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Cooling Externality of Large-Scale Irrigation

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Abstract

We provide novel evidence that large-scale irrigation heterogeneously shifts the temperature distribution towards cooler temperatures during the months of the growing season relative to the rest of the year. We employ a triple-difference estimator using a 59-year-long panel of weather records paired with the fraction of a county that is irrigated in 393 counties over the Ogallala aquifer. Cooling-by-irrigation propagates downwind and reduces the upper tail of the temperature distribution by up to 3°C (5°F) during the month of August, which has positive externalities on downwind crop yields ($120 million per year) and temperature-induced excess mortality ($240 million per year) that are of equal magnitude as the direct benefits of irrigation by enhancing heat tolerance ($440 million per year). The observed cooling helps explain why the US has seen less warming, especially of very hot temperatures, than what climate models project. Our findings highlight that weather shocks in highly irrigated areas are not exogenous but are influenced by human responses in the form of irrigation.

Keywords: Irrigation, Temperature, Adaptation to Climate Change
JEL Codes: Q54, Q1, Q25

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There is a strong consensus that human activity is causing the climate to change[1], i.e., that greenhouse gas emissions are affecting the climate and numerous natural systems. There have been many studies in the economics literature documenting the reverse link, i.e., the effect of a changing climate and the depletion of natural resources on human systems and how humans can adapt to changing conditions.[2]

We provide novel evidence of an additional feedback loop that has received less attention, namely that adaptive behavior to climatic conditions itself has a measurable effect on the climate, especially in downwind areas, and the economic value this externality generates. In the context of agricultural production, adaptive behavior to better cope with hotter temperatures under the constraint of limited water resources induces significant regional changes in irrigation practices – both decreases as aquifers run dry and increases via irrigation expansion – which, as we show, affect local warming dynamics. More precisely, we empirically demonstrate that the widespread adoption of large-scale irrigation over the Ogallala aquifer has been historically responsible for a sizable and economically meaningful cooling externality affecting regional weather patterns in the southern US by reducing extreme heat, while by the same token areas that had to reduce irrigation as portions of the Ogallala aquifer got depleted saw additional warming.

Our paper makes five major contributions to the literature. First, a common theme that has emerged from recent empirical studies involving temperature effects is the detrimental impact of the upper tail of the temperature distribution. While adaptive behavior may counter-balance some of the harmful effects of higher temperatures[3], such strategies come at their own cost[4] and, in the case of irrigation intensification, remain subject to the availability of water suitable for sustainable irrigation.[5] To the best of our knowledge, there is limited *causal* evidence that adaptation to climate-induced constraints – such as the need for irrigation in the western tail of the Corn Belt or its progressive decline in northwestern Texas

[1]The American Association for the Advancement of Science put out a statement on December 9, 2006 that "the scientific evidence is clear: global climate change caused by human activities is occurring now."

[2]A select list includes the effect on agriculture (Schlenker and Roberts 2009, Burke and Emerick 2016), energy demand (Auffhammer and Aroonruengsawat 2011), mortality (Barreca, Clay, Deschenes, Greenstone and Shapiro 2016), labor supply (Graff Zivin and Neidell 2014), GDP growth (Dell, Jones and Olken 2012, Burke, Hsiang and Miguel 2015), amenity value of climate (Albouy, Graf, Kellogg and Wolff 2016) or freshwater supply (World Bank Group 2016).

[3]For instance, alternative crop varieties (Butler and Huybers 2013, Moscona and Sastry 2021) or the adaptation of irrigation (Haqiqi, Grogan, Hertel and Schlenker 2021) can reduce the sensitivity to extreme heat.

[4]Higher heat tolerance can only be achieved at the cost of lower average yields (Schlenker, Roberts and Lobell 2013)

[5]While some world regions have been in the position to grow large-scale irrigation in the long run (e.g., along the Ganges or the Yangtze), others have dramatically affected freshwater resources with significant consequences on irrigation practices (e.g., around the Aral Sea).

– has itself a measurable effect on the climate. While there have been farming myths (e.g., "the rain will follow the plow"), we demonstrate that large-scale irrigation can cause sizable local temperature changes. Such cooling via irrigation manifests heterogeneously along the entire temperature distribution with largest effects on the hottest temperatures and subsists besides the reduction in maximal temperatures related to cropland intensification (Mueller, Butler, McKinnon, Rhines, Tingley, Holbrook and Huybers 2016). Our findings are consistent with Grosset, Papp and Taylor (2023), who show that a large-scale tree planting program in response to the Dust Bowl has direct effects on downwind temperatures and precipitation.

Second, we show that the cooling-by-irrigation phenomenon propagates and significantly affects downwind areas. We quantify such positive externality on a few examples with high economic relevance. In terms of agricultural production, reducing crop exposure to extreme heat boosts yields. As far as corn and soybeans production is concerned, we find that some counties benefit even more from irrigation practices from their upwind neighbors than from their own "on-the-spot" irrigation efforts aiming at enhancing heat tolerance of irrigated crops. In terms of human health, we show that intensive irrigation is associated with a reduction in excess mortality during heat episodes for populations living downwind of irrigated land. The effects on these two sectors are a lower bound, as other sectors of the economy will also benefit from a decrease in extreme heat as soon as they are located downwind.

Third, our paper provides a partial explanation for why the observed warming trends, especially for hotter temperatures, has been lower than what is projected by climate models over the agricultural area in the United States (Schlenker 2020). We show that without the expansion of irrigation, the temperature trend would have been significantly altered in downwind areas.

Fourth, our paper has implications on the damages estimates of climate change. As regional irrigation practices are bound to continue to evolve in the coming decades due to increasing constraints on freshwater resources or new irrigation technologies, it is important to understand the extent to which irrigation is causing a cooling externality on extreme temperatures in order to anticipate the implications of these changes on local weather patterns besides the primary effect on crops and with numerous indirect effects on population health, the economy as well as ecosystems.

Fifth, our study has methodological implications for panel models which have become common place in the economics literature (Dell, Jones and Olken 2014). These paper generally assert that year-to-year weather shocks are exogenous. As we show below, in areas close to highly-irrigated agriculture, they are influenced by human behavior and therefore endogenous.

Building a 59-year-long panel linking daily weather records with irrigation data interpolated at the yearly level in a vast area surrounding the Ogallala aquifer (see Figure 1), we empirically investigate the effect of large-scale irrigation on downwind summertime temperatures. Our identification relies on the comparison of temperature distributions along three dimensions, namely in the long-run (across years), spatially (between counties with varying irrigation practices) and in the short-run (across the months of the growing season relative to the rest of the year). We find substantial cooling effect of irrigation that heterogeneously affects the entire summertime temperature distribution and induces important externalities propagating to the downwind county. In the region of interest, our fixed-effect specification detects that this cooling-by-irrigation externality is strongest in August and with respect to the highest temperature percentiles. Quantitatively, we estimate that irrigating all of a county's surface causes the August temperature distributions in downwind counties to shift the 95$^{\text{th}}$ temperature percentile by -3.4°C and the 5$^{\text{th}}$ temperature percentile by -1.5°C. Importantly, we observe this relationship is symmetric: while areas that expanded irrigation saw a reduction in their hottest temperatures, areas that decreased the irrigated area saw an increase, suggesting that continued irrigation temporarily limits temperature increases, but this cooling effect ceases as soon as irrigation stops.

While the cooling-by-irrigation phenomenon is likely to affect multiple dimensions of economic relevance, we focus on the quantification of two externalities that have been found in the past to have the highest monetized cost of extreme heat in rural agricultural areas: agricultural yield losses, for which we focus on corn and soybeans because they represent predominant crops in the area and the two largest crops by planting area in the US, as well as temperature-induced mortality.

First, by locally decreasing hot summertime temperatures, irrigation helps to safeguard yields not only for irrigated crops by increasing tolerance to hotter and drier weather, but also in nearby agricultural-intensive areas located downwind by reducing their exposure to harmful degree-days. We quantify this positive externality in the form of avoided yield losses for corn and soybeans and find this indirect (externalized) effect that is due to a cooling of temperatures to be *on average* 27% of the direct effect of irrigation on making the crop less vulnerable to hot temperatures. Although it is smaller on average, it can be locally important as there is significant heterogeneity. In some circumstances, counties benefit as much from the cooling effect induced by irrigation in upwind neighbors as from their own irrigation efforts. The effect may protect up to 9% of total corn production and 12% of total soybean production in specific counties and during relatively hot years. Moreover, this cooling externality of large-scale irrigation on downwind temperatures also benefits other crop varieties besides corn and soybeans, and we hence provide a lower bound of the overall effect.

Second, in terms of human health, intensive irrigation appears to curb the exposure to extreme heat for populations living in downwind areas, with beneficial consequences on reduced mortality during heat episodes. By fitting a regional and summer-specific temperature-mortality response function, we estimate that irrigation around the Ogallala has reduced 1,579 premature deaths since 1959, net of any harvesting effect. Again, a similar positive externality also exists with respect to animal health, with potentially significant effects on cattle farming which is intensive in the Great Plains.[6]

Our paper is organized as follows. Section 1 describes the context of our study and motivates the research question. Section 2 introduces the variables of interest and the underlying data. Section 3 describes and motivates the empirical strategy relying on a three-way fixed effect model. Section 4 presents and discusses the corresponding results while Section 5 examines the economic implications of the previous findings on the examples of boosted corn and soybean production (5.1) and reduced human mortality (5.2). Section 6 concludes and highlights perspectives for further investigation regarding the cooling-by-irrigation externality.

1 Study Setting and Motivation

Only a few regions benefit from an appropriate geology to sustain large-scale and intensive irrigation for agriculture. In the US, exceptional irrigation conditions are offered by one of the vastest aquifer system in the world, namely the High Plains Aquifer (see Figure 1). Also known as the "Ogallala Aquifer", this shallow groundwater reservoir covers a total surface of about 450,000 km^2, i.e. about the size of California or 1.8 times the area of the Great Lakes combined. Located in the Great Plains, it is shared by eight states in the central southern US. It is formed by three connected networks: the northern system covers most of Nebraska and only small portions of South Dakota, Wyoming, Colorado and Kansas; the central system is mostly located in Kansas and the northern tip of Texas but also covers the Oklahoma panhandle and small sections of Colorado and New Mexico; the southern system is shared between northwestern Texas and eastern New Mexico. The water is flowing, through porous soil and between impermeable layers, from the northern to the southern system at an average speed of only 45m per year under unperturbed conditions.[7]

Thanks to its unique positioning relative to the Ogallala aquifer in terms of overlapping

[6]More than 2,000 cattle died in Kansas during a single heat stress episode over June 2022.
[7]See `http://www.hpwd.org/aquifers/`.

area, underlying water volume[8] and upstream location on the northern High Plains system, Nebraska is the most vastly irrigated state in the US to this date, both in absolute irrigated area (34,800km^2 of irrigated land in 2017) and in relative proportion to its surface (17% in 2017).[9] Historically, however, and until the end of the 1950's, the irrigation hot-spot in eastern Nebraska was falling far behind several counties in northwestern Texas which had experienced the fastest growth in irrigation adoption after World War II (see Figure A15). In fact, large-scale irrigation in both Nebraska and Texas began in the second half of the 1940's, when the invention of center pivot irrigation and the widespread adoption of motorized groundwater pumps made it possible to fully exploit the Ogallala aquifer's unique irrigation potential (Hornbeck and Keskin 2014). More than half of all Nebraskan counties have been consistently growing their irrigation capacities over the last 80 years with some counties irrigating about 75% of their total land surface in 2017. The opposite trend is observed for some counties in northwestern Texas that irrigated an even higher proportion of their area in 1959 but could not expand any further due to the geological constraints imposed by the limited water recharge upstream. Over the last 59 years, high-irrigating counties in this region subsequently experienced a progressive decline in their irrigated land proportion. The divergent irrigation trajectories followed by, on the one hand, Nebraska (increasing its irrigation coverage) and, on the other hand, northwestern Texas (decreasing irrigation coverage) – due to their locations at opposite ends of the Ogallala aquifer – illustrate the critical importance of a sustainable water use management in agreement with the constraints imposed by hydrology as well as geology. Also, this contrast raises questions about the long-run viability of irrigation practices as currently practiced in the Great Plains in general (Harding and Snyder 2012). At the same time, it offers us the possibility to test whether the observed relationship is symmetric for increases and decreases in irrigation.

From a climate perspective, Nebraska and South Dakota are of particular interest as these states belong to the few regions in the US (besides some areas in Iowa) which did not experience any warming in their summertime temperatures over the last few decades (Schlenker 2020). In fact, coupled general circulation models typically fail to replicate the so-called "warming hole" actually observed as of the 1950's in summertime temperature trends over the Central US (Kunkel, Liang, Zhu and Lin 2006), allegedly due to the phenomenon's relatively fine scale requiring regional circulation-precipitation models (Pan, Ar-

[8]About two thirds of all water in the Ogallala aquifer is physically stored in Nebraska.

[9]This compares to the 31,700km^2 of irrigated land in the Central Valley (8% of total surface in California) and the 19,600km^2 of irrigated land around the Mississippi river in Arkansas (15% of total surface in Arkansas). In terms of total water use for irrigation, Nebraska ranks only 7$^{\text{th}}$ (behind California, Idaho, Arkansas, Montana, Colorado and Wyoming). In the present paper, we exclusively focus on the measure of irrigation in terms of irrigated land area.

ritt, Takle, Gutowski, Anderson and Segal 2004).[10] While Pan et al. (2004) conceive that "[t]he observed cooling may be partly attributable to irrigation on local scales", they eventually largely dismiss the role of irrigation in explaining the overall warming hole phenomenon despite working with a regional model. Their main argument is the mismatch in spatial scales between the relatively small total surface of irrigated land in the Great Plains and the relatively large extent of the observed warming hole. In fact, climatologists typically relate the warming hole in the Central US to the interaction of decadal oscillations in sea surface temperature in the Pacific and Atlantic oceans (Kunkel et al. 2006, Wang, Schubert, Suarez, Chen, Hoerling, Kumar and Pegion 2009, Robinson, Ruedy and Hansen 2002) without considering the potentially additional local influence of irrigation. Robinson et al. (2002) find that warmer sea surface temperatures over the tropical Pacific decrease temperatures in the Central US by impeding insulation through increased cloud cover and precipitation. Weaver (2013) further examine the role of the Great Plains low-level jet to induce additional precipitation and subsequent cooling of surface temperatures in this region specifically in the summer, without consideration for potential fine-scale impacts via irrigation practices.

Mueller et al. (2016) previously empirically estimated whether human management decisions can affect temperatures. Their preferred explanatory mechanism involves cropland intensification. They also find – specifically with respect to Nebraska, Arkansas and some parts in the western US – that greater irrigation trends are statistically significantly associated with some decline in *extreme* temperatures. Acknowledging the above literature, they nevertheless envisage that agricultural practices during the growing season may actually drive some degree of summertime cooling, especially with respect to hot temperature extremes in the Midwest.[11] However, their analysis relies on a correlation of trends in cropland intensification and trends in temperature, where it is less clear whether intensification caused cooling or whether cooling causes intensification. The novelty of our paper is threefold: first, we use a triple-difference estimator comparing summer months when land is irrigated to remaining months to make the identification more defensible. Second, we focus not only on the county itself but also on the beneficial cooling externality on neighboring countries. Third, we focus on irrigation over the Ogallala rather than cropland intensification. We detect a significant cooling-by-irrigation externality on the entire temperature distribution (and not only on the hot extremes, i.e., temperature extremes) and mainly for downwind areas (and

[10] Without relying on any irrigation information, Pan et al. (2004) predict a cool spot over a region in southeastern Nebraska when simulating maximum summertime temperature in the 2040's. This spot roughly corresponds to the nowadays most densely irrigated area in the US.

[11] Over their chosen time period, 1910-2014, Mueller et al. (2016) find evidence for some cooling of the 95^{th} percentile in the quantile regression in trends for daily temperature maxima. By contrast, they consider that "Midwest cooling is less evident" in the 50^{th} percentile and that there is some warming at the 5^{th} percentile of the quantile regression in trends for daily temperature maxima.

not only within-county effects). Therefore, while irrigation is unlikely to predominantly contribute to the long-run and large-scale cooling dynamics observed over the Central US as of the 1950's and which scientists attribute to hemispheric-scale natural forces shaping regional climate, we argue it may nevertheless leave some idiosyncratic, transient cooling signature in local weather patterns.

