−79.88	34.30	18.77	4.72	11.75	−5.10	0.008	0.00	0.797	NS
Dillon	−79.36	34.41	18.36	3.95	11.15	−101.28	0.056	0.12	0.139	NS
Florence	−79.73	34.19	18.75	6.01	12.38	−154.90	0.083	0.27	0.013	S
Georgetown	−79.57	33.44	19.40	5.51	12.45	−15.30	0.014	0.01	0.668	NS
Greenwood	−82.15	34.25	17.52	4.54	11.03	−81.87	0.046	0.13	0.101	NS
Horry	−78.72	33.82	17.93	7.10	12.52	−163.44	0.088	0.30	0.008	S
Laurens	−82.02	34.50	17.26	3.16	10.21	−161.44	0.085	0.31	0.008	S
Lee	−80.23	34.21	18.32	4.38	11.35	−126.65	0.069	0.13	0.137	NS
Lexington	−81.12	33.94	19.05	5.95	12.50	−165.03	0.088	0.32	0.006	S
Marion	−79.25	34.19	17.56	5.07	11.32	13.69	−0.001	0.00	0.969	NS
McCormick	−82.19	33.66	18.43	5.28	11.86	−265.82	0.138	0.51	0.000	S
Oconee	−82.88	34.67	17.11	6.04	11.58	−82.42	0.047	0.10	0.149	NS
Orangeburg	−80.85	33.46	19.30	6.58	12.94	−139.26	0.076	0.27	0.014	S
Pickens	−82.72	34.88	16.72	3.22	9.97	−132.51	0.071	0.25	0.017	S
Richland	−80.99	33.97	19.08	6.79	12.93	−136.93	0.075	0.23	0.026	S
Saluda	−81.77	33.99	17.83	3.94	10.89	−108.33	0.059	0.18	0.047	S
Spartanburg	−82.21	34.91	16.67	4.78	10.73	−83.52	0.047	0.13	0.105	NS
Sumter	−80.36	33.94	17.92	4.59	11.26	−12.64	0.012	0.00	0.775	NS
Union	−81.67	34.61	17.53	2.43	9.98	−118.43	0.064	0.27	0.013	S
Williamsburg	−79.86	33.81	19.51	4.84	12.18	−163.12	0.087	0.27	0.012	S
York	−81.06	34.98	16.83	3.88	10.36	−106.29	0.058	0.17	0.056	NS
Average			**18.33**	**5.24**	**11.78**	**−133.34**	**0.072**	**0.23**	**0.141**	
Total "S"										**20**
Total "NS"										**11**

temperature was statistically significant for 20 out of the 31 counties (64 %). The overall temperature rise averaged 0.072˚C per year for all 31 counties. The increase was even higher (average = 0.089˚C per year) for the 20 counties with a significant temperature increase over the previous two decades.

3.2. Historical Trends in Chill Values

Examples of the regression analyses conducted to evaluate the historical trend in annual chill hours (using the T(t) < 7.2˚C model) for four counties in South Carolina are shown in Figure 3. Because of the increasing trends in temperature, Barnwell and Beaufort counties had decreasing trends in annual chill hours, resulting in p-values < 0.05. These results indicate that the decreasing trends in chill hours accumulation over the previous two decades were statistically significant for these counties. For Marion and Spartanburg counties, on the other hand, the observed trends in chill hours were not statistically significant (p-values > 0.05).

