Enhancing the productivity, resilience, and sustainability of domestic produce food systems

Protocol for US Fruit and Vegetable Crop Modeling

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BACKGROUND

Fruits and vegetables are important parts of a healthy, balanced diet in our daily lives. Climate change could impact fruit and vegetable production in the United States. Fruit and vegetable production could decline or increase in the current production areas. There may also be opportunities to produce fruit and vegetables in new areas of the United States under future climate scenarios.

GOAL

Assess the climate change impact on fruit and vegetable production and potential adaptations, including possible shifts in production area in the United States.

SELECTION OF REPRESENTATIVE COUNTIES

Eight fruit and vegetable crops are studied within a current NIFA-funded project (Award #: 2017-68002-26789), "Fruit & Vegetable Supply Chains: Climate Adaptation & Mitigation Opportunities"—potatoes, carrots, green (snap) beans, oranges, spinach, strawberries, sweet corn, and tomatoes. For efficiency, counties for open-field crop modeling were selected in a manner that considered the presence of all eight crops. The total production acreage for all eight crops was tabulated for all crop reporting districts (CRDs), using data from the most recent USDA AgCensus (2012). The CRDs were then sorted in a descending manner, choosing the highest acreage CRDs necessary to capture 80% of all acreage for these eight crops. This resulted in a list of 31 CRDs. The counties having the highest target crop acreage within each of these CRDs were then selected for all subsequent open-field crop modeling in the project (see Table 2 & Figure 1), with an additional Florida county—St. Johns—due to the importance of its potato production.

CROP MODELS

Up to five mechanistic crop models (Table 1) will be used for some of the crops, such as potatoes, and fewer for others. Statistical modeling for all crops will be led by Dr. Kaiyu Guan (University of Illinois). The mechanistic models include SIMPLE (developed at the University of Florida), CropSyst (developed at Washington State University) (Stöckle et al. 1994; Stöckle et al. 2003; Stöckle et al. 2014), LINTUL-POTATO-DSS (developed at Wageningen University) (Haverkort et al. 2015), EPIC (via a USDA collaboration), and DSSAT CSM-Substor-Potato (Raymundo et al. 2017).

Table 1: Mechanistic crop models that will be used for fruit and vegetable simulations.

No.	Crop Model	Reference
1	SIMPLE	Unpublished
2	CropSyst	Stöckle et al. (1994)
3	LINTUL-POTATO-DSS	Haverkort et al. (2015)
4	EPIC	Williams et al. (1989)
5	CSM-Substor-Potato	Raymundo et al. (2017)

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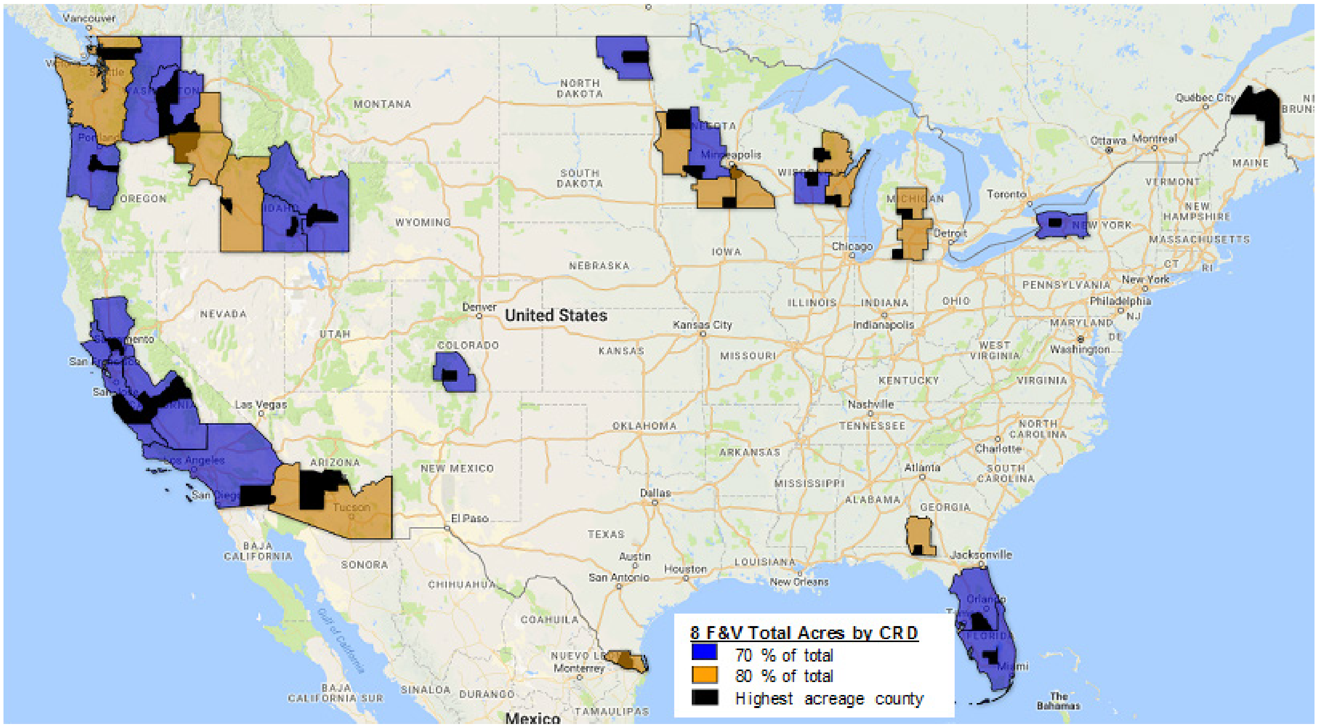
Table 2: Counties selected for open-field crop modeling.[1]