In fact, as illustrated in Figure 2, the observed 59-year-long evolution of average temperature changes[12] in the 99$^{\text{th}}$, 50$^{\text{th}}$ and 5$^{\text{th}}$ temperature percentiles in counties around the Ogallala already suggests the existence of a cooling phenomenon where irrigated land expanded in upwind counties (e.g., upstream of the Ogallala aquifer in eastern Nebraska) and, conversely, of a warming phenomenon where irrigated land declined in upwind counties (e.g., downstream of the Ogallala aquifer in northwestern Texas). Every bubble in Figure 2 corresponds to one of the 393 counties in the region of interest, with the size being proportional to the average irrigated land proportion as observed in the upwind county and the color being proportional to the observed irrigation trend in upwind neighbors.[13] Strikingly, counties with upwind irrigation in decline (red) have been, on average, warming the most in their 99$^{\text{th}}$ and 50$^{\text{th}}$ temperature percentiles during summer months, while those with increases in irrigation in their upwind neighbors (blue) have seen the highest degree of cooling. In other words, there is a vertical stratification of the warming/cooling dynamics according to upwind irrigation practices that can only be seen during summer months, when irrigation is actually taking place, but not during the rest of the year. Such stratification appears to be mostly pronounced with respect to hotter temperature percentiles and almost absent from the evolution of the 5$^{\text{th}}$ temperature percentile. Figure 2 therefore suggests[14] the existence of a fine-scale mechanism – likely involving direct evaporation of irrigated water as well as stimulated transpiration by plants (Lobell, Bonfils, Kueppers and Snyder 2008, Mahmood, Foster, Keeling, Hubbard, Carlson and Leeper 2006, Harding and Snyder 2012), that is not only localized in space (visible at the county-level resolution) but also in time (as farmers

[12] Average changes in the 99$^{\text{th}}$, 50$^{\text{th}}$ and 5$^{\text{st}}$ temperature percentiles are calculated as the estimated trend in monthly county-level observations of the respective temperature percentile over the 1959-2017 period (in °C/y) multiplied by the duration of the time window (i.e., 59 years).

[13] Note that most (upwind) counties in the region of interest hardly irrigate at all, and only see a very limited change in their irrigated land proportion over time (small bubbles are typically white). Conversely, upwind counties that practice large-scale irrigation have been either on a steadily increasing or decreasing trend (large bubbles are either blue or red).

[14] Since (upwind) counties with the strongest decline/increase in irrigation are mostly in Texas/Nebraska (see Figure 1) and since Texas is likely to have warmed more than Nebraska irrespective of irrigation practices, this preliminary observation of a correlation in the raw data is only suggestive of the cooling-by-irrigation effect and needs to be complemented as explained in Section 3. We also note, however, that virtually none of the control counties (in white) have been heating/cooling in a similar fashion despite being distributed under all possible latitudes in the region of study – an important detail which motivates the existence of an irrigation-specific effect irrespective of the previous reservation.

only irrigate cropland during specific months of the year).

2 Data

2.1 Irrigation Data

We extract year-by-county information about irrigated acres from each of the 20 USDA censuses which occurred between 1900 and 2017[15], and normalize by county area. The widespread adoption of large-scale irrigation has only been possible after World War II and the introduction of both pivot irrigation and motorized groundwater pumps (Hornbeck and Keskin 2014) – with only a few documented exceptions in Colorado and in Scotts Bluff county, Western Nebraska.[16] Figures A15 and A16 show, for each county in the region of study and by state, the county-by-county evolution of irrigated land proportion as well as the number of observed counties for each available census year. 1959 is the first year in the data for which (at least) some irrigation information is available in *every* county of the region of interest and will therefore serve as starting year in the subsequent analysis.

As the opportunity to irrigate cropland primarily depends on the proximity to a river or on the availability of water in an underlying aquifer, large-scale irrigation remains spatially restricted to specific counties, with record levels only found in Nebraska or Texas – although at different points in time as explained above. The irrigated land proportion has been steadily increasing in most of Nebraskan counties since 1959: by 2017, half of all counties in Nebraska irrigate more than 15% of their land, with some counties in eastern Nebraska reaching US-wide records of approximately 75%. However, such evolution is in stark contrast with the situation in (northwestern) Texas, where multiple counties achieved their peak irrigation levels (up to 75%) in 1959 and have observed a steadily declining trajectory since then. Several counties in Kansas have been irrigating more and more land since 1959 but in moderate proportions (in any event below 25%) when compared to Nebraska, and the few counties in Colorado that were already irrigating in 1959 have been maintaining their moderate irrigation levels throughout the period. Most counties in Colorado, however, never adopted large-scale irrigation, similarly to counties in New Mexico, South Dakota and Wyoming. In light of the above, it appears that the evolution of irrigated proportions displays significant serial as well as spatial correlation.

[15] Agricultural censuses took place in 1900, 1910, 1920, 1930, 1940, 1950, 1954, 1959, 1964, 1969, 1974, 1978, 1982, 1987, 1992, 1997, 2002, 2007, 2012 and 2017, years which are marked by vertical lines in Figures A15 and A16

[16] Early irrigation experiments have been conducted for instance in Scotts Bluff as early as 1890 by using an atypical network of canals and aeromotor windmills for the irrigation and production of sugar beets. See https://www.nps.gov/nr/travel/scotts_bluff/essay_agriculture.html

To facilitate visualization of the raw data, we estimate long-run time trends in irrigation as the slope coefficients $\hat{\iota}_i$, separately estimated for each county i:

$$I_{iy} = \iota_{io} + \iota_i y + e_{iy} \tag{1}$$

where I_{iy} measures the proportion of irrigated area in county i in census year y (as of 1959). The quantity ι_{io} is the county-specific intercept, while the coefficient ι_i measures the county-specific trend in irrigation and e_{iy} is the county-specific error term. Figure 1 shows the resulting map of $\hat{\iota}_{\cdot}$ in the region of interest.

2.2 Temperature Data

Temperature records are collected from an extended version of the fine-scaled dataset used by Schlenker and Roberts (2009), which combines data from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) with information gathered by a fixed set of weather stations. The raw data correspond to daily minima and maxima in temperature over a 4km-by-4km grid covering the region of interest from January 1st, 1959 to December 31st, 2017. The uptake of large-scale irrigation occurred as of the 1940's following the invention of center pivots and the introduction of motorized groundwater pumps. However, the full coverage of the region by meteorological stations is only complete by the end of the 1950's (see Figure A17 and Figure A18).[17]

For each grid cell and for each day within that period, we interpolate a (sinusoidal) temperature profile following Snyder (1985) to calculate the amount of time spent at each possible 1°C-wide temperature bin (e.g., amount of time in a given day and for a given grid cell for which the temperature falls between 19°C and 20°C, between 20°C and 21°C, etc.). These daily counts are then aggregated to a county-by-month resolution to construct individual distributions in temperature for each of the 393 counties around the Ogallala aquifer and for each of the 708 months between 1959 and 2017.[18] Specifically, the time spent at each 1°C interval allows us to construct the cumulative density function for each month. In order to detect potentially heterogeneous effects at different temperature levels, we extract from each of these individual county-by-month temperature distributions a set of temperature percentiles (namely, from warmest to coolest: the 99th, 95th, 90th, 75th, 50th, 25th, 10th, 5th and 1st temperature percentiles).

To facilitate the visualization of the raw data and in line with the earlier approach

[17]On top of this, 1959 is the first census year for which some irrigation information is available in every county of the region of interest (see below as well as Figures A15 and A16).

[18]While previous studies average the weather data by the cropland area in each PRISM grid, our main interest is the effect of irrigation on weather throughout a county and we hence do not weight grids.

adopted towards the raw irrigation data, we estimate for each county and month of the year the long-run warming or cooling behavior by computing time trends in each of our chosen temperature percentiles p over the period of interest. Formally, for any given county i (e.g., Lincoln) and month m (e.g., April), we separately estimate the slope coefficients $\hat{\theta}^p_{im}$ of the regression:

$$T^p_{imy} = \theta^p_{imo} + \theta^p_{im} y + e^p_{imy} \tag{2}$$

where T^p_{imy} is the temperature level at some chosen percentile p, in county i during month m of year y. θ^p_{imo} is the county-month-percentile specific intercept, θ^p_{im} measures the county-month-percentile specific warming (or cooling) trend and e^p_{imy} is the county-month-percentile specific error term. Figure 2 illustrates the distributions of $\hat{\theta}^{99}_{\cdot m}$, $\hat{\theta}^{50}_{\cdot m}$ and $\hat{\theta}^{5}_{\cdot m}$ (up to a factor 2017-1959+1=59) for each month m of the year and Figure A19 shows maps of $\hat{\theta}^{99}_{\cdot April}$, $\hat{\theta}^{99}_{\cdot July}$, $\hat{\theta}^{50}_{\cdot April}$ and $\hat{\theta}^{50}_{\cdot July}$.

2.3 Precipitation Data

Precipitation correlates with both temperature and irrigation levels as more rain is typically associated with higher temperatures and lower requirements for irrigation. If omitted from the analysis, precipitation may thus confound the naively estimated effect of irrigation on temperature and negatively bias estimates.

Precipitation data come from the same source as our temperature variables (see Section 2.2). The raw data consist in daily observations of total precipitation levels on a 4km-by-4km grid over the region of interest, which we adjust to monthly totals at the county level. Figure A20 illustrates the raw data under the form of maps in precipitation trends for April and July. More specifically, it represents long-run changes in precipitation as measured by the slope coefficients ρ_{im} in the regression:

$$R_{imy} = \rho_{imo} + \rho_{im} y + e_{imy} \tag{3}$$

where R_{imy} is the total rainfall (precipitation) in county i during month m in year y. The quantity ρ_{imo} measures the county-month specific intercept, while the coefficient ρ_{im} is the county-month specific trend in rainfall and e_{imy} is the county-month specific error term.

2.4 Wind Data

In order to explore the extent to which irrigation induces a (cooling) externality on neighboring counties, we exploit additional information about dominant wind directions. Since the dependent variable measures drybulb air temperature, any potential cooling effect of irrigation should only propagate downwind. Verifying the absence (or more nuanced presence) of any externality on counties located crosswind or upwind may thus serve as a falsification check to validate our specification.

For this purpose, we use hourly measures of latitudinal and longitudinal wind speeds between 1979 and 2019 on a 0.125° grid from the North American Land Data Assimilation System (NLDAS). From the orthogonal wind speed components averaged at county level, we deduce the hourly dominant direction of wind flow and, for each county in the region of interest and month of the year, we eventually select among all adjacent counties – even if located *outside* the region of interest – those which are most often located up-, cross- and downwind. Importantly, we do not construct the average wind direction but rather choose the county that is *most frequently* upwind as "upwind" county, etc. Wind direction may be more or less consistent over the day (and *a fortiori* over the month), and in some instance flip by 180 degrees for parts of the day, so that an *average* wind direction would be less meaningful than selecting the county that is *most often* associated with a chosen direction. Clearly, the proposed identification of "upwind", "crosswind" and "downwind" neighboring counties only accounts for the *dominant* wind direction and may therefore hide some of the variation inherent to changing wind patterns over any given month. However, we argue this approximation is facilitated in the present case by the fact that wind is predominantly blowing from South to North during summer months, as shown by the monthly distributions of hourly wind directions aggregated across all counties in the area of interest and over the entire 1979-2017 period (see Figure A21). As this observation holds at an aggregated level, it necessarily also holds individually for most counties in the region of interest – a feature which facilitates the identification strategy proposed in Section 3. On top of this, we assume that wind speed observations made between 1979 and 2019 are representative of overall wind flow conditions for the entire period between 1959 to 2017, an assumption we can only partially validate by restricting the data to smaller subsets and verifying this does not materially influence the classification into up-, cross- and downwind counties.[19]

2.5 Corn and Soybeans Yield Data

For each year in the 1959-2017 period, we extract yield data for corn and soybeans in each of the 393 counties in the region of interest from the National Agricultural Statistical Service (NASS) provided by the US Department of Agriculture.[20] Yields are computed as total

[19]For instance, our classification is hardly affected when considering a much smaller proportion of the wind dataset (e.g., 2007-2019, representing the most recent third).

[20]NASS does not report production data for soybeans in each of Wyoming, Colorado and New Mexico.

yearly county-level production divided by the number of harvested acres.

2.6 Mortality and Population Data

Similarly to Barreca et al. (2016), we rely on the Multiple Cause of Death (MOCD) data which has publicly available county-level information about deaths counts for each month between January 1959 and December 1988. For the counties of the region of interest, we restrict the data to the period from April to September because, on the one hand, the cooling-by-irrigation externality is restricted to the growing season (i.e., we are not concerned with excess mortality due to extremely cold days during winter months) and, on the other hand, the mortality literature documents a temporal displacement of deaths caused by heat episodes (harvesting) which may last more than one month.[21] The data also includes categorical information about causes of death and age of the decedent, but we do not exploit these levels of information and pool all deaths together in order to work with county-by-year data.

In order to compute mortality rates, defined as the number of deaths per 100,000 people, we collect county-level population counts from the Centers of Disease Control and Prevention (CDC) for each year between 1968 and 1988. In order to complement this data to cover the entire 1959-1988 period, we use population counts from the decennial US Censuses of 1950 and 1960 and linearly interpolate county-level population data for each year between 1950 and 1960 as well as between 1960 and 1968.

Eventually, while our temperature-mortality response function is fitted on the 30-year-period spanning from 1959 to 1988, we will extrapolate the model fit to estimate death counts until 2017. For this purpose, we rely on intercensal population estimates from the US Census Bureau for each year between 1989 and 2017.

3 Empirical Strategy

We identify the effect of irrigation on local temperature in the region of interest around the Ogallala by comparing monthly temperature percentiles along three dimensions, namely in the long-run (across 59 years), spatially (between counties with varying irrigation levels) and in the short-run (across months during the growing season and relative to the rest of the year). While we do not actually observe irrigation at the monthly level and have to rely on linearly interpolated data (across agricultural census years) at the yearly level, we exploit the fact that irrigation is highly seasonal and it generally occurs between April and September,

[21] In the literature, the preferred duration of the displacement window to capture harvesting varies substantially, between one month (e.g., (Barreca et al. 2016)) to up to one year (e.g., (Deschênes and Greenstone 2011)).

at least in our study region, when the soil water deficit is highest and the growing season is active. Estimating the time profile of the delayed cooling effect is unfortunately not feasible as we don't have the data on when irrigation is exactly applied. Our data allows us to explore whether temperature-related externalities may spatially propagate from one irrigated county to its neighbors. In fact, as our dependent variable in temperature percentiles is related to air temperature measures, one would expect such effects to travel with the dominant wind direction. We compute the effect of irrigation on temperature for each month between April and September by interacting month-level dummies with year-level irrigation data observed in same, up-, cross- and downwind counties. Such specification is given by

$$T^p_{imy} = \sum_{n=4}^{9} \boldsymbol{\beta}^p_n \, \boldsymbol{I}_{iny} \, \mathbb{1}_{\{n=m\}} + \varepsilon^p_{imy} \tag{4}$$

where the vector $\boldsymbol{I}_{imy} = (I_{iy}, I_{i_{up}(m)y}, I_{i_{cross}(m)y}, I_{i_{down}(m)y})'$ measures the proportion of irrigated area in county i as well as in its (month-specific) up-, cross- and downwind neighbors ($i_{up}(m)$, $i_{cross}(m)$ and $i_{down}(m)$ respectively), $\mathbb{1}_{\{n=m\}}$ is a dummy variable equal to 1 in month m and zero otherwise and ε^p_{imy} is the error term. Note that, while the available irrigation information I_{iy} in itself is independent of the month, its influence on temperature is mediated by wind for which we have monthly observations, implying that $\boldsymbol{I}_{imy}$ is month-dependent. Equation (4) fixes October to March as reference period for comparison, a modelling choice that reflects the fact that no irrigation is taking place during that half of the year.