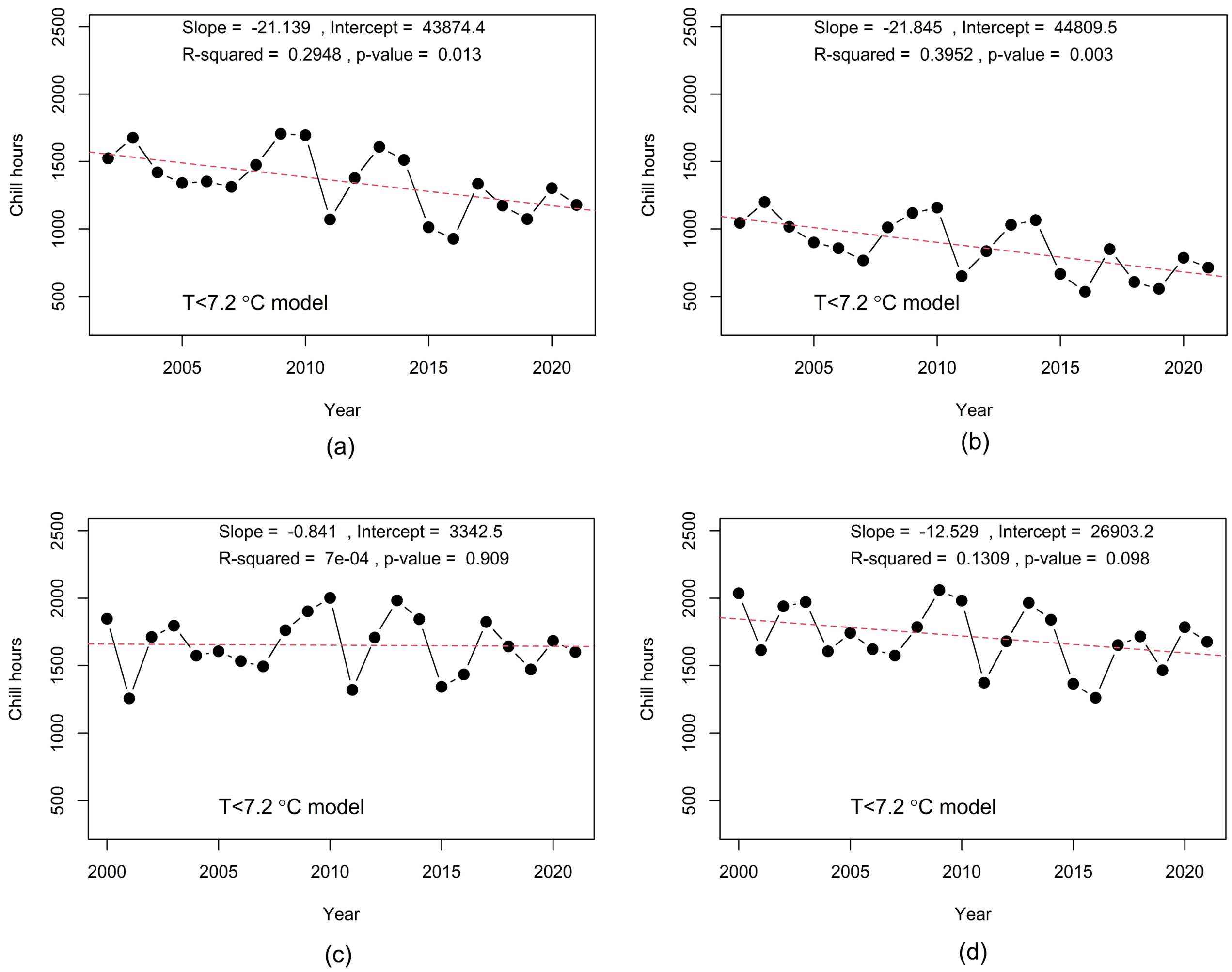

Figure 3. Regression analysis of annual Chill hours and year for four counties in South Carolina. The dashed red line is the regression line. (a) Barnwell county; (b) Beaufort county; (c) Marion county; (d) Spartanburg county.

The summary statistics for the annual chill values and the results of regression analysis for each county using the four chill models are shown in Table 3 for the T(t) < 7.2˚C model, Table 4 for the 0˚C < T(t) < 7.2˚C model, Table 5 for the Utah model, and Table 6 for the Dynamic model. Because of the different definitions of what a chill value represents for each model, there were considerable variations in the magnitude of the annual chill value results among models. For example, on average, for all counties, the annual chill values were 1536 chill hours, 1178 chill hours, 432 chill units, and 75 chill portions for the T(t) < 7.2˚C, 0˚C < T(t) < 7.2˚C, Utah, and Dynamic model, respectively.

3.2.1. Results of the T(t) < 7.2˚C Model (Chill Hours)

Table 3 shows that the regression analysis for each county always resulted in a negative slope. The negative slope means that the general tendency had been for the annual chill hours in South Carolina to decrease over the previous two decades. Although the slope of the line varied widely by county, the average slope for all counties was −17.7, representing an average decrease of 17.7 chill hours per year. Using this model, the decline in chill hours was statistically significant for 20 of the 31 counties included in this study, which coincided with the results reported for the temperature data.

3.2.2. Results of the 0˚C < T(t) < 7.2˚C Model (Chill Hours)

The linear regressions for the 0˚C < T(t) < 7.2˚C model (Table 4) resulted in a negative slope for all counties except for Marion County. The overall slope for all the counties was −8.6, representing an average decrease in chill hours calculated with this model of 8.6 chill hours per year. However, the p-values indicate that using this model, which only accounts for temperatures above freezing when calculating chill hours, only 11 out of the 31 counties experienced a statistically significant decrease in chill hours over the previous two decades.

3.2.3. Results of the Utah Model (Chill Units)

The results for the Utah model (Table 5) also show a negative slope for all counties except for Marion County. The average slope for all counties was −17.0, similar to the slope obtained with the T(t) < 7.2˚C model. However, since the chill units calculated with the Utah model are not equivalent to chill hours, the two results are not comparable. However, the general tendency for this model had also been for the chill units to decrease over time. Yet, the p-values indicate that only 9 of the 31 counties resulted in a significant decrease in chill units calculated using the Utah model.

3.2.4. Results of the Dynamic Model (Chill Portions)

The regression results of the Dynamic model (Table 6) show that four counties (Darlington, Georgetown, Marion, and Union) resulted in positive slopes. In contrast, the other twenty-seven counties resulted in negative slopes. The overall average slope obtained with the Dynamic model for all counties was −0.395, representing an average decrease of around 0.4 chill portions per year. However,

Table 3. Average chill hours accumulated using the T(t) < 7.2˚C model and regression analysis results between chill hours versus year for each county in South Carolina from 2002 to 2022 (S = significant, NS = not signifi-cant at $\alpha = 0.05$).