No.	State	State Crop Reporting District (CRD)	Target Crop Area in the CRD (ha)	County	Target Crop Area in the County (ha)
1	Arizona	AZ80	7,223	Maricopa	3,173
2	California	CA51	186,624	Fresno	59,003
3		CA80	35,381	Imperial	11,168
4		CA40	24,658	Monterey	15,228
5		CA50	32,326	Yolo	16,223
6	Colorado	CO80	22,900	Rio Grande	7,438
7	Florida	FL80	181,203	Hendry	41,242
8		FL50	64,226	Polk	29,880
9		FL50	64,226	St. Johns[2]	6,020
10	Georgia	GA70	10,002	Decatur	6,264
11	Idaho	ID90	100,707	Bingham	31,262
12		ID70	7,275	Canyon	3,143
13		ID80	35,569	Minidoka	12,770
14	Maine	ME10	23,205	Aroostook	23,205
15	Michigan	MI50	9,746	Montcalm	7,230
16		MI80	6,240	St. Joseph	3,748
17	Minnesota	MN90	12,464	Dakota	3,505
18		MN80	12,763	Freeborn	2,512
19		MN40	6,460	Otter Tail	4,266
20		MN50	22,859	Renville	9,813
21	New York	NY40	19,728	Genesee	4,295
22	North Dakota	ND30	25,906	Walsh	13,448
23	Oregon	OR10	16,180	Marion	6,932
24		OR30	10,380	Umatilla	7,788
25	Texas	TX97	7,291	Hidalgo	6,601
26	Washington	WA20	27,984	Benton	25,024
27		WA50	63,672	Grant	30,033
28		WA10	9,899	Skagit	5,515
29		WA90	7,152	Walla Walla	6,990
30	Wisconsin	WI60	6,307	Fond du Lac	2,052
31		WI30	9,361	Langlade	6,596
32		WI50	55,503	Portage	26,549

[1] Note: Not all eight target crops (carrots, green beans, oranges, potatoes, spinach, strawberries, sweet corn, and tomatoes) can be grown in all 32 of these counties. Counties where open-field production is not possible (e.g. oranges in northern areas) will not be included in the modeling plan for that crop.
[2] St. Johns County included to ensure representative modeling of potatoes in northern Florida.

Figure 1: Crop reporting districts (CRDs) making up 70% and 80% of total target crop acreage, as well as the highest target crop acreage county in each CRD.



Source: USDA 2012 Ag Census (quickstats.nass.usda.gov), NASS CDL, WAEES Fill-in

CROP MODEL PARAMETERIZATION

a. Crop models will be parameterized with available field experimental data.

b. The parameterizations for crop models depend on crop-specific characteristics (see details in the Appendix for each crop). For example, potatoes in the US are harvested well before the natural maturity of the crop by killing the vines. The accumulated temperature requirement of a model for the baseline will be set for each county (assuming different maturity types for each county), assuming that canopy cover for potatoes will still be about 80% at the harvest date. This might need to be redefined for each new crop.

c. Crop models need to be calibrated to the observed yield data shown in Table A1 for each crop.

d. Crop-specific planting dates for the baseline and future scenarios are shown in Table A2 for each crop (see legend for details).

e. Full irrigation will be assumed to have been applied to avoid/minimize any water stress. It will be assumed that there are no nutrient limitations.