Clearly, specification (4) is by no means causal and would merely reflect the existence of some *association* between temperature and irrigation features. Several factors may correlate with local evolution in both temperature and irrigation levels. For instance, more rain is typically associated with higher temperatures and lower requirements for irrigation, lower latitudes in the region of interest reflect hotter climate conditions as well as lower irrigation potential due to the characteristics inherent to the Ogallala aquifer, elevation translates into cooler temperatures and more difficult irrigation conditions, thickness of the sedimentary deposit correlates with groundwater potential for irrigation (see Taylor (2021)) and may influence temperature via the influence of soil moisture, several soil characteristics such as permeability, erodibility or clay content may influence local water capacity, etc. If omitted from the analysis or uncontrolled for in the specification, such confounders could bias the naively estimated "effect" of irrigation on temperature.

Therefore, we propose to augment specification (4) into the following three-way fixed effect model with additional controls for monthly precipitation levels:

$$T^p_{imy} = \sum_{n=4}^{9} \boldsymbol{\beta}^p_n \, \boldsymbol{I}_{iny} \, \mathbb{1}_{\{n=m\}} + \boldsymbol{\gamma}^p \boldsymbol{R}_{iL(m,y)} + \pi^p_{im} + \sigma^p_{my} + \tau^p_{iy} + \varepsilon^p_{imy} \tag{5}$$

where the vector $\boldsymbol{R}_{iL(m,y)} = (R_{iL(m,y)}, R_{i_{up}(m-1)L(m,y)}, R_{i_{cross}(m-1)L(m,y)}, R_{i_{down}(m-1)L(m,y)})'$ measures previous-month[22] precipitation levels in current, up- cross- and downwind counties and π^p_{im}, σ^p_{my} and τ^p_{iy} respectively denote county-by-month, month-by-year and county-by-year fixed effects. Note that it would be inappropriate in specification (5) to control for contemporaneous precipitation information as same-month precipitation levels may itself be influenced by irrigation as well as precipitation in downwind areas.[23] As such, contemporaneous precipitation levels would constitute a "bad control" if included in our regression framework. In light of the above considerations, all of our specifications will control for observed county-level measures of precipitation but with a 1-month lag. As we show below, including or excluding precipitation (whether lagged, both in time or space, or concurrent levels are included and whether they are allowed to vary by month) has very limited effects on our temperature coefficients. Since both crop yields and temperature-induced excess-mortality responds much more strongly to temperature than precipitation, we focus on the former as it is the main driver of the estimated economic benefits.

Also, note that the proposed set of fixed effects absorbs a vast panel of omitted features (including any time-invariant confounders such as latitude, elevation, sedimentary soil depth, groundwater potential, soil permeability, erodibility or local water capacity) and therefore constitutes our preferred specification in the remainder.

For any chosen temperature percentile p, the set of 24 coefficients of interest (i.e., individual elements of the row vectors $\boldsymbol{\beta}^p_n$) measures the average month-specific effects of irrigation in the same, up-, cross- and downwind counties relative to the reference period (which runs from October to March), net of the influence of previous-month precipitation and from any county-by-month, month-by-year and county-by-year specificities. Given that irrigation is measured as the proportion of irrigated land, a "unit-increase" in irrigation reflects the fact to fully irrigate a county that was not previously irrigated at all. By construction, such coefficients are estimated *jointly* for same, up-, cross- and downwind counties so that spillover effects in various directions are simultaneously estimated, net from each other and net from the same-county effect. Importantly, identification originates from variations of the variables

[22] $L(m, y)$ denotes the monthly lag operator. For instance, $L(1, y) = (12, y - 1)$ and $L(2, y) = (1, y)$.

[23] Several studies – see for instance (Barnston and Schickedanz 1984, Moore and Rojstaczer 2001, Alter, Fan, Lintner and Weaver 2015, DeAngelis, Dominguez, Fan, Robock, Kustu and Robinson 2010) – substantiate that intensive irrigation in the Great Plains may result in higher downwind precipitation levels.

of interest across counties, over years and between months. Any simple comparison of temperature percentiles between month n of the growing season and the reference period in a given irrigated county would be inappropriate as observed differences may in fact result from changes unrelated to irrigation and that occur in *all* counties within the region of interest. Similarly, any simple comparison between irrigated and non-irrigated counties in any given month n of the growing season would fail to account for the fact that irrigated counties are typically already hotter in the spring and before irrigation actually takes place. The underlying identification assumption is that, in the absence of irrigation, an actually fully irrigated county *would* have experienced a parallel warming (or cooling) between the reference period and month n when compared to a non-irrigated county.

As intensive irrigation can be reasonably expected to peak in the hottest months of the year, we should expect to find the largest coefficient magnitudes during July and August and to detect only small effects (if any) in the early season (April) and late season (September). Similarly, since the dependent variable relates to drybulb air temperature, any cooling externality should be expected to propagate exclusively downwind, meaning that the spillover effects coming from cross- and downwind counties should be estimated close to zero, or at least statistically indistinguishable from zero. This set of intuitive predictions with respect to the relative magnitudes of the cooling-by-irrigation externality across months of the growing season and to the expected direction of spillover effects from irrigating neighbors located cross- and downwind allow to empirically appreciate and assess the performance of the estimation strategy, the results of which are presented in the following section.

4 Results

For each of the 99th, 95th, 90th, 75th, 50th, 25th, 10th, 5th and 1st temperature percentiles, specification (5) consistently suggests the existence of some highly statistically significant *cooling* externality offered by irrigation practiced in upwind neighbors, with a peak effect in August. Results are summarized for the 99th, 90th, 75th, 50th, 25th and 5th temperature percentiles in Figure 3 as well as Table 1, where standard errors are two-way clustered by county and year. The cooling externality is most pronounced with respect to warmer temperatures and progressively decreases in magnitude with cooler temperature percentiles. Quantitatively, the fact to fully irrigate an upwind county is estimated to translate, in August and relatively to the October-March period, into a -3.05°C drop in the 99th temperature percentile and only into a -1.45°C decrease in the 5th temperature percentile, with intermediate values for the other percentiles (e.g., -1.95°C for median temperatures). Same-county irrigation is not detected to cause any comparable cooling effect, with point estimates remaining in any event below .4°C in absolute value and typically much lower statistical significance. Given that most of the economic implications involving temperature effects in the summer relate to extreme heat, the significant externality from upwind irrigation on the hottest temperatures is of greatest interest and will be discussed in more details in Section 5 with respect to the examples of improved agricultural production as well as reduced excess human mortality.

While the cooling-by-irrigation externality appears to be strongest in August, results do not typically exhibit statistical significance in either April or in September, which is consistent with the fact that these early- and late-season months are outside of the peak irrigation season and validates the choice of October-March as a reference period. As predicted, the cooling-by-irrigation effect as measured by the drybulb air temperature travels with (and not against or across) the dominant wind direction. In fact, coefficients in front of regressors pertaining to the upwind irrigation information are *systematically* much larger in magnitude than their equivalent coefficients for cross- and downwind regressors. Similarly, the former coefficients typically achieve much higher statistical significance levels and are all statistically significant at the 1% level in each of June, July and August (except for the 5^{th} temperature percentile in July), which corresponds to the hottest months with presumably the highest levels in irrigation. The fact that the latter coefficients are regularly significant (albeit smaller in magnitude) may reflect the limitations inherent to our classification along the dominant wind direction. In fact, such classification is only most frequently true and does not account for the fact that wind flow may largely diverge from its modal direction over the duration of a month. For instance, our classification does not capture bi-modal distributions of wind directions, although shifts as large as 180° are not uncommon in practice. As such, the cooling externality coming from upwind counties is – for some fraction of time – erroneously classified as coming from cross- or downwind. Figure A12 therefore explores an alternative approach to the measure of upwind irrigation by averaging across irrigation levels from all neighboring counties weighted by the amount of time each of these is actually upwind. Estimates remain robust to this change in methodology to account for upwind irrigation. The downside of the weighted average of all neighboring counties is that we have no "faslification" sample in the form of cross- and downwind areas. In the remainder, we therefore focus on the cooling-by-irrigation externality from the upwind direction. This approach is conservative as some of the cooling effect is actually "lost" in favor of other (misclassified) wind directions.

We obtain similar findings under a series of sensitivity checks. Figure A1 compares our baseline results that two-way cluster by county and year to using Conley standard errors that account for both serial as well as spatial correlation with a Bartlett kernel and a 1,000km cutoff distance, with comparable standard errors. Generally, same-county effects are the most precisely estimated with the smallest standard errors at every month between April and September. Comparatively larger standard errors for coefficients related to neighboring counties is likely to reflect the greater uncertainty inherited from the wind data via the classification into up-, cross- and downwind neighbors.

Sensitivity checks to the chosen specification in terms of irrigation controls from neighboring counties are explored in the Appendix (see Tables A1 - A3 for regression results and graphical visualizations in Figures A2-A8 where we compare baseline estimates against modifications). Given the spatial correlation in irrigation trends, exclusively including the county itself or any one neighbor gives significant results. As soon as upwind irrigation trends are excluded, they become the stable dominant driver of observed temperature trends. Similarly, we explore the sensitivity to various precipitation controls in Figures A9-A11), where we vary what controls to include (if any at all). Including / excluding various effects has an indiscernible effect on our estimated temperature effects.

In order to test the robustness of our model findings, we also fit specification (5) on separate subsets of the initial data. As shown on Figure 1, the northern and southern halves of the dataset have seen fundamentally different irrigation dynamics, and we propose to verify whether each of these two observed dynamics *individually* confirm the existence of some cooling-by-irrigation externality. Results for the northern part (including Nebraska, Colorado, Wyoming, South Dakota and Kansas) and the southern part (including Texas, Oklahoma and New Mexico) are displayed in Tables A4 and A5 respectively, as well as in Figures A13 and A14. While the magnitudes of the upwind irrigation externality estimated for the northern half remain in rough agreement with initial results, those estimated for the southern half are smaller and slightly less statistically significant, likely due to the much smaller amount of irrigated counties in the southern half (see Figure 1). Irrespective of this, these also confirm the overall conclusions made earlier – in particular with respect to the cooling-by-irrigation externality originating predominantly in upwind irrigation areas. Importantly, this confirmation is found despite the fact that the northern part consists of counties with a strong *increase* in irrigation, while the southern part consists of counties with a strong *decrease* in irrigation. This is in line with the observation already made in Figure 2 where counties which historically saw a decline in irrigation induced some warming in neighboring areas. Such symmetric relationship has, to the best of our knowledge, not yet been documented in the literature.

5 Discussion

In order to illustrate some practical consequences of the cooling-by-irrigation externality, we evaluate its unintended but beneficial effects for counties located downwind in the form of avoided yield losses for agricultural production (Section 5.1) as well as on avoided excess mortality (Section 5.2). In particular, we show that the cooling-by-irrigation externality can generate locally sizable effects, with certain counties benefiting *more* from upwind than from own irrigation practices when growing corn or soybeans, and with specific counties seeing substantially lower mortality during heat episodes thanks to upwind irrigation.

5.1 Irrigation externality on downwind agricultural yields

Large-scale irrigation has historically allowed farmers to grow crops in parts of the Great Plains that would otherwise be locally unsuitable for intensive agriculture. For instance, corn and soybeans require a substantial amount of water for healthy growth and are very vulnerable to droughts due to their shallow root systems. In the US, large-scale corn production is primarily found in the Corn Belt – where corn is predominantly rainfed with the notable exception of its western tail located in Nebraska and which is heavily irrigated – as well as in specific regions with access to abundant water supply for irrigation such as above the Ogallala aquifer or in the Arkansas delta. In fact, the very disposition of the Ogallala aquifer can be easily recognized from a map of average corn area grown in the US.[24] Soybeans are typically grown in rotation with corn due to complementary behavior in nitrogen uptake (corn) and deposition (soybeans) in the soil and can therefore be found within the same counties.

Besides allowing farmers to adjust water supply to precipitation conditions, irrigation serves as an adaptation strategy against heat (Li, Guan, Peng, Franz, Wardlow and Pan 2020, Taylor 2021) as it increases the vegetation's tolerance to high temperatures. While yields for corn and soybeans only marginally benefit from moderate degree-days over the growing season, they severely suffer from particularly hot degree-days (Schlenker and Roberts 2009). A primary consequence of irrigation is the alteration of this non-linear response function linking crop yields to heat exposure so that plants become more resilient to extreme temperatures (the "direct effect").[25] On top of this beneficial effect which occurs on the spot,

[24] See, for instance, Map 1 in Schlenker (2020)

[25] For instance, when fitting the piece-wise linear specification proposed by Schlenker and Roberts (2009) on historic log yields for corn (or soybeans) between 1959 and 2017 in the region of interest, we find (i) a steeper slope coefficient for the detrimental effect of heat and (ii) an earlier threshold for such effects to manifest in non-irrigating counties when compared to irrigating counties.

we have shown above that irrigation is also responsible for cooling downwind temperatures.[26] Figure 4 illustrates the practical implications of this externality in terms of degree-days on the example of Merrick county, NE and shows how irrigation in upwind neighbors has been historically responsible for a substantial reduction in heat exposure. This secondary and unintended effect on temperature patterns in turn indirectly benefits plant growth in counties located downwind by cooling the entire temperature distribution and thereby protecting crops from extreme heat exposure (the "indirect effect"). In other words, farmers who practice large-scale irrigation do not only benefit from such investment in the form of higher yields in their own fields but unintentionally also favor production levels in neighboring fields located downwind. We propose to quantify this positive externality at the county level in the form of avoided corn and soybean production losses, and to compare these benefits to those induced by the direct effect in the region of interest. In order to appreciate each of these effects in isolation, we simulate counterfactual production outcomes respectively (i) under actual heat exposure *but for alternative response functions to heat* (i.e., with and without the direct effect of irrigation) and (ii) for actual response functions to heat *but under alternative heat exposure* (i.e., with and without the indirect effect of irrigation).

In order to quantify the direct effect of irrigation on agricultural production, we compute the temperature exposure of every county in the region of interest, over the entire growing season (i.e., from April to September) and for each year between 1959 and 2017. We then combine these distributions with observed yields to empirically estimate irrigation-dependent heat response functions under actual irrigation levels, and estimate a counterfactual scenario without irrigation. The estimation is conducted separately for corn and soybeans. In order to model the sensitivity of the heat response function to irrigation, we adapt the piece-wise linear specification in (log) yield proposed by Schlenker and Roberts (2009) by allowing the effect of harmful degree-days to vary linearly in a county's irrigation level. Using the same methodology as in Schlenker and Roberts (2009) and the same break-point temperatures separating beneficial from harmful degree-days, we find, with respect to corn, a positive slope of 0.00024 (p-value below 1%) for degree-days between 10 and 29°C and a linearly-varying slope of $-0.00354+0.00467\times I_{iy}$ (with respective p-values below 1%) for harmful degree-days. With respect to soybeans, we find a positive slope of 0.00043 (p-value below 1%) for degree-days between 10 and 30°C and a linearly-varying slope of $-0.00551 + 0.01156 \times I_{iy}$ (with respective p-values below 1%) for harmful degree-days. The respective irrigation-dependent slopes suggest that, for counties irrigated at 25% of their surface, the substitution of a full

[26] Using satellite measurements of daytime land surface temperature in Nebraska between 2003 and 2016, (Li et al. 2020) find that irrigation is correlated with some local cooling effect but do not investigate spatial spillover effects.

day at 33°C with a full day at 34°C during the growing season is associated, on average, with approximate declines of 0.35% in corn and 0.55% in soybean yields for non-irrigated counties but a decline of only 0.24% in corn and 0.26% in soybean yields. Left panels in Figure 5 (corn) and Figure 6 (soybeans) illustrate the spatial distribution of avoided production losses in absolute levels as well as relatively to total production. On aggregate over the 1959-2017 period and according to the proposed methodology, the direct effect is responsible for the additional production of 3.8 billion bushels of corn and .6 billion bushels of soybeans, respectively representing about 5% and 6% of total production or $26 billion (inflation-adjusted to $2017) in aggregate market value.[27] Virtually all of these avoided production losses occur within the boundary of the Ogallala aquifer, in agreement with areas where large-scale irrigation is possible: 64% of the total corn and 67% of total soybean production in the region of interest comes from Nebraska, and high proportions of the beneficial effect of irrigation on yields are also found in this particular state (66% for corn and 82% for soybeans). Nevertheless, the direct effect also achieves sizeable proportions of additional production in counties located in northwestern Texas (up to 30% for corn and 50% for soybeans) and western Kansas (up to 26% for corn and 45% for soybeans), where temperatures are higher and total agricultural production is more limited on average than in eastern Nebraska.