County	Annual Chill Hours			Regression Results				
	Max	Min	Mean	Intercept	Slope	R^2	p-value	S or NS
Aiken	1742	741	1357	95979.4	−46.948	0.31	0.059	NS
Anderson	2028	1197	1673	42415.8	−20.265	0.29	0.010	S
Bamberg	2683	906	1361	35623.6	−17.042	0.10	0.160	NS
Barnwell	1705	927	1353	43874.4	−21.139	0.29	0.013	S
Beaufort	1199	535	868	44809.5	−21.845	0.40	0.003	S
Berkeley	1577	769	1203	47250.6	−22.903	0.35	0.004	S
Charleston	1365	626	989	35069.6	−16.951	0.28	0.011	S
Chester	2392	1493	1981	48551.9	−23.164	0.35	0.004	S
Chesterfield	2182	1203	1809	42307.3	−20.143	0.22	0.029	S
Colleton	1636	834	1290	39650.9	−19.080	0.28	0.011	S
Darlington	1976	1169	1597	4663.2	−1.525	0.00	0.838	NS
Dillon	2057	1424	1732	27242.4	−12.698	0.12	0.155	NS
Florence	1759	1040	1419	36533.1	−17.465	0.24	0.020	S
Georgetown	1712	1057	1426	10486.7	−4.506	0.02	0.526	NS
Greenwood	2009	1273	1692	28228.5	−13.199	0.16	0.061	NS
Horry	1726	828	1264	40556.0	−19.543	0.27	0.014	S
Laurens	2314	1492	1908	43646.7	−20.761	0.30	0.008	S
Lee	1958	1079	1643	48329.4	−23.245	0.25	0.037	S
Lexington	1774	977	1401	38014.3	−18.211	0.29	0.010	S
Marion	2001	1256	1651	3342.5	−0.841	0.00	0.909	NS
McCormick	2126	1022	1517	79013.5	−38.546	0.54	0.000	S
Oconee	1795	941	1485	28198.0	−13.287	0.13	0.096	NS
Orangeburg	1607	895	1275	34882.6	−16.716	0.24	0.021	S
Pickens	2304	1536	1921	41578.5	−19.725	0.32	0.006	S
Richland	1581	852	1274	33708.1	−16.132	0.22	0.029	S
Saluda	2094	1367	1776	30755.3	−14.414	0.19	0.044	S
Spartanburg	2059	1261	1714	26903.2	−12.529	0.13	0.098	NS
Sumter	2160	1291	1671	9180.6	−3.735	0.01	0.689	NS
Union	2365	1592	1989	32986.4	−15.418	0.23	0.023	S
Williamsburg	1928	1036	1531	45849.7	−22.043	0.28	0.011	S
York	2240	1479	1847	29206.2	−13.608	0.16	0.069	NS
Average	**1937**	**1100**	**1536**	**37,059**	**−17.665**	**0.225**	**0.128**	
Total "S"								**20**
Total "NS"								**11**

Table 4. Average chill hours accumulated using the 0˚C < T(t) < 7.2˚C model and regression analysis results between chill hours versus year for each county in South Carolina from 2002 to 2022 (S = significant, NS = not significant at $\alpha = 0.05$).

County	Annual Chill hours			Regression Results				
	Max	Min	Mean	Intercept	Slope	R^2	p-value	S or NS
Aiken	1305	728	1094	52024.1	−25.269	0.25	0.095	NS
Anderson	1462	967	1295	22766.7	−10.680	0.21	0.031	S
Bamberg	1841	792	1090	17385.6	−8.105	0.06	0.277	NS
Barnwell	1295	797	1097	25472.1	−12.118	0.27	0.019	S
Beaufort	1072	497	779	39444.1	−19.222	0.47	0.001	S
Berkeley	1363	693	1028	37697.5	−18.239	0.36	0.003	S
Charleston	1123	560	848	23269.2	−11.152	0.24	0.021	S
Chester	1541	1053	1360	5002.9	−1.812	0.01	0.667	NS
Chesterfield	1590	981	1308	18340.8	−8.472	0.14	0.088	NS
Colleton	1231	770	1031	18189.0	−8.534	0.18	0.046	S
Darlington	1409	927	1210	−1622.0	1.409	0.01	0.726	NS
Dillon	1513	1032	1278	19666.0	−9.153	0.18	0.067	NS
Florence	1318	862	1124	21034.8	−9.903	0.23	0.023	S
Georgetown	1288	792	1122	4805.6	−1.832	0.01	0.693	NS
Greenwood	1426	959	1275	13640.7	−6.151	0.10	0.162	NS
Horry	1331	782	1042	25268.6	−12.050	0.26	0.016	S
Laurens	1517	1059	1335	4622.5	−1.635	0.01	0.684	NS
Lee	1435	844	1216	37707.0	−18.168	0.42	0.004	S
Lexington	1326	821	1111	20919.7	−9.853	0.24	0.022	S
Marion	1449	1002	1261	585.1	0.336	0.00	0.937	NS
McCormick	1478	936	1224	32128.0	−15.372	0.32	0.006	S
Oconee	1478	803	1229	17697.1	−8.191	0.09	0.186	NS
Orangeburg	1274	762	1051	17675.0	−8.269	0.15	0.075	NS
Pickens	1567	1095	1358	13207.1	−5.894	0.10	0.154	NS
Richland	1274	749	1072	19613.3	−9.222	0.16	0.062	NS
Saluda	1427	1047	1285	10089.1	−4.379	0.07	0.237	NS
Spartanburg	1554	981	1315	16262.9	−7.435	0.10	0.154	NS
Sumter	1428	979	1252	6319.9	−2.521	0.02	0.574	NS
Union	1557	1041	1334	5287.6	−1.967	0.01	0.618	NS
Williamsburg	1389	865	1158	17292.2	−8.025	0.13	0.106	NS
York	1550	1066	1334	13961.6	−6.281	0.10	0.149	NS
Average	**1413**	**879**	**1178**	**18,573**	**−8.650**	**0.158**	**0.223**	
Total "S"								**11**
Total "NS"								**20**

Table 5. Average chill units accumulated using the Utah model and regression analysis results between chill units versus year for each county in South Carolina from 2002 to 2022 (S = significant, NS = not significant at $\alpha = 0.05$).