SOIL DATA

Soil data will not be required for this form of crop modeling, which assumes the complete absence of any water stress (fully irrigated conditions).

CLIMATE DATA

Daily weather data are available for each of the 32 counties (a 4×4 km grid cell used per location). The weather data include separate files—one for the historical period (1980-2016) and one for future periods (2020-2099). The baseline period is 1981-2010 and the future periods are 2021-2050 for the 2030s and 2041-2070 for the 2050s. The weather files include maximum and minimum temperature, precipitation, solar radiation, maximum and minimum relative humidity, and wind speed. Because global climate models (GCMs) tend to project from almost no change to up to 8% higher solar fluxes than baseline data, depending on the location in the United States, solar radiation data were adjusted for minimum change compared to baseline data. The daily weather data were extracted from a web accessible folder (http://cloud.insideidaho.org/webservices.html#waf) maintained by the University of Idaho, based on the methodology described in Abatzoglou and Brown (2012) and Abatzoglou (2013).

The historical gridded daily weather data are based on a methodology that blends desirable attributes of gridded climate data and desirable temporal attributes of regional-scale reanalysis and daily gauge-based precipitation to derive a high-resolution gridded surface meteorological dataset covering the continental United States (Abatzoglou 2013). For future weather, climate simulations from five global climate models (Table 2) in the Coupled Model Intercomparison Project, Phase 5 (CMIP5) were statistically downscaled over the contiguous United States using the Multivariate Adaptive Constructed Analogs (MACA) method with a joint bias correction of daily temperature and precipitation (Abatzoglou and Brown 2012). Downscaled data were trained using the 1/24th degree resolution gridded surface meteorological dataset of Abatzoglou (2013). Note that rainfall is not required as the mechanistic crop modeling will not consider the possibility of water stress.

CO_2 FERTILIZATION EFFECT

It is generally accepted that higher future atmospheric CO_2 concentrations will stimulate growth. However, the magnitude of the effect is subject to uncertainty and would likely be constrained under nutrient limitations (Kimball 2016). As most fruit and vegetables in the US receive adequate fertilizer and irrigation, such constraints of the CO_2 fertilizer effect are unlikely for the future scenarios considered within this project. The yearly changing atmospheric CO_2 concentrations for the baseline (1981-2010) and future periods (2030s and 2050s) under the RCP8.5 scenario are shown in Table 4. These annual CO_2 concentrations will be used when simulating the baseline and the future scenarios. In order to present an additional scenario without the CO_2 fertilization effect, the CO_2 concentration will be held constant at 360 ppm (corresponding to the concentration in 1995, half way through the baseline period).

Table 3: General circulation models (GCM) used for future scenarios.

No.	GCM
1	GFDL-ESM2M
2	HadGEM2-ES365
3	IPSL-CM5A-LR
4	MIROC-ESM-CHEM
5	NorESM1-M

SIMULATION OF CLIMATE CHANGE IMPACT AND ADAPTATION

Climate change and adaptation scenarios are shown in Table 5. Planting dates for the baseline (and future without adaptation) and future (with adaptation) scenarios are supplied in Table A2. The season length for the baseline and future scenarios is kept the same and is also supplied in Table A2.

Table 5: Protocol for US fruit and vegetable simulations.

No.	Scenarios	Time Period	Planting Dates
1	Baseline	1981-2010	From Table A2
2	2030sNoAdaptation without elevated CO_2	2021-2050	Same as baseline
3	2050sNoAdaptation without elevated CO_2	2041-2070	Same as baseline
4	2030sNoAdaptation with elevated CO_2	2021-2050	Same as baseline
5	2050sNoAdaptation with elevated CO_2	2041-2070	Same as baseline
6	2030sAdaptation with elevated CO_2	2021-2050	From Table A2
7	2050sAdaptation with elevated CO2	2041-2070	From Table A2

Table 4: Yearly atmospheric CO_2 concentration for the baseline (1981-2010) and future periods (2030s and 2050s) under the RCP8.5 scenario.