In order to estimate avoided production losses due to the indirect effect, we empirically determine the heat response functions of corn and soybeans using the piece-wise linear specification in (log) yield proposed by Schlenker and Roberts (2009), i.e., without consideration for irrigation information. With respect to corn, the effect of beneficial degree-days (i.e., 10-29°C) becomes 0.00026 (p-value below 1%) and the effect of harmful degree-days above 29°C is fixed at -0.00325 (p-value below 1%); with respect to soybeans, the effect of beneficial degree-days (i.e., 10-30°C) becomes 0.00048 (p-value below 1%) and the effect of harmful degree-days is fixed at -0.00483 (p-value below 1%). The slopes of harmful degree-days respectively suggests that the substitution of a full day at 33°C with a full day at 34°C is associated, on average, with approximate declines of 0.33% in corn and 0.48% in soybean yields – which is in relatively close agreement with the previous models under no-irrigation conditions. These irrigation-invariant response functions are then separately applied to the actual heat distribution and to a simulated counterfactual scenario from which the cooling-by-irrigation effect from upwind irrigation has been subtracted.[28] More precisely, month-

[27]Historical corn and soybean prices are downloaded from *Quick Stats* by the National Agricultural Statistics Service (NASS) of the US Department of Agriculture.

[28]For simplicity and in order to produce conservative estimates, we neglect to take into account the cooling effect detected for irrigation in same, cross- and downwind counties (see Table 1). The cooling effect originating from same-county irrigation is not statistically significant with respect to hottest temperatures, for which the impact on corn yields is most important, and remains substantially smaller in magnitude when compared to the effect from upwind-county irrigation. Similarly, the cooling effect measured with respect

specific counterfactual temperature percentiles are predicted based on the effects obtained from fitting specification (5). A cumulative distribution function of heat exposure is linearly interpolated between the 0.001st, 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, 99th and 99.999th temperature percentiles for each individual month of the growing season in order to construct the cumulative distribution function of heat exposure over the entire growing season. Since irrigation is responsible for some cooling, the counterfactual distributions (without irrigation) display a slightly heavier exposure to warmer temperatures, and especially so with respect to the warmest temperature percentiles.

Right panels in Figure 5 (corn) and Figure 6 (soybeans) illustrate the spatial distribution of avoided production losses due to the indirect effect in absolute levels as well as relatively to total production. On aggregate over the 1959-2017 period and according to the proposed methodology, the indirect effect is responsible for the additional production of 1.2 billion bushels of corn and 0.1 billion bushels of soybeans, respectively representing about 1.6% and 1.4% of total production or $7 billion (inflation-adjusted to $2017) in aggregate market value. Again, the majority of avoided losses due to the indirect effect can be allocated to Nebraska (72% for corn and 82% for soybeans) and almost all of these avoided production losses occur within the boundary of the Ogallala, with large year-to-year and county-level fluctuations depending on specific weather conditions. For instance, during extreme heat episodes, avoided losses may constitute up to 9% of total corn production or 12% of total soybean production in some selected counties. Figures A22 and A23 show the yearly evolution of avoided production losses in absolute terms and in proportions to total production for the overall region of interest and for Nebraska in particular. Over the period of interest, the proportion of avoided losses has been ramping up until the mid-1970's before stabilizing at around 1.5-2% on average, implying that the long-run evolution of avoided losses, in volume, roughly follows the overall trend in production. By contrast, short-run shocks (e.g., during the heat wave of 2012) evolve in opposite directions. Indeed, particularly hot years are associated with both a marked decline in total production and a surge in the amount of avoided crop losses due to the strong non-linearity in the yield response to extreme temperatures. By contrast, years deprived from extreme heat episodes (e.g., in years following the eruption of Mount Pinatubo in 1991) see relatively high yields irrespective of the cooling-by-irrigation effect. In 2012, avoided losses culminated at 46 million bushels of corn and 7 million bushels of soybeans (or an aggregate of $445 million given the market value in 2012)[29], a record level due to an extreme heat episode. Although exceptional in the last decade, such situations

to cross- and downwind irrigation levels reaches lower statistical significance and exhibits much smaller coefficients than for upwind irrigation levels.

[29]This compares to 183 million bushels of corn and 40 million of bushels of soybeans (or an aggregate of $1,963 million) for avoided losses due to the direct effect in 2012 alone.

may in fact become far more frequent in the context of an overall warming climate and exacerbated heat episodes.

In light of the above, the indirect effect appears to be *smaller* by an average factor of 3.7 (in terms of market value) than the direct effect. This is in rough agreement with (Li et al. 2020) who explore a similar question in Nebraska and estimate that "16% or irrigation yield increase is due to irrigation cooling, while the rest (84%) is due to water supply and other factors".[30] However, in contrast to the "on-the-spot" feature of the direct effect, the indirect effect consists in an *externality* and is typically shifted by one county northwards – in agreement with the fact that wind predominantly blows from South to North in the region of interest during the growing season (see Figure A21). This raises the question as to whether the indirect effect occasionally benefits individual counties *more* than the direct effect. Figure 7 answers this point by illustrating the ratio of the indirect effect to the direct effect for Nebraskan counties, which concentrate the bulk of the corn and soybean production in the region of interest. In several counties, the cooling externality caused by irrigation in upwind neighbors and measured in the form of avoided corn production losses is as important, or even more important, than the direct effect of same-county irrigation. Such situations are typically observed in counties located immediately downwind from intensively irrigated areas (for instance, north of the Platte River in Nebraska) that do not significantly irrigate themselves. While these areas do not encompass major corn- or soybean producing counties, it is important to stress that the cooling-by-irrigation effect is responsible for additional positive externalities on the economy via the spillover it generates on local weather for instance with respect to the production of other heat-sensitive crops, the reduction in energy demand (less AC), the protection of entire ecosystems against extreme heat, the preservation of labor productivity, etc. Below, we explore the arguably most important of such additional benefits, namely the reduced excess mortality during summer months thanks to the reduced exposure to extreme heat for populations living in downwind areas.

5.2 Irrigation externality on downwind mortality

Restricting the mortality data from April to September in each year between 1959 to 1988 in the region of interest, we adapt the temperature-mortality response function proposed by Deschênes and Greenstone (2011) by fitting the following two-way fixed effect model

$$M_{iy} = \phi T_{iy}^{35} + \chi P_{iy} + \psi_i + \omega_y + \epsilon_{iy} \tag{6}$$

[30](Li et al. 2020) do not explore spillover effects related to the cooling-by-irrigation externality and still detect a considerable "on-the-spot" effect on daytime land surface temperature measurements (-1.63°C in July).

where M_{iy} is the mortality rate (per 100,000 inhabitants) in county i observed during the 183 days between April 1st and September 30th in year y, T^{35}_{iy} is the cumulative amount of time (in days) spent above $35°C$ by county i during the April-September period of year y, P_{iy} is the total precipitation level in county i during the April-September period of year y, ψ_i are county fixed effects, ω_y are time fixed effects for each (half of) year y and ϵ_{iy} is the error term.[31] Similarly to Deschênes and Greenstone (2011), we weight equation (6) by (the square root of) county-level population, since larger counties are likely to produce more precise estimates. Eventually, we cluster standard errors by state to allow for arbitrary correlation within counties of the same state. The modification to Deschênes and Greenstone (2011) is that we estimate the time spent above 35°C using the full temperature distribution on a day rather than average temperature on a day - the reasoning being that we found heterogeneous impacts with higher cooling for upper percentiles of the temperature distribution. The coefficient of interest is estimated to be $\hat{\phi} = .921^{**}$ with a standard error of .4514. This suggests that, on average and holding precipitation level constant, exchanging a full day *below* $35°C$ between April and September with a full day *above* $35°C$ in any given county of the region of interest is associated with an additional mortality of .921 deaths per 100,000 people in the same county.

Using a similar methodology as for the quantification of the indirect effect of irrigation in improving corn yields (see Section 5.1), we estimate a counterfactual world without the cooling-by-irrigation externality and measure the additional amount of time spent in each county above the 35°C threshold between April and September. Figure 8 shows for how many more days each county in the region of interest would have been exposed to temperatures above 35°C during the heat wave of 2012. In numerous counties within the boundary of the Ogallala aquifer, this amount of time exceeds 1 full day and reaches up to 4 days in several counties. Adjusting these amounts computed for every year between 1959 and 2017 by a factor .921 and for historic county-specific population levels, we estimate that the cooling-by-irrigation externality has allowed to avoid an aggregate of 1,579 premature deaths in the region of interest excluding counties with the highest population density and that fall outside the boundary of the Ogallala.[32] On average, this represents about 27 avoided

[31] We also fit a more flexible version of equation (6) given by $M_{iy} = \sum_{j \in J} \phi_j T_{iyj} + \chi P_{iy} + \psi_i + \omega_y + \epsilon_{iy}$, where J is the set of seven separate temperature bins (below $5°C$, 5-$10°C$, 10-$15°C$, 15-$20°C$, 20-$25°C$, 30-$35°C$ and above $35°C$) and T_{iyj} is the cumulative amount of time (in days) spent in bracket j. Note that, in this alternative specification, the 25-$30°C$ bin is omitted and serves as baseline category. None of the estimated $\hat{\phi}_j$ is statistically significant (not even at the 10% significance level) *except* for $\hat{\phi}_{35°} = 1.614^{**}$ (with a standard error of .728), meaning that exchanging a full day spent between 25 and $30°C$ with a full day above $35°C$ is associated with an 1.614 additional deaths per 100,000. For simplicity, in the remainder, we keep the more conservative estimate obtained by fitting (6).

[32] These counties are Dallas, TX (48113), Tarrant, TX (48439) and Oklahoma city, OK (40109). In terms of population levels, these counties constitute outliers when compared to the remaining counties of the region

deaths per summer, with peaks as high as 47 avoided deaths during particularly hot years (see Figure A24). Such years, however, are likely to be the most representative for future conditions given the present context of a warming world. Using the EPA's Value of a Statistical Life (VSL) of $7.4 million in $2006 (or $9.0 million in $2017) "regardless of the age, income, or other population characteristics of the affected population" (as recommended by the EPA)[33], these counts translate into $14 billion ($2017) in total and $241 million per summer of unintended benefits due to irrigation. We argue these figures constitute lower bounds on the beneficial externality of large-scale irrigation given that, besides this important reduction in terms of human mortality, the cooling-by-irrigation effect is likely to generate several additional benefits in terms of reduced morbidity, higher comfort or even animal health, with potentially significant effects on cattle farming in the Great Plains.

6 Conclusions

We empirically show that large-scale irrigation is responsible for a significant cooling externality which affects the entire distribution of summertime temperature and is most effective at cooling the higher end of the temperature distribution by combining monthly temperature records over 59 years with irrigation statistics interpolated at the yearly level for every county in a vast region around the Ogallala aquifer. The cooling effect extends strongly to downwind counties. Our identification strategy relies on a three-way fixed effects setup that compares changes in irrigation over time and space to changes in temperature distributions during the growing season relative to the remainder of the year. Our findings provide a partial explanation for the observed larger-scale warming hole observed in the Central United States as of the 1950's. Conceptually, the unintended beneficial feedback mechanism which we identify with respect to intensive irrigation is remarkable because it suggests that adaptive behavior to regional climate (and by extension also to climate change or rising constraints in water availability from freshwater aquifers) can have measurable and sizeable effects on the climate – a channel which, to our knowledge, has not yet been accounted for in the adaptation literature but certainly deserves more attention.

Practically, from an agricultural perspective, we show that large-scale irrigation does not only benefit plant growth directly by controlling water supply and enhancing heat tolerance of crops ($26 billion in aggregate and inflation-adjusted market value for corn and soybeans

of interest. Including these counties in the scope of the analysis mechanically increases the total number of avoided premature deaths to 1,683, due to the interaction of *de minimis* irrigation levels in upwind counties with very large population levels, but without this being reasonably representative of the cooling-by-irrigation externality.

[33] See `https://www.epa.gov/environmental-economics/mortality-risk-valuation`

over 1959-2017) but also indirectly by increasing yields through avoiding harmful degree-days in downwind areas (\$7 billion). Although being comparatively smaller in overall, this positive externality appears to be occasionally, at the county-level, even more important than the direct effect of irrigation on corn production with respect to its adaptation to heat. As extreme heat is also detrimental to other spheres of the economy besides agriculture, such as labor productivity or local population and ecosystem health, we argue that the benefits of the cooling-by-irrigation externality actually *exceed* those from a purely agricultural perspective, a consideration which we explore on the important example of reduced excess mortality for populations living in downwind areas of irrigated land. We estimate that, over the period and region of interest, 1,579 premature deaths (\$14 billion based on the VSL recommended by the EPA) have been historically avoided over our 59-year-long sample thanks to the unintended but beneficial cooling effect of intensive irrigation. During particularly hot summers, which are likely to be the most informative for future climate conditions, the benefit in reduced mortality can reach up to 47 avoided deaths in downwind areas of irrigation-intensive counties. Besides improving crop yields and reducing human mortality, the cooling-by-irrigation externality carries several additional benefits of economic relevance, for instance in terms of reduced morbidity, higher comfort and reduced cattle mortality during heat episodes, thereby locally facilitating adaptive behavior to climate change - as far as water availability permits.

Despite having significantly improved crop yields in the Great Plains and generated sizable positive externalities on the economy over the last 59 years, large-scale irrigation as historically allowed by the Ogallala aquifer is unlikely to be replicable in other agricultural settings within the US given fundamental geological constraints in freshwater availability. On the contrary, the progressive depletion of the Ogallala aquifer may result not only in profound changes in local agricultural production and productivity, but also in a localized warming of summertime temperatures, a situation which is already empirically observed downstream of the Ogallala aquifer and for which the indirect consequences could significantly exacerbate potential losses in sectors seemingly unrelated to agriculture.

Finally, our study suggests that the common argument that year-to-year weather shocks are random and exogenous does not hold for highly-irrigated areas, where the upper tail of the temperature distribution can be lowered by as much as 3°C in August downwind for highly irrigated areas.

References

Albouy, David, Walter Graf, Ryan Kellogg, and Hendrik Wolff, "Climate Amenities, Climate Change, and American Quality of Life," *Journal of the Association of Environmental and Resource Economists*, March 2016, *3* (1), 205–246. Publisher: The University of Chicago Press.

Alter, Ross E., Ying Fan, Benjamin R. Lintner, and Christopher P. Weaver, "Observational Evidence that Great Plains Irrigation Has Enhanced Summer Precipitation Intensity and Totals in the Midwestern United States," *Journal of Hydrometeorology*, August 2015, *16* (4), 1717–1735.

Auffhammer, Maximilian and Anin Aroonruengsawat, "Simulating the impacts of climate change, prices and population on California's residential electricity consumption," *Climatic Change*, December 2011, *109* (1), 191–210.

Barnston, Anthony G. and Paul T. Schickedanz, "The Effect of Irrigation on Warm Season Precipitation in the Southern Great Plains," *Journal of Climate and Applied Meteorology*, June 1984, *23* (6), 865–888.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro, "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century," *Journal of Political Economy*, February 2016, *124* (1), 105–159. Publisher: The University of Chicago Press.

Burke, Marshall and Kyle Emerick, "Adaptation to Climate Change: Evidence from US Agriculture," *American Economic Journal: Applied Economics*, August 2016, *8* (3), 106–140.

____, Solomon M. Hsiang, and Edward Miguel, "Global non-linear effect of temperature on economic production," *Nature*, November 2015, *527* (7577), 235–239. Number: 7577 Publisher: Nature Publishing Group.

Butler, Ethan E. and Peter Huybers, "Adaptation of US maize to temperature variations," *Nature Climate Change*, January 2013, *3* (1), 68–72.

DeAngelis, Anthony, Francina Dominguez, Ying Fan, Alan Robock, M. Deniz Kustu, and David Robinson, "Evidence of enhanced precipitation due to irrigation over the Great Plains of the United States," *Journal of Geophysical Research*, August 2010, *115* (D15), D15115.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken, "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, July 2012, *4* (3), 66–95.