County	Annual Chill Units			Regression Results				
	Max	Min	Mean	Intercept	Slope	R^2	p-value	S or NS
Aiken	842	−160	286	77023.2	−38.073	0.19	0.159	NS
Anderson	1277	109	812	40438.1	−19.710	0.18	0.048	S
Bamberg	1243	−464	180	28128.7	−13.901	0.05	0.304	NS
Barnwell	870	−371	269	61924.1	−30.651	0.31	0.010	S
Beaufort	100	−1174	−442	101566.7	−50.713	0.51	0.000	S
Berkeley	717	−741	77	79720.7	−39.614	0.32	0.006	S
Charleston	238	−1040	−338	57436.7	−28.736	0.25	0.018	S
Chester	1262	416	843	13196.5	−6.145	0.03	0.452	NS
Chesterfield	1528	136	733	31848.3	−15.477	0.11	0.137	NS
Colleton	964	−426	142	15264.6	−7.522	0.02	0.538	NS
Darlington	850	−322	394	−3217.3	1.796	0.00	0.853	NS
Dillon	962	132	569	28892.1	−14.098	0.09	0.212	NS
Florence	849	−303	275	49696.0	−24.582	0.24	0.022	S
Georgetown	816	−478	216	4610.7	−2.186	0.00	0.846	NS
Greenwood	1134	117	667	18323.2	−8.782	0.04	0.359	NS
Horry	934	−514	254	59838.7	−29.637	0.25	0.017	S
Laurens	1098	378	786	12414.3	−5.784	0.03	0.446	NS
Lee	914	−267	538	47262.1	−23.263	0.16	0.099	NS
Lexington	785	−503	227	52338.1	−25.919	0.23	0.023	S
Marion	1034	−58	573	−5714.9	3.128	0.01	0.725	NS
McCormick	1030	−311	528	55477.5	−27.331	0.25	0.019	S
Oconee	1302	−278	713	23725.0	−11.446	0.04	0.376	NS
Orangeburg	748	−614	142	42684.0	−21.160	0.17	0.059	NS
Pickens	1350	493	935	15676.9	−7.333	0.04	0.400	NS
Richland	734	−538	185	44182.1	−21.884	0.15	0.076	NS
Saluda	1066	208	598	19740.0	−9.521	0.06	0.260	NS
Spartanburg	1348	166	860	23329.7	−11.176	0.07	0.228	NS
Sumter	1138	−14	553	9014.3	−4.208	0.01	0.709	NS
Union	1118	351	746	7965.2	−3.591	0.01	0.615	NS
Williamsburg	768	−461	242	33612.3	−16.598	0.12	0.108	NS
York	1220	330	819	29240.5	−14.137	0.13	0.105	NS
Average	**975**	**−200**	**432**	**34,698**	**−17.040**	**0.131**	**0.266**	
Total "S"								**9**
Total "NS"								**22**

Table 6. Average chill portions accumulated using the Dynamic model and regression analysis results between chill portions versus year for each county in South Carolina from 2002 to 2022 (S = significant, NS = not significant at $\alpha = 0.05$).

County	Annual Chill Portions			Regression Results				
	Max	Min	Mean	Intercept	Slope	R^2	p-value	S or NS
Aiken	85	57	69	2690.4	−1.301	0.21	0.131	NS
Anderson	98	66	85	1102.3	−0.506	0.15	0.077	NS
Bamberg	98	29	67	547.0	−0.239	0.01	0.619	NS
Barnwell	83	53	72	1168.0	−0.545	0.15	0.086	NS
Beaufort	69	34	56	2106.4	−1.020	0.38	0.004	S
Berkeley	79	45	65	1541.5	−0.735	0.21	0.030	S
Charleston	72	36	58	1165.8	−0.551	0.15	0.075	NS
Chester	98	70	88	581.5	−0.246	0.05	0.304	NS
Chesterfield	109	64	83	1138.9	−0.525	0.13	0.094	NS
Colleton	91	49	66	363.2	−0.148	0.01	0.695	NS
Darlington	84	57	74	72.4	0.001	0.00	0.998	NS
Dillon	92	58	77	1623.8	−0.770	0.20	0.052	NS
Florence	87	57	72	1234.8	−0.578	0.20	0.039	S
Georgetown	84	48	68	−14.9	0.041	0.00	0.909	NS
Greenwood	97	65	83	530.1	−0.222	0.03	0.433	NS
Horry	90	56	74	1213.7	−0.567	0.15	0.076	NS
Laurens	96	69	85	227.9	−0.071	0.00	0.799	NS
Lee	91	51	77	1168.8	−0.544	0.09	0.238	NS
Lexington	83	47	71	1038.3	−0.481	0.11	0.128	NS
Marion	92	63	79	−158.1	0.118	0.01	0.676	NS
McCormick	94	56	76	1291.8	−0.605	0.13	0.099	NS
Oconee	100	57	83	745.8	−0.330	0.04	0.349	NS
Orangeburg	83	52	68	849.0	−0.388	0.09	0.185	NS
Pickens	100	75	89	692.5	−0.300	0.09	0.185	NS
Richland	85	47	69	859.2	−0.393	0.07	0.241	NS
Saluda	92	67	81	677.7	−0.297	0.08	0.216	NS
Spartanburg	100	66	88	743.7	−0.326	0.07	0.227	NS
Sumter	92	52	77	259.0	−0.090	0.00	0.804	NS
Union	96	70	84	−86.6	0.085	0.00	0.759	NS
Williamsburg	82	52	68	884.6	−0.406	0.09	0.183	NS
York	98	73	87	687.3	−0.299	0.07	0.234	NS
Average	**90**	**56**	**75**	**869**	**−0.395**	**0.096**	**0.321**	
Total "S"								**3**
Total "NS"								**28**

only Beaufort, Berkeley, and Florence counties significantly reduced chill portions calculated with the Dynamic model. These results suggest that the Dynamic model was less sensitive to the observed changes in temperature than the other models.