Baseline		2030s		2050s	
Year	CO_2 (ppm)	Year	CO_2 (ppm)	Year	CO_2 (ppm)
1981	340	2021	419	2041	494
1982	341	2022	422	2042	499
1983	342	2023	425	2043	504
1984	344	2024	428	2044	508
1985	345	2025	431	2045	513
1986	347	2026	435	2046	519
1987	349	2027	438	2047	524
1988	351	2028	442	2048	529
1989	352	2029	445	2049	535
1990	354	2030	449	2050	541
1991	355	2031	452	2051	546
1992	356	2032	456	2052	552
1993	357	2033	460	2053	558
1994	358	2034	464	2054	564
1995	360	2035	468	2055	571
1996	361	2036	472	2056	577
1997	363	2037	476	2057	583
1998	365	2038	481	2058	590
1999	367	2039	485	2059	597
2000	369	2040	489	2060	604
2001	370	2041	494	2061	611
2002	373	2042	499	2062	618
2003	375	2043	504	2063	625
2004	377	2044	508	2064	632
2005	379	2045	513	2065	639
2006	381	2046	519	2066	647
2007	383	2047	524	2067	654
2008	385	2048	529	2068	662
2009	387	2049	535	2069	669
2010	389	2050	541	2070	677

MULTI-MODEL ENSEMBLE

Each model will be used to simulate the baseline (1 simulation), as well as the impact and adaptation for two future periods (without and with adaptation) (Table 5), with five GCMs (Table 3), with elevated atmospheric CO_2. The future impact, without adaptation, will also be simulated without elevated atmospheric CO_2 to quantify the CO_2 impact. The simulations per model and grid cell (or location) for 30 years include: 1 baseline + 5 GCMs × 2030s with elevated CO_2 + 5 GCMs × 2050s with elevated CO_2 + 5 GCMs × 2030s without elevated CO_2 + 5 GCMs × 2050s without elevated CO_2 + 5 GCMs × 2030s with elevated CO_2 and adaptation + 5 GCMs × 2050s with elevated CO_2 + adaptation). Note that future adaptation will not be simulated without elevated CO_2.

The ensemble-based yield and crop transpiration impact will be calculated using the following steps:

1. Calculate the simulated mean dry matter yield for climate change scenarios across 30 years (1981-2010) per single CM-GCM at each county (grid cell/location).
2. Calculate the simulated mean dry matter yield for climate change scenarios across 30 years (2021-2050 and 2041-2070 with and without adaptation) per single CM-GCM at each county. The scenario without adaptation will be simulated with 360 ppm CO_2 to allow calculation of the future CO_2 effect.
3. Calculate the relative dry matter yield impact (%) per single CM and per GCM for each county, region, and the whole United States. Note that CM and GCM simulation results must be kept separate at this stage for calculating uncertainties across CMs and GCMs.
4. The mean of the CMs × GCMs is then considered as the model ensemble mean, with 25% and 75%-tiles quantifying the uncertainty range.

OUTPUT

Modelers supply annual dry matter yield (at 0% moisture), total biomass (all above-ground biomass plus yield at 0% moisture), and crop transpiration.

All simulated annual data will be added to the supplied template (one file with all simulations per crop) and sent to the University of Florida for processing.

The simulated data will be used to calculate % change under future climates, with and without adaptation, and the effect of elevated CO_2.

N, P, and K uptake will be calculated after the crop simulations at the University of Florida based on simulated biomass and yield and standard nutrient concentrations from the literature. A lower nutrient concentration under elevated atmospheric CO_2 will be considered. Ensemble mean and uncertainty ranges aggregated at the county, region, and national scale for impact and adaptation for each future period relative to the baseline period will be calculated at the University of Florida from the simulated data.

Any proportion of harvestable product left in the field (e.g., due to size or technology) will be calculated elsewhere.

OUTPUT FILE NAMING

Once the simulation has been completed, the results will be saved into the provided template ("Template-summary.xlsx"). If the model does not simulate one of the outputs, add "na" in each of the cells. The template files need to be renamed using the 2-LETTER model and 2-LETTER crop code from Table 6.

Result file names: ModelCode-CropCode.xlsx. (e.g., the result file of the CropSyst model for potato should be CS-Po.xlsx)

Table 6: 2-LETTER code for models and crops.