____, ____, and ____, "What Do We Learn from the Weather? The New Climate-Economy Literature," *Journal of Economic Literature*, September 2014, *52* (3).

Deschênes, Olivier and Michael Greenstone, "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US," *American Economic Journal: Applied Economics*, October 2011, *3* (4), 152–185.

Grosset, Florian, Anna Papp, and Charles Taylor, "Rain Follows the Forest: Land Use Policy, Climate Change, and Adaptation," *Working Paper*, 2023.

Haqiqi, Iman, Danielle S. Grogan, Thomas W. Hertel, and Wolfram Schlenker, "Quantifying the impacts of compound extremes on agriculture," *Hydrology and Earth Systmen Sciences*, February 2021, *25* (2), 551–564.

Harding, Keith J. and Peter K. Snyder, "Modeling the Atmospheric Response to Irrigation in the Great Plains.: Part I: General Impacts on Precipitation and the Energy Budget," *Journal of Hydrometeorology*, 2012, *13* (6), 1667–1686. Publisher: American Meteorological Society.

Hornbeck, Richard and Pinar Keskin, "The Historically Evolving Impact of the Ogallala Aquifer: Agricultural Adaptation to Groundwater and Drought," *American Economic Journal: Applied Economics*, January 2014, *6* (1), 190–219.

Kunkel, Kenneth E., Xin-Zhong Liang, Jinhong Zhu, and Yiruo Lin, "Can CGCMs Simulate the Twentieth-Century "Warming Hole" in the Central United States?," *Journal of Climate*, September 2006, *19* (17), 4137–4153.

Li, Yan, Kaiyu Guan, Bin Peng, Trenton E. Franz, Brian Wardlow, and Ming Pan, "Quantifying irrigation cooling benefits to maize yield in the US Midwest," *Global Change Biology*, May 2020, *26* (5), 3065–3078.

Lobell, David B., Celine J. Bonfils, Lara M. Kueppers, and Mark A. Snyder, "Irrigation cooling effect on temperature and heat index extremes," *Geophysical Research Letters*, 2008, *35* (9). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2008GL034145.

Mahmood, R, S Foster, T Keeling, K Hubbard, C Carlson, and R Leeper, "Impacts of irrigation on 20th century temperature in the northern Great Plains," *Global and Planetary Change*, November 2006, *54* (1-2), 1–18.

Moore, Nathan and Stuart Rojstaczer, "Irrigation-Induced Rainfall and the Great Plains," *Journal of Applied Meteorology*, August 2001, *40* (8), 1297–1309.

Moscona, Jacob and Karthik A. Sastry, "Does Directed Innovation Mitigate Climate Damage? Evidence from US Agriculture," 2021.

Mueller, Nathaniel D., Ethan E. Butler, Karen A. McKinnon, Andrew Rhines, Martin Tingley, N. Michele Holbrook, and Peter Huybers, "Cooling of US Midwest summer temperature extremes from cropland intensification," *Nature Climate Change*, March 2016, *6* (3), 317–322.

Pan, Zaitao, Raymond W. Arritt, Eugene S. Takle, William J. Gutowski, Christopher J. Anderson, and Moti Segal, "Altered hydrologic feedback in a warming climate introduces a "warming hole": ALTERED FEEDBACK IN A WARMING CLIMATE," *Geophysical Research Letters*, September 2004, *31* (17), n/a–n/a.

Robinson, Walter A., Reto Ruedy, and James E. Hansen, "General circulation model simulations of recent cooling in the east-central United States," *Journal of Geophysical Research: Atmospheres*, 2002, *107* (D24), ACL 4–1–ACL 4–14. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2001JD001577.

Schlenker, Wolfram, "Environmental Drivers of Agricultural Productivity Growth and Socioeconomic Spillovers," 2020, p. 24.

____ and Michael J. Roberts, "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, September 2009, *106* (37), 15594–15598.

____ , ____ , and David B. Lobell, "US maize adaptability," *Nature Climate Change*, August 2013, *3* (8), 690–691.

Snyder, R, "Hand calculating degree days," *Agricultural and Forest Meteorology*, October 1985, *35* (1-4), 353–358.

Taylor, Charles A, "Irrigation and Climate Change: Long-run Adaptation and its Externalities," 2021, p. 49.

Wang, Hailan, Siegfried Schubert, Max Suarez, Junye Chen, Martin Hoerling, Arun Kumar, and Philip Pegion, "Attribution of the Seasonality and Regionality in Climate Trends over the United States during 1950–2000," *Journal of Climate*, 2009, *22* (10), 2571–2590. Publisher: American Meteorological Society.

Weaver, Scott J., "Factors Associated with Decadal Variability in Great Plains Summertime Surface Temperatures," *Journal of Climate*, January 2013, *26* (1), 343–350.

World Bank Group, "High and Dry: Climate Change, Water, and the Economy," Working Paper, World Bank, Washington, DC May 2016. Accepted: 2016-01-14T22:38:01Z.

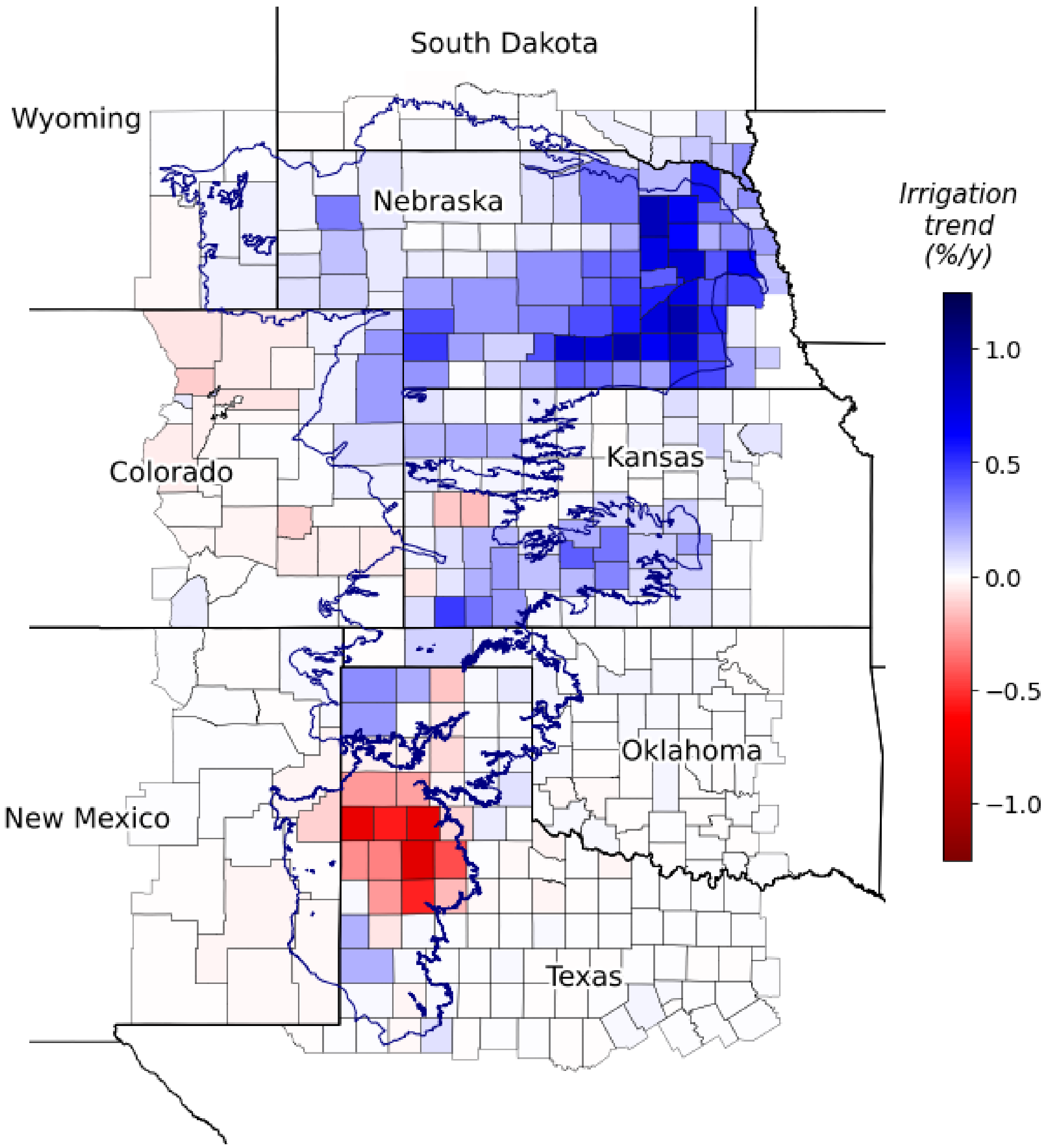
Zivin, Joshua Graff and Matthew Neidell, "Temperature and the Allocation of Time: Implications for Climate Change," *Journal of Labor Economics*, January 2014, *32* (1), 1–26. Publisher: The University of Chicago Press.

Table 1: The Effect of Irrigation on Monthly Temperature Percentiles by Wind Direction

p	n	Irrigation information from								R^2-within
		same		upwind		crosswind		downwind		
99th	Apr	-0.18	(0.38)	0.17	(0.46)	-0.32	(0.68)	-0.68	(0.76)	
	May	-0.20	(0.19)	-0.88	(1.06)	-1.11*	(0.60)	-1.23**	(0.61)	
	Jun	0.19	(0.33)	-2.71**	(1.02)	-0.98*	(0.55)	-0.60	(0.79)	
	Jul	-0.23	(0.41)	-2.51***	(0.85)	-0.76	(0.47)	-1.08	(0.70)	
	Aug	-0.27	(0.46)	-3.05***	(0.96)	-0.82	(0.56)	-1.24	(0.85)	
	Sep	-0.13	(0.23)	-0.83	(1.23)	0.08	(0.57)	-0.38	(0.87)	3.00%
90th	Apr	-0.38	(0.27)	-0.26	(0.36)	-0.20	(0.62)	-0.51	(0.70)	
	May	-0.06	(0.16)	-1.18	(0.85)	-0.72	(0.60)	-0.66	(0.68)	
	Jun	-0.08	(0.23)	-1.88**	(0.78)	-0.63	(0.42)	-0.44	(0.58)	
	Jul	-0.27	(0.31)	-1.87**	(0.80)	-0.77*	(0.40)	-0.77	(0.63)	
	Aug	-0.16	(0.41)	-3.31***	(0.85)	-1.16**	(0.51)	-1.74**	(0.78)	
	Sep	-0.39***	(0.13)	0.35	(1.00)	0.46	(0.42)	0.32	(0.68)	3.00%
75th	Apr	-0.25	(0.25)	-0.22	(0.30)	-0.15	(0.49)	-0.56	(0.63)	
	May	-0.00	(0.17)	-0.71	(0.70)	-0.40	(0.54)	-0.67	(0.63)	
	Jun	-0.01	(0.19)	-1.86**	(0.72)	-0.54	(0.40)	-0.25	(0.55)	
	Jul	-0.25	(0.22)	-1.61**	(0.65)	-0.60*	(0.31)	-0.47	(0.52)	
	Aug	-0.18	(0.26)	-2.36***	(0.75)	-0.94**	(0.41)	-1.45**	(0.70)	
	Sep	-0.35***	(0.09)	0.55	(0.87)	0.50	(0.34)	0.48	(0.59)	2.17%
50th	Apr	-0.16	(0.19)	-0.21	(0.23)	-0.07	(0.39)	-0.27	(0.50)	
	May	-0.01	(0.14)	-0.72	(0.57)	-0.37	(0.46)	-0.42	(0.53)	
	Jun	-0.01	(0.19)	-1.95***	(0.68)	-0.61	(0.37)	-0.40	(0.49)	
	Jul	-0.23	(0.20)	-1.38***	(0.49)	-0.53**	(0.25)	-0.40	(0.41)	
	Aug	-0.20	(0.22)	-1.95***	(0.65)	-0.74**	(0.36)	-1.08*	(0.56)	
	Sep	-0.33***	(0.11)	0.20	(0.77)	0.20	(0.30)	0.35	(0.51)	1.14%
25th	Apr	-0.11	(0.16)	-0.20	(0.19)	0.07	(0.31)	0.03	(0.41)	
	May	0.01	(0.11)	-0.74	(0.54)	-0.44	(0.45)	-0.65	(0.50)	
	Jun	-0.02	(0.12)	-1.82***	(0.59)	-0.59*	(0.30)	-0.44	(0.42)	
	Jul	-0.30**	(0.14)	-1.12**	(0.46)	-0.36	(0.22)	-0.29	(0.40)	
	Aug	-0.27*	(0.16)	-1.63**	(0.61)	-0.54	(0.35)	-0.94*	(0.54)	
	Sep	-0.30**	(0.12)	0.34	(0.75)	0.18	(0.33)	0.25	(0.57)	0.48%
5th	Apr	-0.09	(0.19)	-0.44	(0.29)	-0.03	(0.43)	0.04	(0.51)	
	May	-0.17**	(0.08)	-0.70	(0.56)	0.17	(0.42)	-0.30	(0.48)	
	Jun	0.06	(0.12)	-1.52**	(0.72)	-0.44	(0.37)	-0.61	(0.54)	
	Jul	-0.31**	(0.13)	-0.85	(0.52)	-0.01	(0.30)	-0.11	(0.54)	
	Aug	-0.34**	(0.14)	-1.45**	(0.72)	-0.38	(0.38)	-0.79	(0.71)	
	Sep	-0.36***	(0.13)	-0.55	(0.68)	-0.01	(0.37)	-0.04	(0.56)	0.10%

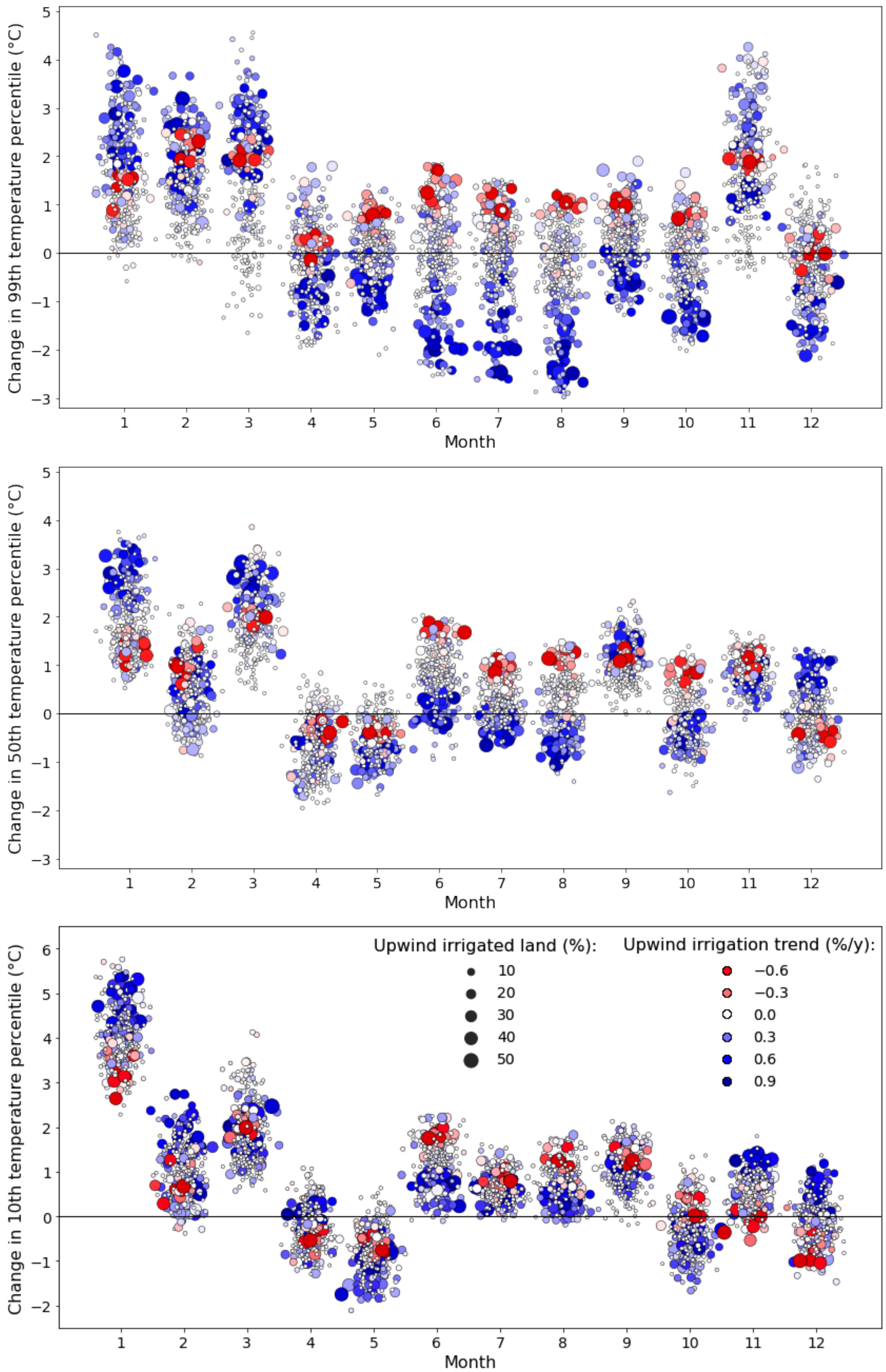
Notes: Each panel (separated by horizontal lines) presents regression results from a joint regression using 278,094 observations and controls for previous-month precipitation - see specification (5). Units are in $^\circ C$/(fraction of county area that is irrigated). The six panels present results for the 99th, 90th, 75th, 50th, 25th and 5th temperature percentiles for each month between April and September relative to the rest of the year. The four middle columns include information on the fraction of the county that is irrigated for same, up-, cross- and downwind counties. Standard errors (in parenthesis) are two-way clustered by county and year. ***, ** and * denote statistical significance respectively at the 1%, 5% and 10% levels. Results are illustrated in Figure 3.