3.3. Annual Chill Accumulation Maps

Average annual chill accumulation maps of South Carolina using the T(t) < 7.2˚C, 0˚C < T(t) < 7.2˚C, Utah, and Dynamic models, are shown in Figures 4-7, respectively. An equal distance procedure was used to divide the state into five geographical areas (colored zones) according to the average annual chill accumulation. At regular intervals, lines of equal chill accumulation (red lines) were also drawn to create additional zones. The resulting maps show some similarities and some differences among the four models. The zones in each map identify areas with similar chilling conditions, which could be used to locate new areas for growing crops with chilling requirements, as suggested by Linvill (1990) [10]. In general, the chill accumulation in South Carolina tended to increase from south to north and from the coastal areas in the southeast to the mountainous regions in the northwestern part of the state.

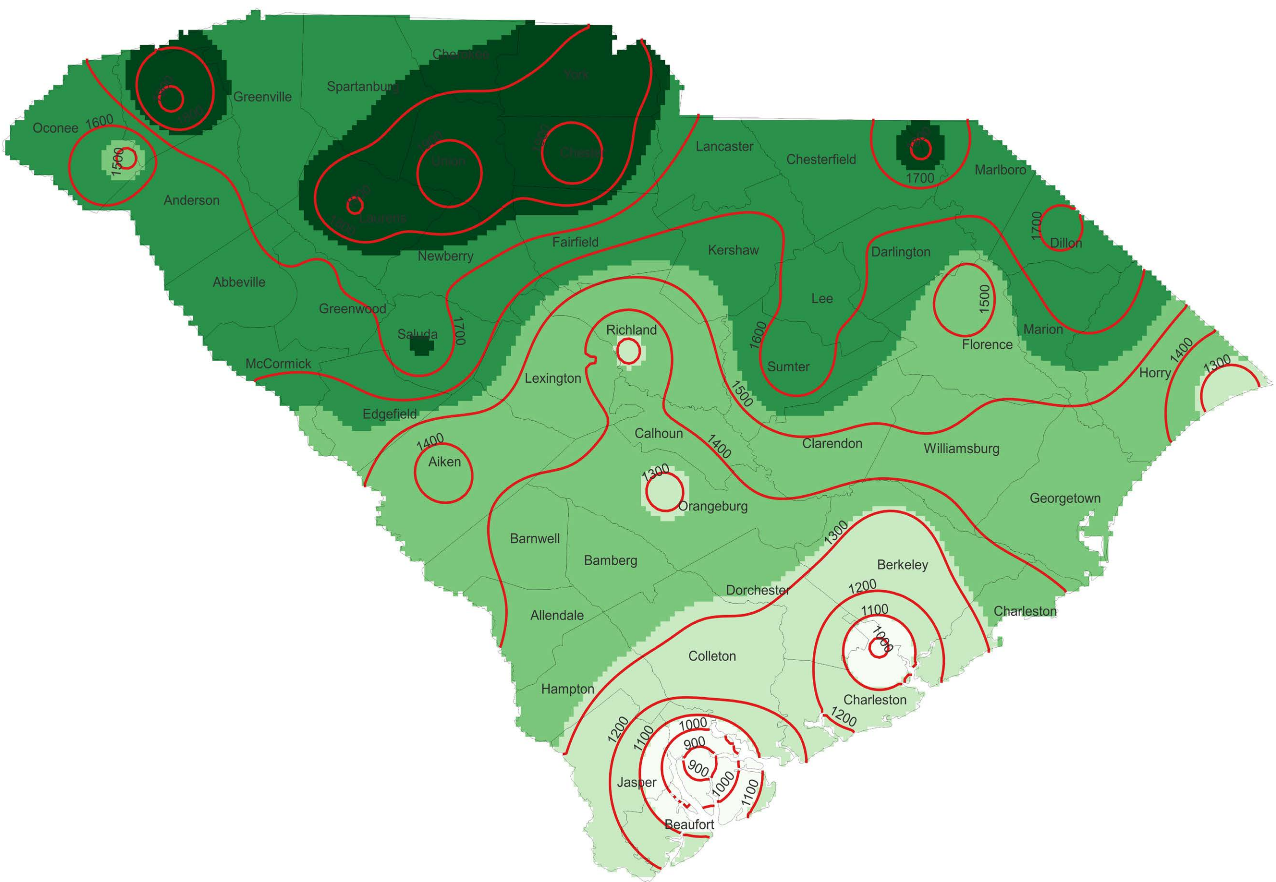

Figure 4. Average annual chill hours map of South Carolina using the T(t) < 7.2˚C model. The red lines are the contour lines for annual chill hours.