No.	Crop Model	2-Letter Name Code	Crop	2-Letter Name Code
1	SIMPLE	SI	Potato	Po
2	CropSyst	CS	Tomato	To
3	LINTUL-POTATO-DSS	LI	Sweet Corn	Sw
4	EPIC	EP	Orange	Or
5	DSSAT CSM-Substor-Potato	DC	Carrot	Ca
6			Green Bean	Gb
7			Strawberry	St
8			Spinach	Sp

SOURCE OF WEATHER DATA AND OUTPUT TEMPLATE

Daily weather data are available for each of the 32 counties (a 4×4 km grid cell) in a zip-file. The zip file includes a separate folder with weather data for the historical period (1980-2016) for the 32 locations and five folders, one for each GCM, for the future periods (2020-2099) with weather files for 32 locations. The weather file uses up to the first 6 letters from the county name for the file name.

All weather input data needed for the simulations will be provided by the University of Florida, along with a file for the yearly atmospheric CO_2 concentration and a template file for the output simulations.

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Appendix A: Potato

POTATO-SPECIFIC PARAMETERIZATION

Potatoes in the United States are harvested well before the natural maturity of the crop by killing the vines. The accumulated temperature requirement of a model for the baseline will be set for each county (assuming different maturity types for each county), assuming that canopy cover for potatoes will be about 80% at the harvest date. Crop models will be calibrated (harvest index should be kept between 0.5 and 0.9) to the reported gridded yield data from the year 2000 from Monfreda et al. (2008), which were corrected with yield data from variety trials from recent years (Table A1).

Table A1: Baseline potato tuber dry weight (use the corrected yields in last column for calibration) for the counties selected for modeling. Observed yields from Manfredo et al. (2008) for the year 2000 were increased by 3.6 t/ha to reflect the yield potential of more recent years, based on a comparison of several variety trial yields from recent years with the year 2000 data. As Fresno and Yolo (CA) had extremely low reported yields in Manfredo et al. (2008), yields for these two counties were replaced with nearby variety trial yields.

No.	State	County	Observed Tuber Dry Weight (t/ha)	Corrected Tuber Dry Weight (t/ha) (for calibration)
1	Arizona	Maricopa	7.26	10.86
2	California	Fresno	2.62	9.53
3	California	Imperial	7.47	11.07
4	California	Monterey	6.58	10.18
5	California	Yolo	2.75	9.53
6	Colorado	Rio Grande	8.53	12.13
7	Florida	Hendry	6.42	10.02
8	Florida	Polk	5.30	8.90
9	Florida	St. Johns	5.29	8.89
10	Georgia	Decatur	3.51	7.11
11	Idaho	Bingham	8.02	11.62
12	Idaho	Canyon	9.71	13.31
13	Idaho	Minidoka	9.26	12.86
14	Maine	Aroostook	5.65	9.25
15	Michigan	Montcalm	7.58	11.18
16	Michigan	St. Joseph	6.81	10.41
17	Minnesota	Dakota	3.25	6.85
18	Minnesota	Freeborn	6.49	10.09
19	Minnesota	Otter Tail	8.51	12.11
20	Minnesota	Renville	7.95	11.55
21	New York	Genesee	5.93	9.53
22	North Dakota	Walsh	4.49	8.09
23	Oregon	Marion	6.49	10.09
24	Oregon	Umatilla	13.33	16.93
25	Texas	Hidalgo	4.34	7.94
26	Washington	Benton	13.95	17.55
27	Washington	Grant	13.35	16.95
28	Washington	Skagit	4.59	8.19
29	Washington	Walla Walla	14.38	17.98
30	Wisconsin	Fond du Lac	2.06	5.66
31	Wisconsin	Langlade	7.72	11.32
32	Wisconsin	Portage	8.87	12.47

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Table A2: Baseline and future potato planting dates for the adaptation scenarios. For future scenarios without adaptation, the planting dates are the same as for the baseline period. The planting date will be applied to each year at a location. Planting dates are from CropSyst simulations, which determines the planting date based on a 15-day window above a base mean temperature of 13 °C. The potato season length data for the baseline and future scenarios are from Sacks et al. (2010). The season length (days from sowing to harvest) is the same for baseline and future scenarios, with and without adaptation. The season length should be used to calculate the harvest dates.