Figure 1: Irrigation Trends over Ogallala Aquifer 1959-2017



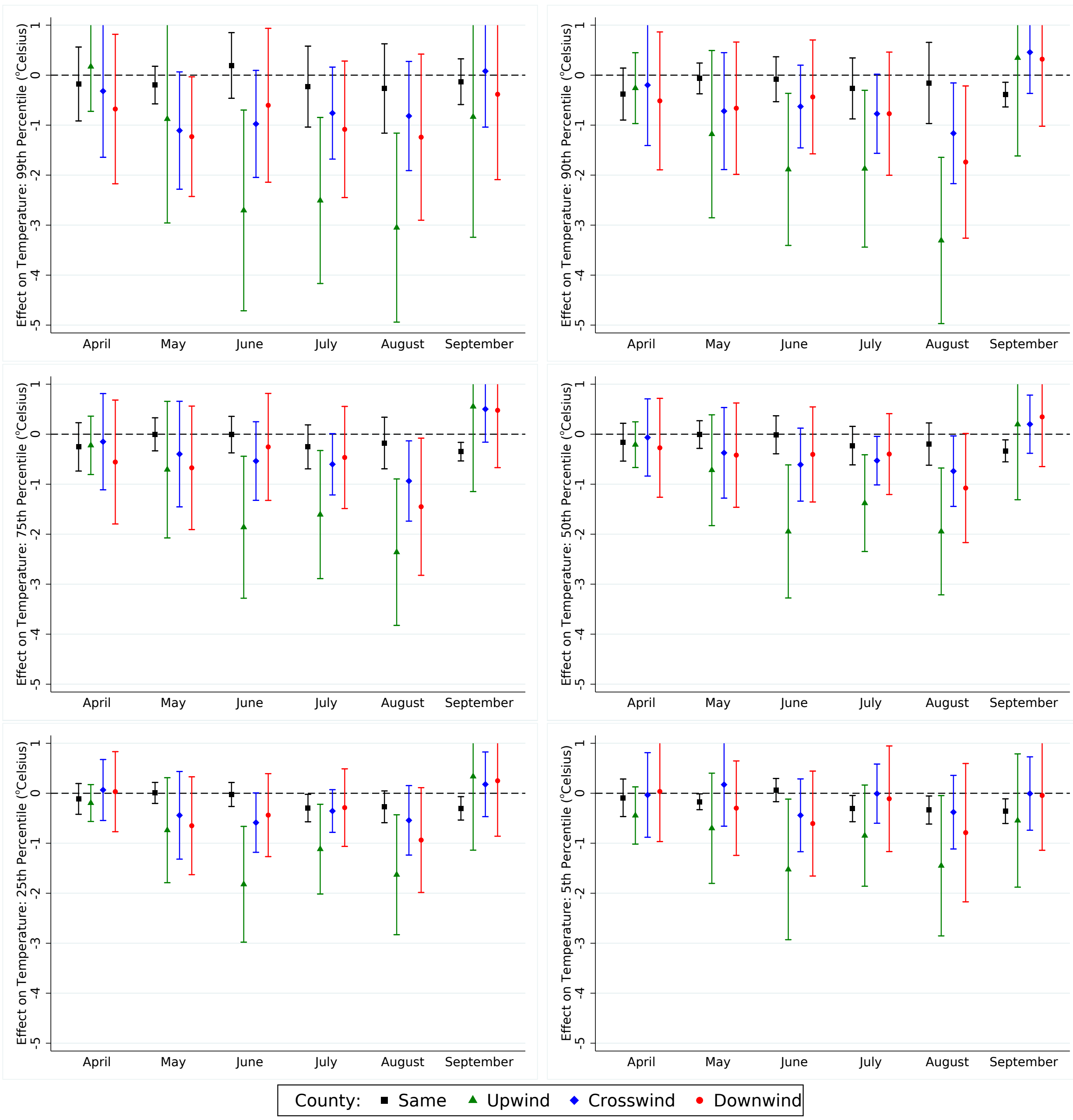
Notes: Figure displays the 393 counties (i) with centroid coordinates falling between the minimum/maximum latitude and longitude of the Ogallala aquifer (or crossing its boundary). They are color-coded by the observed irrigation trend ($\hat{\iota}_i$) over the 1959-2017 period: counties which saw an increase (decrease) in irrigation are in blue (red).

Figure 2: Change in Temperature Percentiles by Month of Year and Upwind Irrigation Trend



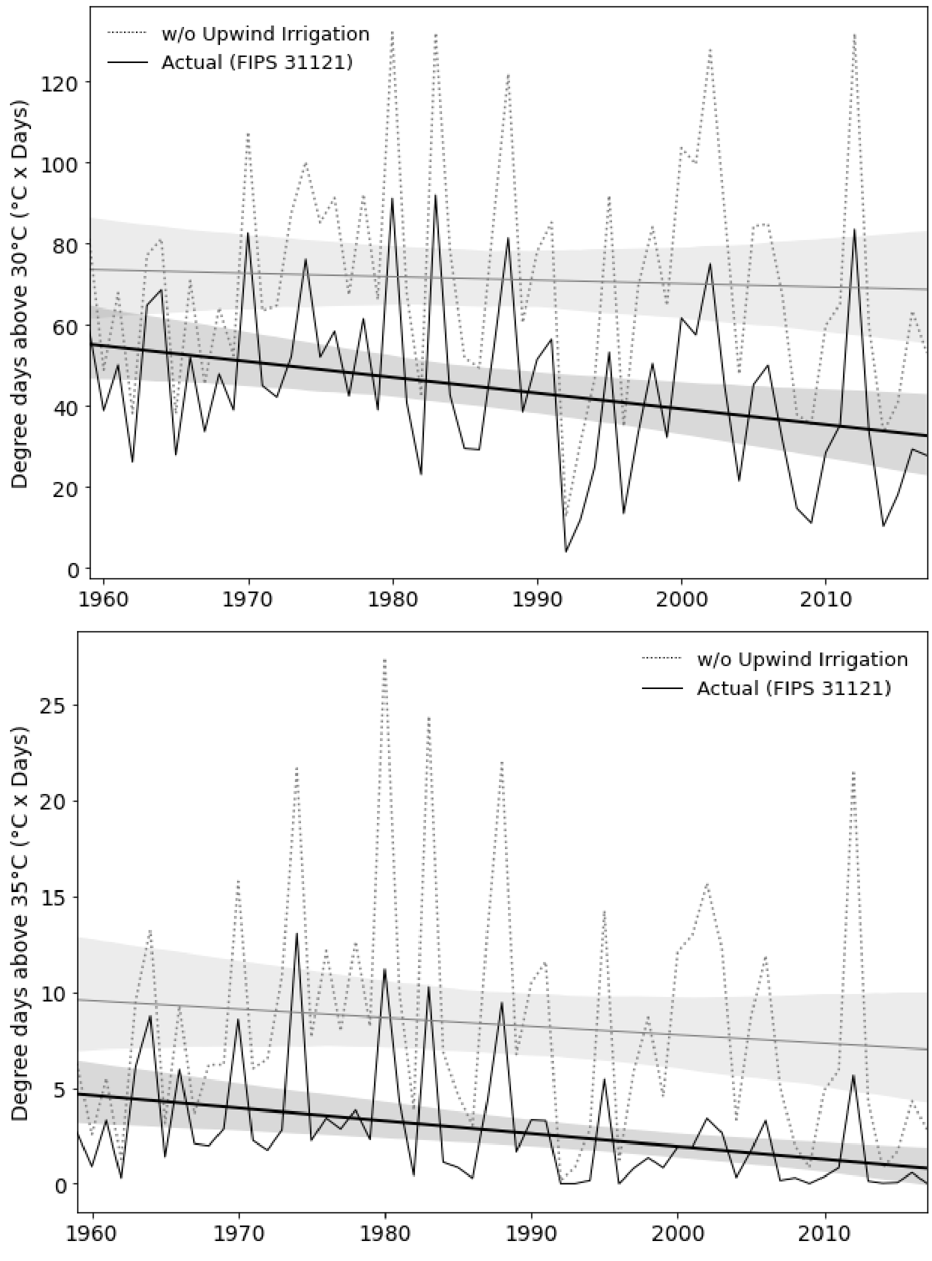
Notes: Average change in the 99th (**top**), 50th (**middle**) and 10th (**bottom**) temperature percentiles over the 1959-2017 period as a function of the month (horizontally jittered) for each of the 393 counties in the region of interest. Each county is represented by a bubble, the size and color of which respectively indicate the average proportion of irrigated land and the irrigation trend observed in the county's upwind neighbor.

Figure 3: Effect of Irrigation on Monthly Temperature Percentiles by Wind Direction



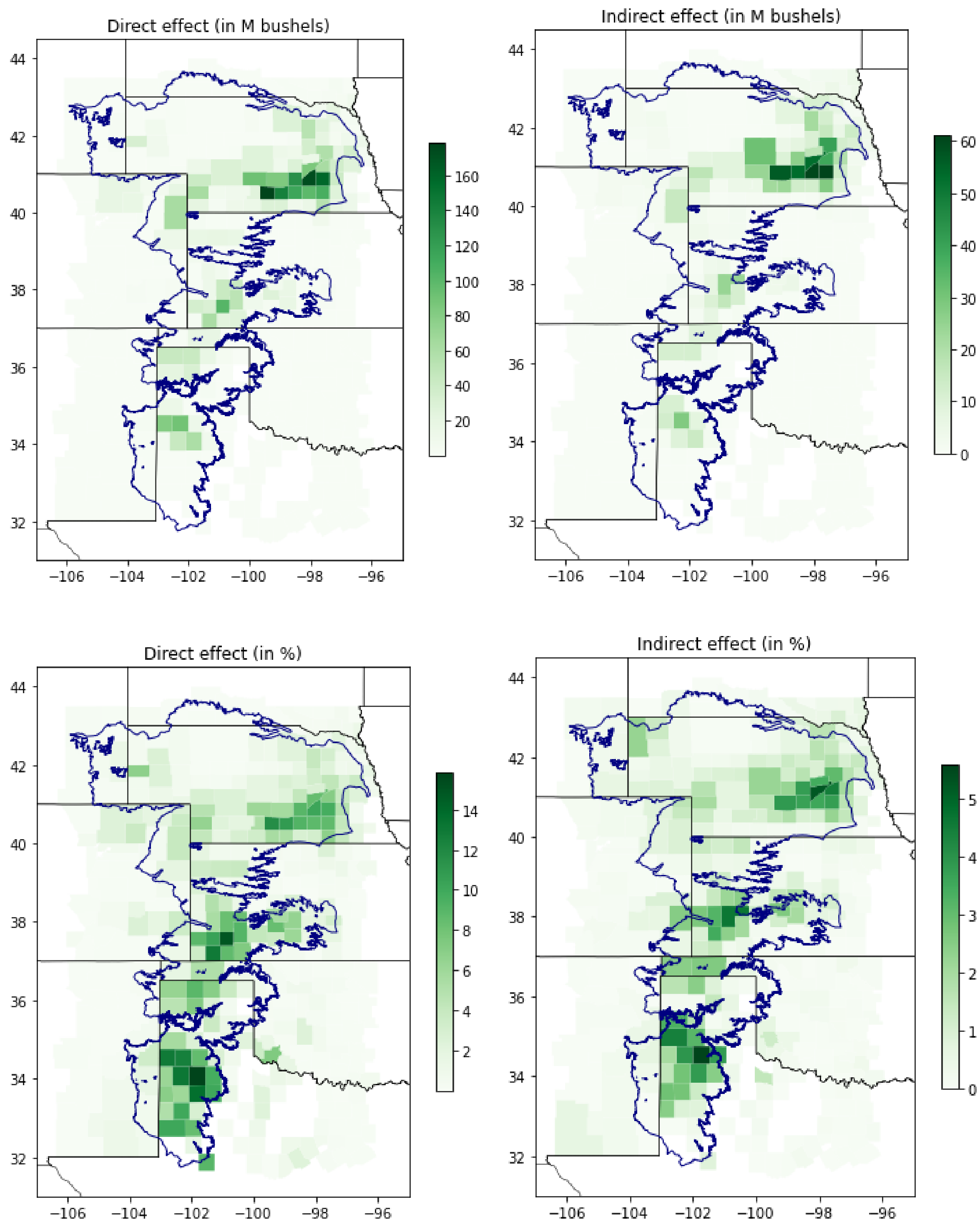
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The six panels show results for the 99$^{\text{th}}$, 90$^{\text{th}}$, 75$^{\text{th}}$, 50$^{\text{th}}$, 25$^{\text{th}}$ and 5$^{\text{th}}$ temperature percentiles, respectively. Each specification estimates 24 β_n^p coefficients jointly while controlling for previous-month precipitation - see specification (5). Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated. Figures illustrate results from Table 1.