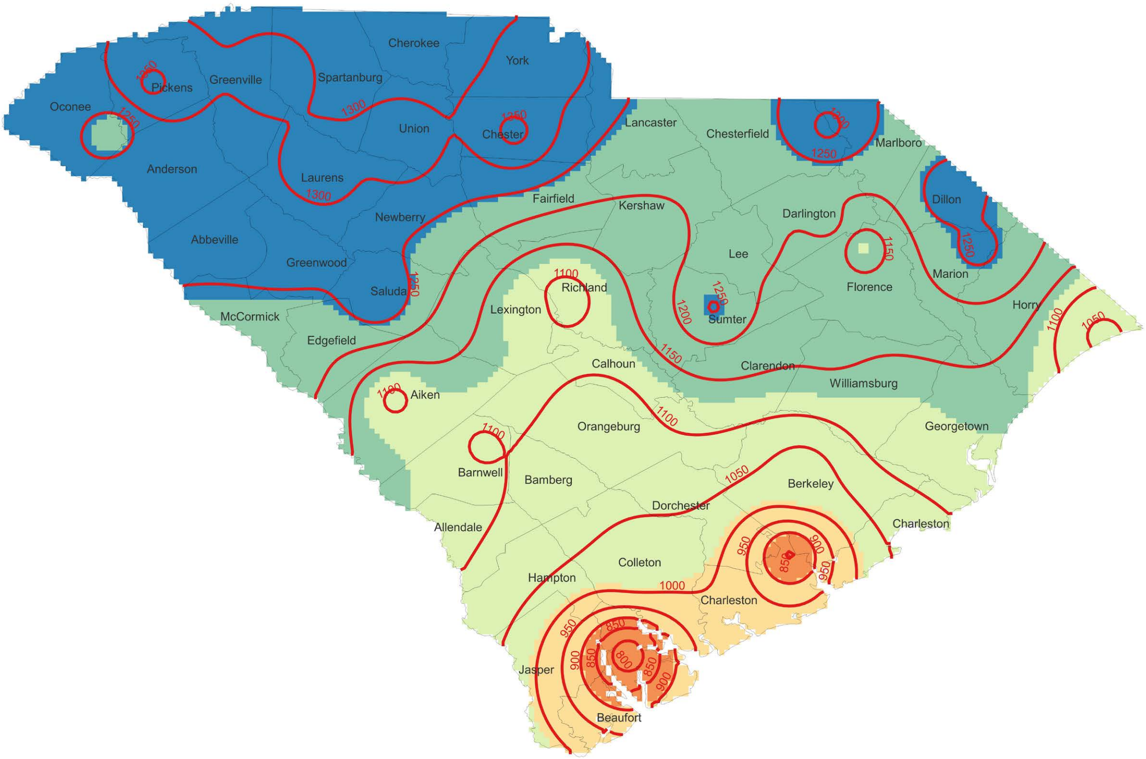

Figure 5. Average annual chill hours map of South Carolina using the 0˚C < T(t) < 7.2˚C model. The red lines are the contour lines for annual chill hours.

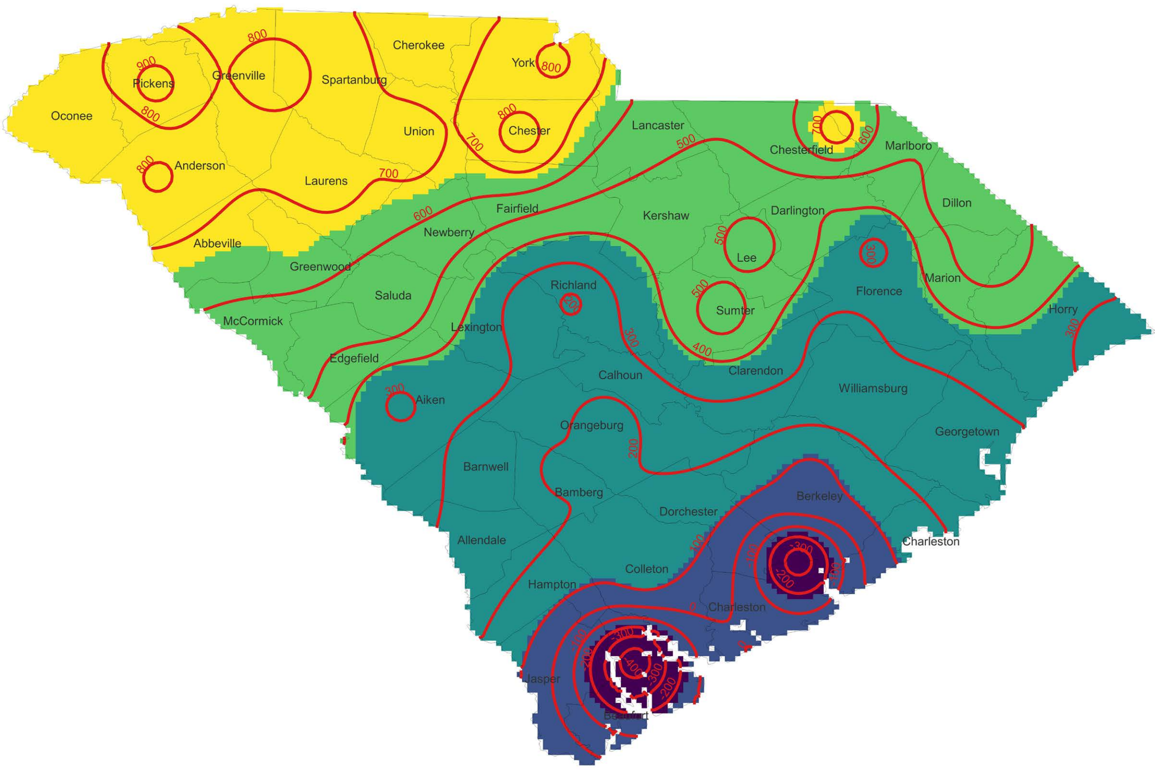

Figure 6. Average annual chill unit map of South Carolina using the Utah model. The red lines are the contour lines for annual chill units.