No.	State	County	Temperature-Based Planting Date (Day of Year)			Season Length (Days)
			Baseline	2030sAdaptation	2050sAdaptation	Baseline and Future Scenarios
1	Arizona	Maricopa	21	9	4	120
2	California	Fresno	64	45	32	120
3	California	Imperial	9	4	2	120
4	California	Monterey	51	24	13	120
5	California	Yolo	67	47	34	120
6	Colorado	Rio Grande	148	133	124	131
7	Florida	Hendry	2	1	1	110
8	Florida	Polk	3	2	2	110
9	Florida	St. Johns	8	7	4	110
10	Georgia	Decatur	26	18	15	130
11	Idaho	Bingham	138	118	110	140
12	Idaho	Canyon	120	98	87	140
13	Idaho	Minidoka	134	115	106	140
14	Maine	Aroostook	149	135	128	155
15	Michigan	Montcalm	132	117	112	114
16	Michigan	St. Joseph	118	108	104	114
17	Minnesota	Dakota	124	112	108	107
18	Minnesota	Freeborn	125	113	109	127
19	Minnesota	Otter Tail	134	123	118	127
20	Minnesota	Renville	123	113	110	127
21	New York	Genesee	125	112	107	110
22	North Dakota	Walsh	130	118	114	125
23	Oregon	Marion	127	105	96	130
24	Oregon	Umatilla	116	96	88	153
25	Texas	Hidalgo	3	2	2	110
26	Washington	Benton	117	97	89	148
27	Washington	Grant	125	106	98	148
28	Washington	Skagit	136	115	103	125
29	Washington	Walla Walla	115	94	83	148
30	Wisconsin	Fond du Lac	127	114	109	119
31	Wisconsin	Langlade	137	122	118	139
32	Wisconsin	Portage	130	116	111	139

Appendix B: Tomato

TOMATO-SPECIFIC PARAMETERIZATION

Tomatoes are harvested when a thermal time of 1214 degree-days (DD) is reached (Tbase = 10 °C), which has been found to work well for processing tomatoes in the most productive California counties. If the thermal time achieved is 1214 DD by harvest, then the harvest index is 0.63 for standard. However, in some cold regions, the tomato season will stop if the daily temperature for 7 consecutive days is less than 10 °C. Moreover, if the daily temperature for 14 consecutive days is less than 10 °C, the harvest index at harvest will be reduced and eventually becomes zero. An adjustment factor is used to adjust the standard harvest index, which is obtained from the linear relationships between the harvest indexes and degree-days. The adjustment factor multiplies the standard harvest index to yield the actual harvest index.

Table A3: Baseline and future tomato planting dates for the adaptation scenarios. For future scenarios without adaptation, the planting dates are the same as for the baseline period. The planting date will be applied to each year at a location. Planting dates are determined based on a 15-day window above a base mean temperature of 15 °C.

No.	State	County	Temperature-Based Planting Date (Day of Year)		
			Baseline	2030sAdaptation	2050sAdaptation
1	Arizona	Maricopa	44	25	15
2	California	Fresno	83	67	55
3	California	Imperial	25	13	8
4	California	Monterey	104	67	47
5	California	Yolo	87	70	60
6	Colorado	Rio Grande	160	148	138
7	Florida	Hendry	4	2	2
8	Florida	Polk	6	5	3
9	Florida	St. Johns	19	15	11
10	Georgia	Decatur	44	33	29
11	Idaho	Bingham	149	131	123
12	Idaho	Canyon	134	112	103
13	Idaho	Minidoka	148	129	120
14	Maine	Aroostook	162	147	140
15	Michigan	Montcalm	141	128	123
16	Michigan	St. Joseph	134	119	114
17	Minnesota	Dakota	135	122	116
18	Minnesota	Freeborn	136	123	119
19	Minnesota	Otter Tail	145	133	129
20	Minnesota	Renville	134	122	118
21	New York	Genesee	137	123	117
22	North Dakota	Walsh	138	128	125
23	Oregon	Marion	143	132	121
24	Oregon	Umatilla	131	118	107
25	Texas	Hidalgo	9	6	4
26	Washington	Benton	132	119	109
27	Washington	Grant	137	126	116
28	Washington	Skagit	160	141	123
29	Washington	Walla Walla	130	113	104
30	Wisconsin	Fond du Lac	138	124	119
31	Wisconsin	Langlade	151	134	130
32	Wisconsin	Portage	141	127	123