Figure 4: Degree-days in Merrick County (NE) With and Without Effect of Upwind Irrigation



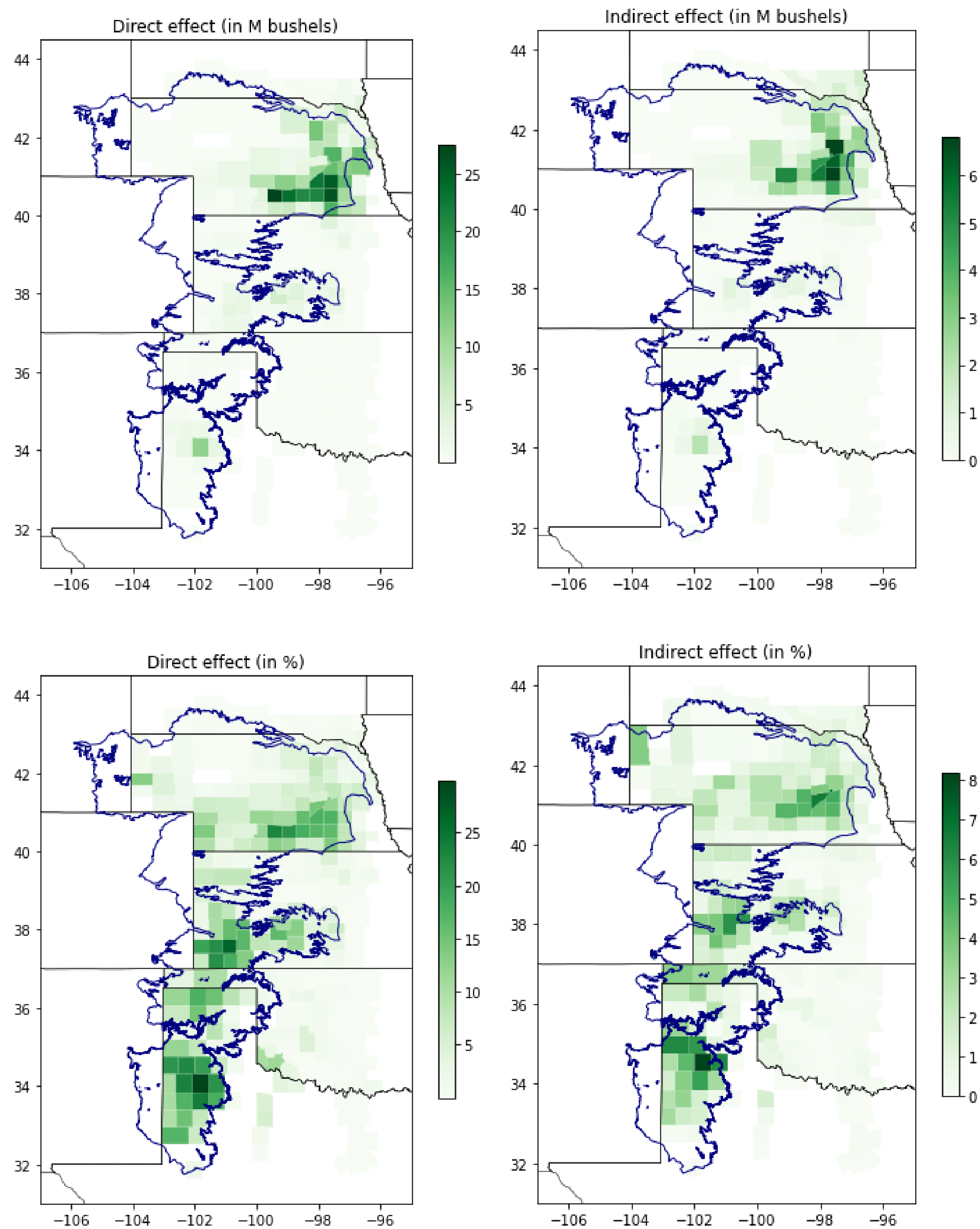
Notes: Figure shows the evolution of actual (continuous black line) and counterfactual (dotted gray line) degree-days above 30°C (**top panel**) and 35°C (**bottom panel**) in county 31121 (Merrick County, NE) aggregated yearly over the April-September period. The counterfactual scenario is based on the simulated temperature distribution in county 31121 after removal of the cooling-by-irrigation externality. Trends are summarized by linear regression lines with shaded 95% confidence bands.

Figure 5: Avoided Corn Production Losses Due to Irrigation



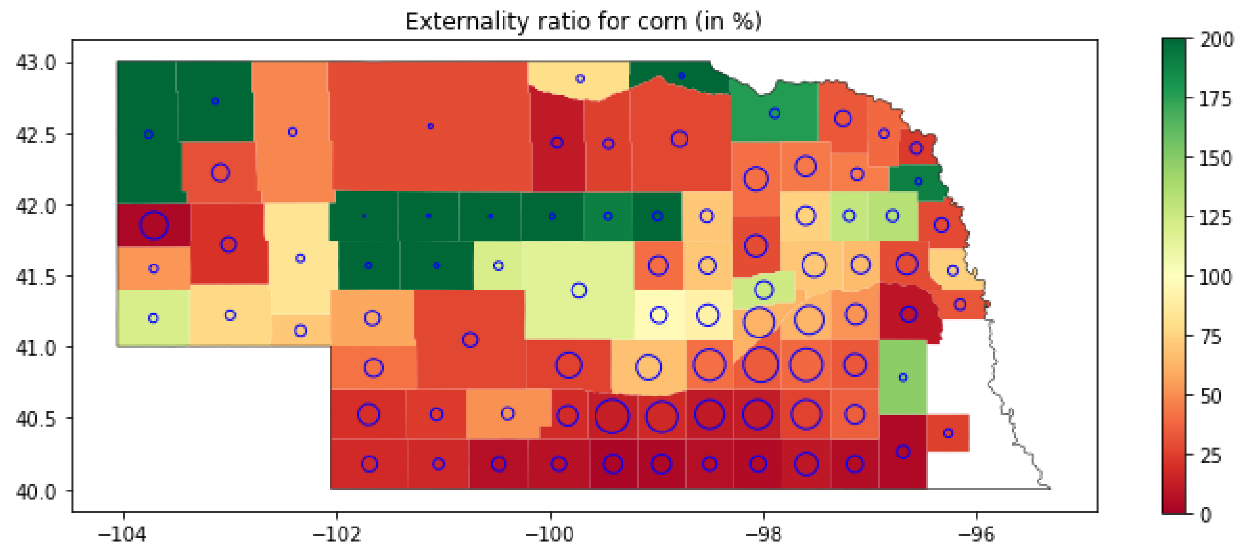
Notes: The left column displays avoided corn production losses via the primary effect of within-county irrigation ("direct effect") i.e., the benefit of irrigation of making yields less susceptible to extreme heat. The right column gives the avoided losses via the cooling externality induced by irrigation in upwind counties ("indirect effect"). The top row gives the benefits in saved (millions of) bushels, while the bottom row shows the results in proportion to total production over the 1959-2017 period.

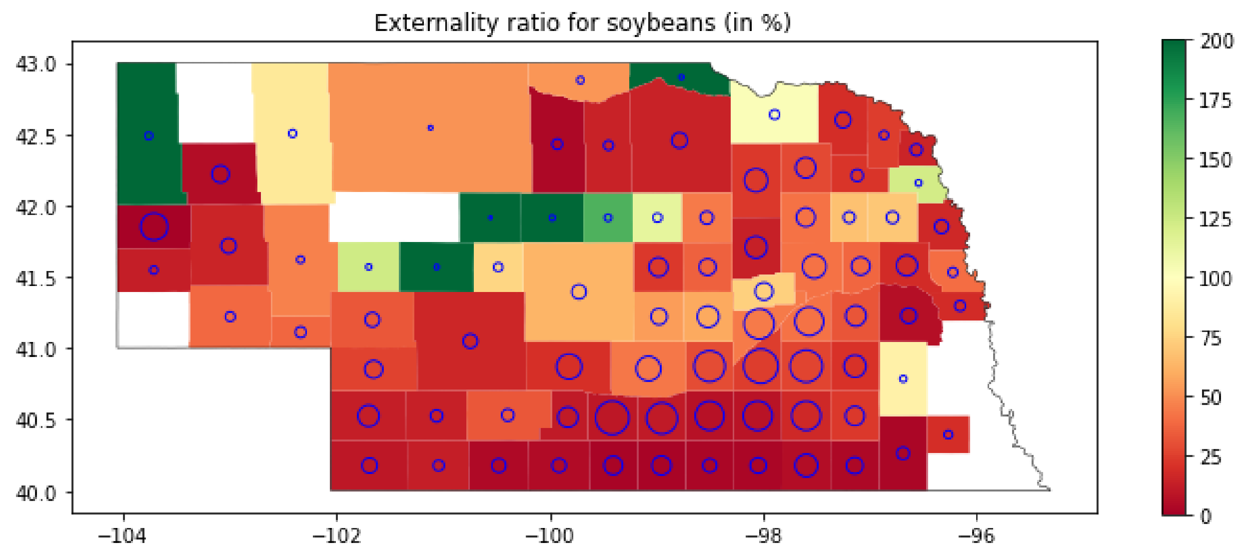
Figure 6: Avoided Soybean Production Losses Due to Irrigation



Notes: The left column displays avoided soybean production losses via the primary effect of within-county irrigation ("direct effect") i.e., the benefit of irrigation of making yields less susceptible to extreme heat. The right column gives the avoided losses via the cooling externality induced by irrigation in upwind counties ("indirect effect"). The top row gives the benefits in saved (millions of) bushels, while the bottom row shows the results in proportion to total production over the 1959-2017 period.

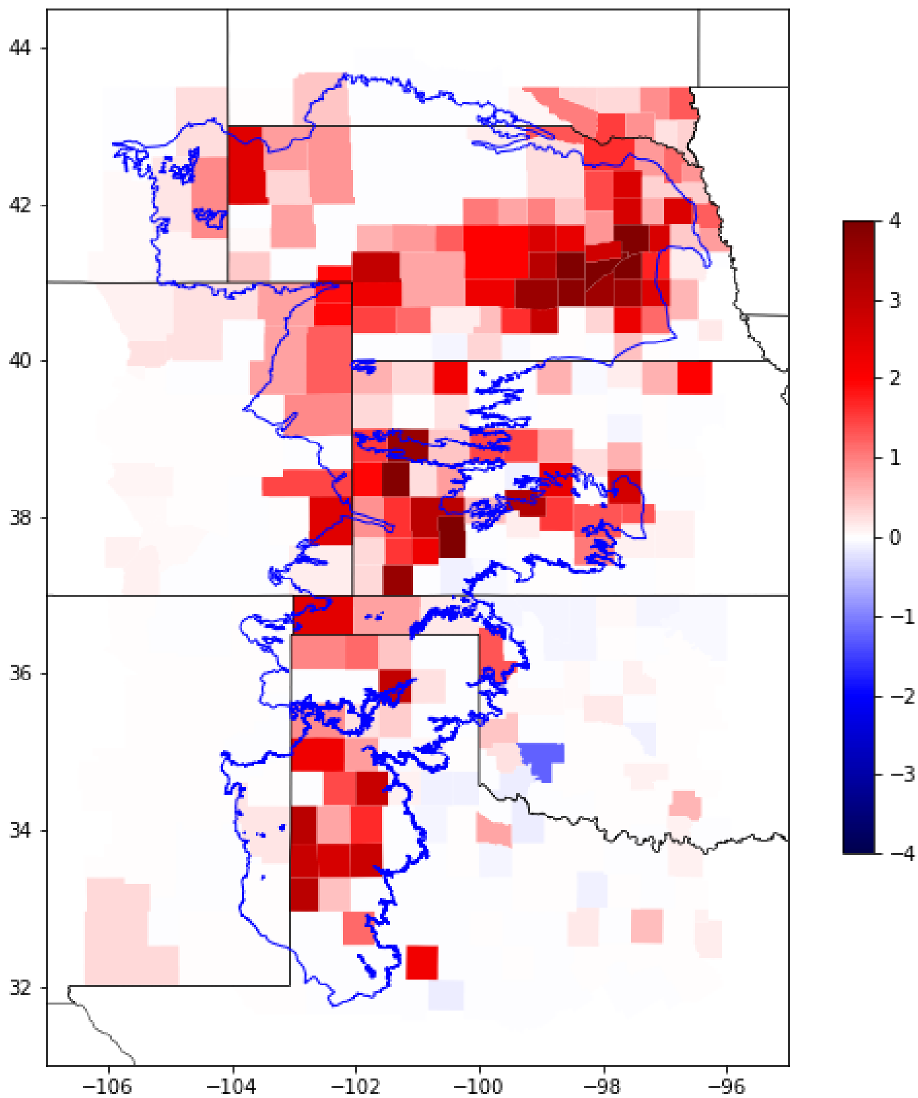
Figure 7: Ratio of Externality Benefits to Direct Own Benefits of Irrigation





Notes: Figures show the ratio of the positive externality (avoided agricultural production losses due to cooling induced by irrigation in upwind neighbors) relative to direct own benefits (avoided production losses due to the effect of within-county irrigation) in Nebraska for each of corn (**top panel**) and soybeans (**bottom panel**). Counties colored in red (green) benefit comparatively *more* from the direct effect (indirect effect), while counties colored in yellow benefit equally from each effect. Color scale is top coded at 200%. The size of blue bubbles is proportional to average fraction of a county that is irrigated in 1959-2017.

Figure 8: Additional Time Spent Above 35°C Without Irrigation in 2012.



Notes: Figure shows the estimated additional time (in number of days) spent above 35°C during April-September in 2012 for a counterfactual world deprived from the cooling-by-irrigation externality. Contour of the Ogallala aquifer is indicated by the line in blue.

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Table A1: Irrigation and Monthly Temperature Percentiles - Same County Only

p	n	Irrigation information from same		R^2-within
99th	Apr	-0.80	(1.55)	
	May	-2.52*	(1.47)	
	Jun	-2.82*	(1.43)	
	Jul	-3.22***	(1.13)	
	Aug	-3.81***	(1.35)	
	Sep	-0.93	(1.71)	2.75%
90th	Apr	-1.07	(1.39)	
	May	-1.88	(1.45)	
	Jun	-2.15*	(1.11)	
	Jul	-2.62**	(1.13)	
	Aug	-4.47***	(1.25)	
	Sep	0.39	(1.35)	2.71%
75th	Apr	-0.92	(1.21)	
	May	-1.26	(1.27)	
	Jun	-1.86*	(1.05)	
	Jul	-2.10**	(0.91)	
	Aug	-3.48***	(1.13)	
	Sep	0.72	(1.14)	1.96%
50th	Apr	-0.54	(0.95)	
	May	-1.07	(1.04)	
	Jun	-2.07**	(0.95)	
	Jul	-1.82***	(0.68)	
	Aug	-2.81***	(0.95)	
	Sep	0.18	(0.97)	0.99%
25th	Apr	-0.16	(0.73)	
	May	-1.27	(0.99)	
	Jun	-2.01**	(0.83)	
	Jul	-1.51**	(0.68)	
	Aug	-2.43**	(0.93)	
	Sep	0.23	(1.04)	0.39%
5th	Apr	-0.36	(0.98)	
	May	-0.70	(0.99)	
	Jun	-1.72*	(1.02)	
	Jul	-0.96	(0.86)	
	Aug	-2.14*	(1.14)	
	Sep	-0.76	(1.03)	0.07%

Notes: Table replicates Table 1, but only includes own-county irrigation. Each panel (separated by horizontal lines) presents regression results from a joint regression using 278,244 observations and controls for previous-month precipitation. Units are in $°C$/(fraction of county area that is irrigated). The six panels present results for the 99^{th}, 90^{th}, 75^{th}, 50^{th}, 25^{th} and 5^{th} temperature percentiles for each month between April and September relative to the rest of the year. Standard errors (in parenthesis) are two-way clustered by county and year. ***, ** and * denote statistical significance respectively at the 1%, 5% and 10% levels.

Table A2: Irrigation and Monthly Temperature Percentiles - Same and Upwind County

p	n	Irrigation information from: same		upwind		R^2-within
99^{th}	Apr	-0.79	(1.04)	-0.01	(0.85)	
	May	-1.75**	(0.78)	-1.11	(1.18)	
	Jun	-0.96	(0.88)	-2.76**	(1.05)	
	Jul	-1.52**	(0.72)	-2.53***	(0.86)	
	Aug	-1.73*	(0.88)	-3.06***	(0.98)	
	Sep	-0.39	(0.95)	-0.78	(1.24)	2.92%
90^{th}	Apr	-0.82	(0.96)	-0.39	(0.71)	
	May	-0.98	(0.87)	-1.33	(0.97)	
	Jun	-0.86	(0.65)	-1.91**	(0.79)	
	Jul	-1.34*	(0.67)	-1.92**	(0.81)	
	Aug	-2.21***	(0.82)	-3.33***	(0.86)	
	Sep	0.14	(0.72)	0.40	(1.01)	2.90%
75^{th}	Apr	-0.68	(0.84)	-0.37	(0.60)	
	May	-0.72	(0.79)	-0.79	(0.81)	
	Jun	-0.59	(0.60)	-1.89**	(0.74)	
	Jul	-0.98*	(0.55)	-1.66**	(0.66)	
	Aug	-1.87**	(0.71)	-2.38***	(0.76)	
	Sep	0.33	(0.59)	0.59	(0.87)	2.08%
50^{th}	Apr	-0.38	(0.67)	-0.26	(0.47)	
	May	-0.54	(0.64)	-0.80	(0.66)	
	Jun	-0.75	(0.53)	-1.98***	(0.69)	
	Jul	-0.86**	(0.43)	-1.42***	(0.50)	
	Aug	-1.48**	(0.57)	-1.96***	(0.66)	
	Sep	0.04	(0.51)	0.21	(0.77)	1.07%
25^{th}	Apr	-0.09	(0.52)	-0.11	(0.35)	
	May	-0.72	(0.60)	-0.84	(0.63)	
	Jun	-0.77*	(0.46)	-1.86***	(0.60)	
	Jul	-0.74*	(0.42)	-1.15**	(0.46)	
	Aug	-1.32**	(0.55)	-1.63**	(0.62)	
	Sep	-0.01	(0.57)	0.35	(0.75)	0.44%
5^{th}	Apr	-0.11	(0.67)	-0.40	(0.52)	
	May	-0.27	(0.59)	-0.67	(0.64)	
	Jun	-0.70	(0.58)	-1.54**	(0.73)	
	Jul	-0.39	(0.56)	-0.84	(0.52)	
	Aug	-1.17*	(0.70)	-1.44**	(0.71)	
	Sep	-0.40	(0.61)	-0.54	(0.69)	0.09%

Notes: Each panel (separated by horizontal lines) presents regression results from a joint regression using 278,174 observations and controls for previous-month precipitation. Units are in $°C/$(fraction of county area that is irrigated). The six panels present results for the 99^{th}, 90^{th}, 75^{th}, 50^{th}, 25^{th} and 5^{th} temperature percentiles for each month between April and September relative to the rest of the year. The two middle columns include information on the fraction of the county that is irrigated for same and upwind counties. Standard errors (in parenthesis) are two-way clustered by county and year. ***, ** and * denote statistical significance respectively at the 1%, 5% and 10% levels.