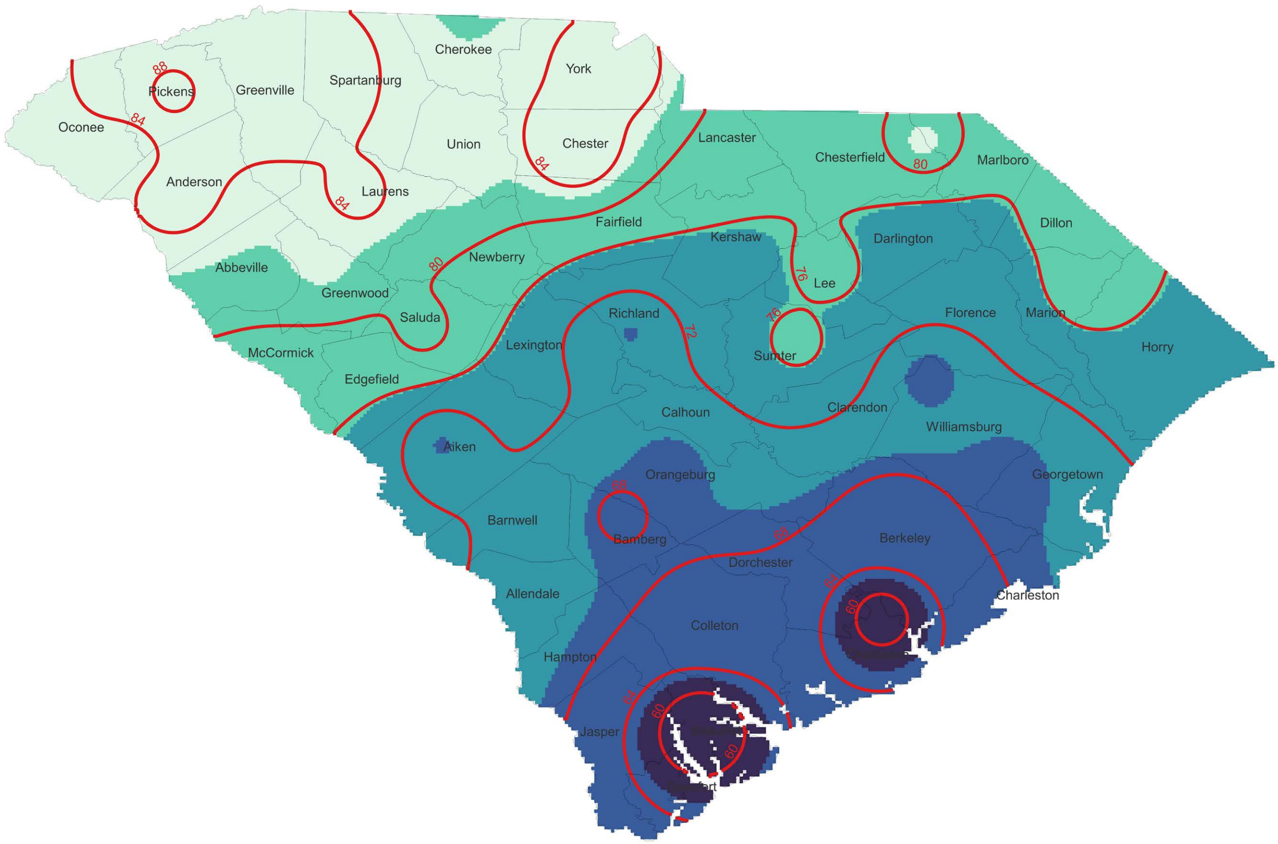

Figure 7. Average annual chill portions map of South Carolina using the Dynamic model. The red lines are the contour lines for annual chill portions.

4. Conclusion

This study addressed whether air temperatures had increased in different counties in South Carolina in the previous two decades. Another question explored was whether the observed temperature changes have significantly impacted the annual chill hours, chill units, and chill portions calculated using four different chill models. The regression analyses between air temperature and year for the various counties showed that temperatures in South Carolina had tended to increase over time for all counties included in the study. The increase in temperature was significant for most of the counties, representing an average increase of 0.089˚C per year. Consequently, due to the temperature increases, the general tendency was for the annual accumulated chill hours, chill units, and chill portions to decrease over the previous two decades. However, there were variations in the sensitivity of the different chill models to the observed changes in temperature. The $T(t) < 7.2$˚C model was the most sensitive to the observed temperature changes, while the dynamic model was the least sensitive. The results of this study could be used as a warning for the peach and other fruit tree industries in South Carolina that are sensitive to chilling requirements to evaluate the potential impacts of the observed trends and start planning adaptation strategies. This study also developed annual chill maps for South Carolina using the results of the four chill models. These maps could be used to visualize the different chill regions of the state, which could help farmers determine the most appropriate zones for planting future fruit trees.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Pörtner, H.O., Roberts, D.C., Tignor, M., Poloczanska, E.S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A. and Rama, B. (2022) Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge.

[2] Asse, D., Chuineb, I., Vitassed, Y., Yoccoz, N.G., Delpierre, N., Badeau, V., Delestrade, A. and Randin, C.F. (2018) Warmer Winters Reduce the Advance of Tree Spring Phenology Induced by Warmer Springs in the Alps. *Agricultural and Forest Meteorology*, **252**, 220-230. https://doi.org/10.1016/j.agrformet.2018.01.030

[3] Prudencio, A.S., Martínez-Gómez, P. and Dicenta, F. (2018) Evaluation of Breaking Dormancy, Flowering and Productivity of Extra-Late and Ultra-Late Flowering Almond Cultivars during Cold and Warm Seasons in South-East of Spain. *Scientia Horticulturae*, **235**, 39-46. https://doi.org/10.1016/j.scienta.2018.02.073

[4] Darbyshire, R., Farrera, I., Martinez-Lüscher, J., Leite, G.B., Mathieu, V., Yaacoubih, A.E. and Legave, J.M. (2017) A Global Evaluation of Apple Flowering Phenology Models for Climate Adaptation. *Agricultural and Forest Meteorology*, **240-241**, 67-77. https://doi.org/10.1016/j.agrformet.2017.03.021

[5] Delgado, A., Dapena, E., Fernandez, E. and Luedeling, E. (2021) Climatic Requirements during Dormancy in Apple Trees from Northwestern Spain—Global Warming May Threaten the Cultivation of High-Chill Cultivars. *European Journal of Agronomy*, **130**, Article ID: 126374. https://doi.org/10.1016/j.eja.2021.126374

[6] Martínez-Lüschera, J., Hadley, P., Ordidge, M., Xuc, X. and Luedeling, E. (2017) Delayed Chilling Appears to Counteract Flowering Advances of Apricotin Southern UK. *Agricultural and Forest Meteorology*, **237-238**, 209-218. https://doi.org/10.1016/j.agrformet.2017.02.017

[7] Rouse, R.E. and Sherman, W.B. (2003) Effective Chilling Temperatures for Low-Chill Subtropical Peaches. *Proceedings of the Florida State Horticultural Society*, **116**, 42-43.

[8] NASS (2022) USDA National Agricultural Statistics Service—Noncitrus Fruits and Nuts. https://usda.library.cornell.edu/concern/publications/zs25x846c

[9] R Core Team (2021) R: A Language and Environment for Statistical Computing. R

Foundation for Statistical Computing, Vienna. https://www.R-project.org/

[10] Linvill, D.E. (1990) Calculating Chilling Hours and Chill Units from Daily Maximum and Minimum Temperature Observations. *HortScience*, **25**, 14-16. https://doi.org/10.21273/HORTSCI.25.1.14

[11] Linsley-Noakes, G.C., Louw, M. and Allan, P. (1995) Estimating Daily Positive Utah Chill Units Using Daily Minimum and Maximum Temperatures. *Journal of the South African Society of Horticultural Science*, **5**, 19-23.

[12] Miranda, C., Santesteban, L.G. and Royo, J.B. (2013) Evaluation and Fitting of Models for Determining Peach Phenological Stages at a Regional Scale. *Agricultural and Forest Meteorology*, **178-179**, 129-139. https://doi.org/10.1016/j.agrformet.2013.04.016

[13] Payero, J.O. and Sekaran, U. (2021) County-Specific Chill Hours Accumulation in South Carolina. *Atmospheric and Climate Sciences*, **11**, 508-519. https://doi.org/10.4236/acs.2021.113030

[14] Zhang, J. and Taylor, C. (2011) The Dynamic Model Provides the Best Description of the Chill Process on 'Sirora' Pistachio Trees in Australia. *HortScience*, **46**, 420-425. https://doi.org/10.21273/HORTSCI.46.3.420

[15] Richardson, E.A., Seeley, S.D. and Walker, D.R. (1974) A Model for Estimating the Completion of Rest for Redhaven and Elberta Peach Trees. *HortScience*, **9**, 331-332. https://doi.org/10.21273/HORTSCI.9.4.331

[16] Alburquerque, N., García-Montiel, F., Carrillo, A. and Burgos, L. (2008) Chilling and Heat Requirements of Sweet Cherry Cultivars and the Relationship between Altitude and the Probability of Satisfying the Chill Requirements. *Environmental and Experimental Botany*, **64**, 162-170. https://doi.org/10.1016/j.envexpbot.2008.01.003

[17] Fishman, S., Erez, T.A. and Couvillon, G.A. (1987) The Temperature Dependence of Dormancy Breaking in Plants: Mathematical Analysis of a Two-Step Model Involving a Cooperative Transition. *Journal of Theoretical Biology*, **124**, 473-483. https://doi.org/10.1016/S0022-5193(87)80221-7

[18] Fishman, S., Erez, T.A. and Couvillon, G.A. (1987) The Temperature Dependence of Dormancy Breaking in Plants: Computer Simulation of Processes Studied under Controlled Temperatures. *Journal of Theoretical Biology*, **126**, 309-321. https://doi.org/10.1016/S0022-5193(87)80237-0

[19] Melke, A. (2015) The Physiology of Chilling Temperature Requirements for Dormancy Release and Bud-Break in Temperate Fruit Trees Grown at Mild Winter Tropical Climate. *Journal of Plant Studies*, **4**, 110-156. https://doi.org/10.5539/jps.v4n2p110

[20] Luedeling, E. and Fernandez, E. (2022) chillR Package: Statistical Methods for Phenology Analysis in Temperate Fruit Trees. https://www.rdocumentation.org/packages/chillR/versions/0.72.7