Table A3: Irrigation and Monthly Temperature Percentiles - Neighboring Counties

p	n	Irrigation information from						R^2-within
		upwind		crosswind		downwind		
99th	Apr	0.11	(0.55)	-0.37	(0.75)	-0.73	(0.85)	
	May	-0.95	(1.07)	-1.16*	(0.59)	-1.30**	(0.63)	
	Jun	-2.64**	(1.00)	-0.90*	(0.52)	-0.54	(0.78)	
	Jul	-2.59***	(0.84)	-0.83*	(0.43)	-1.16	(0.70)	
	Aug	-3.15***	(0.94)	-0.90*	(0.49)	-1.33	(0.84)	
	Sep	-0.88	(1.20)	0.04	(0.54)	-0.43	(0.85)	3.00%
90th	Apr	-0.38	(0.44)	-0.31	(0.68)	-0.63	(0.78)	
	May	-1.20	(0.86)	-0.73	(0.61)	-0.69	(0.69)	
	Jun	-1.92**	(0.76)	-0.64	(0.40)	-0.47	(0.57)	
	Jul	-1.97**	(0.80)	-0.85**	(0.37)	-0.86	(0.63)	
	Aug	-3.37***	(0.82)	-1.21***	(0.45)	-1.79**	(0.76)	
	Sep	0.20	(0.98)	0.34	(0.39)	0.19	(0.67)	3.00%
75th	Apr	-0.31	(0.37)	-0.22	(0.56)	-0.64	(0.70)	
	May	-0.71	(0.71)	-0.39	(0.55)	-0.68	(0.65)	
	Jun	-1.87***	(0.70)	-0.53	(0.37)	-0.26	(0.53)	
	Jul	-1.70**	(0.65)	-0.68**	(0.29)	-0.55	(0.52)	
	Aug	-2.43***	(0.73)	-0.99***	(0.36)	-1.51**	(0.68)	
	Sep	0.42	(0.84)	0.39	(0.31)	0.36	(0.57)	2.17%
50th	Apr	-0.26	(0.29)	-0.11	(0.44)	-0.32	(0.56)	
	May	-0.72	(0.57)	-0.37	(0.46)	-0.42	(0.54)	
	Jun	-1.95***	(0.65)	-0.60*	(0.34)	-0.41	(0.47)	
	Jul	-1.47***	(0.49)	-0.60**	(0.23)	-0.48	(0.41)	
	Aug	-2.02***	(0.63)	-0.80**	(0.32)	-1.15**	(0.54)	
	Sep	0.07	(0.74)	0.10	(0.27)	0.23	(0.49)	1.14%
25th	Apr	-0.23	(0.23)	0.03	(0.34)	-0.00	(0.45)	
	May	-0.74	(0.53)	-0.43	(0.44)	-0.65	(0.50)	
	Jun	-1.83***	(0.57)	-0.59**	(0.28)	-0.45	(0.41)	
	Jul	-1.23***	(0.45)	-0.45**	(0.21)	-0.39	(0.40)	
	Aug	-1.73***	(0.59)	-0.63*	(0.32)	-1.03**	(0.51)	
	Sep	0.22	(0.73)	0.08	(0.31)	0.15	(0.54)	0.48%
5th	Apr	-0.47	(0.34)	-0.06	(0.47)	0.01	(0.56)	
	May	-0.76	(0.57)	0.13	(0.43)	-0.36	(0.49)	
	Jun	-1.50**	(0.69)	-0.41	(0.34)	-0.59	(0.52)	
	Jul	-0.97*	(0.50)	-0.10	(0.28)	-0.21	(0.53)	
	Aug	-1.58**	(0.69)	-0.49	(0.35)	-0.90	(0.68)	
	Sep	-0.68	(0.66)	-0.12	(0.35)	-0.17	(0.54)	0.10%

Notes: Table replicates Table 1, but excluded own irrigation levels . Each panel (separated by horizontal lines) presents regression results from a joint regression using 278,174 observations and controls for previous-month precipitation. Units are in $°C/$(fraction of county area that is irrigated). The six panels present results for the 99^{th}, 90^{th}, 75^{th}, 50^{th}, 25^{th} and 5^{th} temperature percentiles for each month between April and September relative to the rest of the year. The three middle columns include information on the fraction of the county that is irrigated for upwind, crosswind, and downwind counties, respectively. Standard errors (in parenthesis) are two-way clustered by county and year. ***, ** and * denote statistical significance respectively at the 1%, 5% and 10% levels.

Table A4: Irrigation and Monthly Temperature Percentiles - Northern States

p	n	Irrigation information from: same		upwind		crosswind		downwind		R^2-within
99th	Apr	-.32	(.35)	.35	(.36)	-.67	(.44)	-1.30**	(.54)	
	May	-.16	(.23)	-.43	(.86)	-.53	(.39)	-.77	(.57)	
	Jun	.09	(.26)	-2.79***	(.74)	-.87**	(.36)	-.71	(.62)	
	Jul	-.65***	(.22)	-2.86***	(.57)	-.30	(.32)	-1.41***	(.50)	
	Aug	-.68***	(.21)	-3.06***	(.68)	.09	(.30)	-1.01	(.62)	
	Sep	-.08	(.21)	-1.14	(.72)	.18	(.33)	-.98*	(.54)	2.8%
90th	Apr	-.59***	(.22)	-.45*	(.26)	-.32	(.36)	-.64	(.47)	
	May	-.00	(.17)	-1.00*	(.57)	-.34	(.36)	-.12	(.48)	
	Jun	-.19	(.17)	-2.04***	(.51)	-.57**	(.27)	-.55	(.49)	
	Jul	-.72***	(.17)	-2.16***	(.51)	-.34	(.26)	-1.10***	(.38)	
	Aug	-.60***	(.17)	-2.89***	(.56)	-.04	(.25)	-1.18**	(.50)	
	Sep	-.31	(.20)	-.19	(.62)	.15	(.29)	-.52	(.46)	2.6%
75th	Apr	-.31	(.20)	-.46**	(.22)	-.22	(.30)	-.33	(.38)	
	May	.02	(.15)	-.72	(.49)	-.22	(.34)	-.48	(.42)	
	Jun	-.04	(.14)	-1.94***	(.43)	-.47**	(.23)	-.27	(.38)	
	Jul	-.57***	(.15)	-1.79***	(.40)	-.30	(.21)	-.68**	(.32)	
	Aug	-.45***	(.15)	-1.99***	(.49)	-.10	(.23)	-1.05**	(.46)	
	Sep	-.17	(.17)	.03	(.55)	.19	(.27)	-.30	(.40)	2.0%
50th	Apr	-.41**	(.17)	-.41**	(.19)	-.21	(.25)	-.37	(.29)	
	May	.01	(.12)	-.81**	(.41)	-.31	(.29)	-.34	(.37)	
	Jun	-.02	(.13)	-2.05***	(.42)	-.53***	(.19)	-.44	(.34)	
	Jul	-.40***	(.13)	-1.52***	(.32)	-.37**	(.18)	-.59**	(.27)	
	Aug	-.36***	(.12)	-1.82***	(.43)	-.18	(.20)	-.84**	(.38)	
	Sep	-.18	(.13)	-.43	(.45)	-.07	(.27)	-.45	(.42)	1.1%
25th	Apr	-.39**	(.16)	-.30	(.19)	-.24	(.23)	-.32	(.26)	
	May	-.01	(.13)	-.67*	(.38)	-.49*	(.29)	-.64*	(.35)	
	Jun	-.04	(.11)	-1.64***	(.40)	-.47**	(.19)	-.17	(.33)	
	Jul	-.42***	(.12)	-1.19***	(.33)	-.32**	(.16)	-.33	(.30)	
	Aug	-.39***	(.12)	-1.38***	(.40)	-.16	(.21)	-.63*	(.38)	
	Sep	-.13	(.12)	-.21	(.41)	-.20	(.22)	-.51	(.40)	.4%
5th	Apr	-.28	(.24)	-.34	(.30)	-.27	(.34)	-.49	(.44)	
	May	-.18	(.16)	-.53	(.46)	.19	(.31)	-.31	(.41)	
	Jun	.09	(.17)	-.82	(.56)	.02	(.26)	-.09	(.45)	
	Jul	-.33**	(.14)	-.87**	(.43)	-.09	(.22)	-.24	(.47)	
	Aug	-.47***	(.15)	-.99**	(.45)	.10	(.23)	-.37	(.46)	
	Sep	-.20	(.16)	-.78	(.49)	-.13	(.26)	-.31	(.47)	.1%

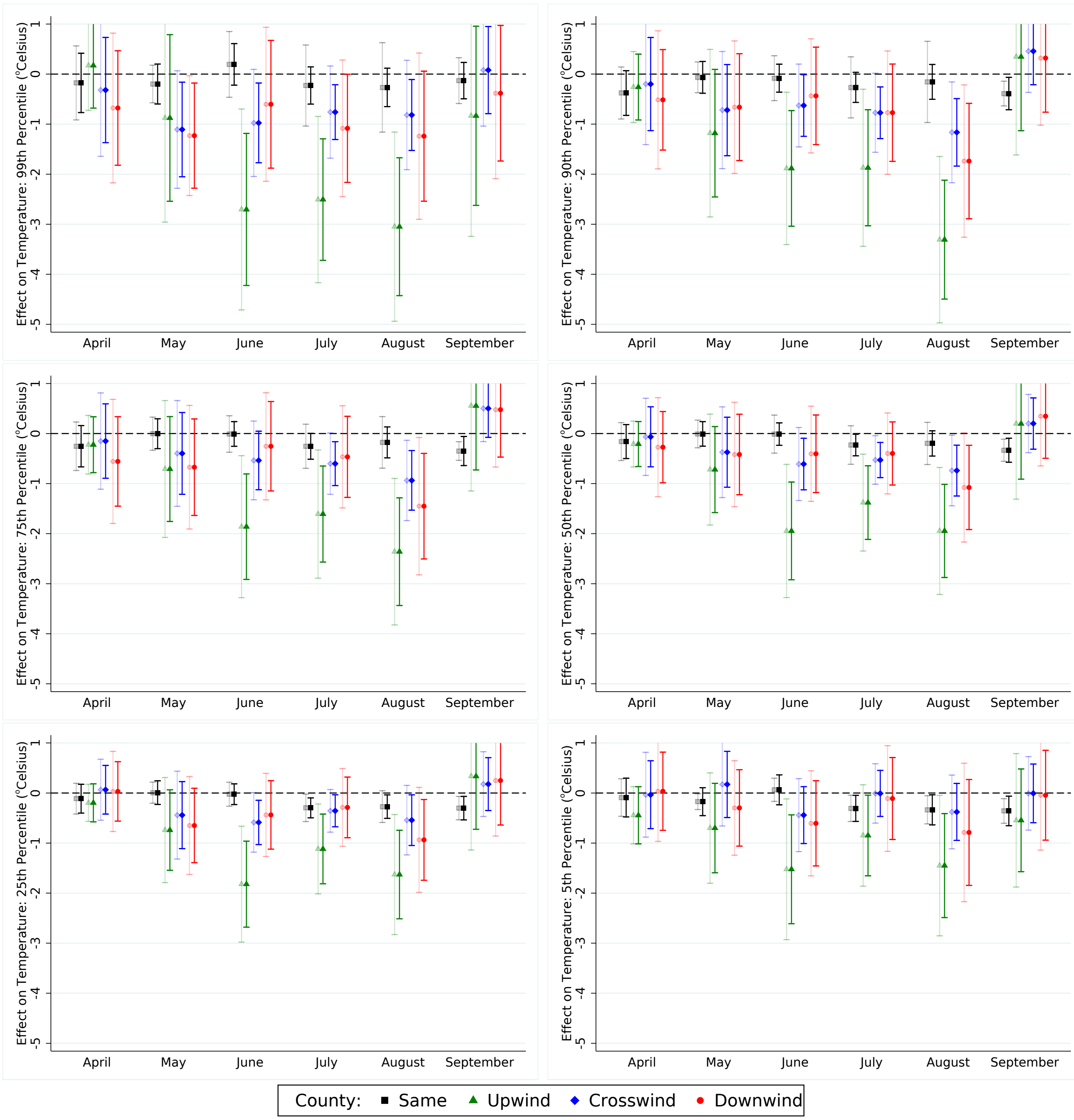
Notes: Table replicates Table 1, but limits the data set to the five northern states (**Nebraska**, **Colorado**, **Wyoming**, **South Dakota** and **Kansas**). Each panel (separated by horizontal lines) presents regression results from a joint regression using 155,610 observations and controls for previous-month precipitation - see specification (5). Units are in $°C$/(fraction of county area that is irrigated). The six panels present results for the 99th, 90th, 75th, 50th, 25th and 5th temperature percentiles for each month between April and September relative to the rest of the year. The four middle columns include information on the fraction of the county that is irrigated for same, up-, cross- and downwind counties. Conley s.e. (in parentheses) are computed using Bartlett kernel and a 1,000km cutoff distance. ***, ** and * denote statistical significance respectively at the 1%, 5% and 10% levels.

Table A5: Irrigation and Monthly Temperature Percentiles - Southern States

p	n	Irrigation information from								R^2-within
		same		upwind		crosswind		downwind		
99^{th}	Apr	.18	(.28)	.20	(.58)	.08	(.54)	.17	(.60)	
	May	.03	(.26)	-.15	(.51)	-.73	(.68)	-.81	(.64)	
	Jun	.21	(.30)	-.87	(.73)	-.19	(.65)	.92	(.76)	
	Jul	.29	(.28)	-1.30**	(.58)	-.82	(.52)	.08	(.68)	
	Aug	.07	(.27)	-1.02*	(.56)	-.40	(.58)	.15	(.56)	
	Sep	-.36	(.27)	-.35	(.58)	.16	(.57)	1.01*	(.61)	3.4%
90^{th}	Apr	.13	(.19)	-.35	(.34)	-.66*	(.38)	-.51	(.43)	
	May	.23	(.21)	-.05	(.40)	-.66	(.52)	-.47	(.57)	
	Jun	.11	(.20)	-.82	(.52)	-.42	(.47)	.31	(.52)	
	Jul	.27	(.21)	-.84**	(.36)	-.78**	(.37)	.32	(.45)	
	Aug	.10	(.23)	-.84**	(.43)	-.35	(.41)	-.02	(.49)	
	Sep	-.34*	(.20)	-.25	(.44)	.43	(.45)	1.16**	(.48)	3.9%
75^{th}	Apr	.10	(.19)	-.49	(.33)	-.45	(.36)	-.97**	(.48)	
	May	.23	(.18)	.13	(.36)	-.30	(.44)	-.15	(.53)	
	Jun	.08	(.20)	-.89**	(.44)	-.33	(.40)	.35	(.50)	
	Jul	.11	(.19)	-.99***	(.37)	-.78**	(.36)	.16	(.47)	
	Aug	-.04	(.22)	-.76*	(.44)	-.46	(.40)	-.15	(.45)	
	Sep	-.48**	(.19)	-.24	(.40)	.36	(.42)	1.12**	(.48)	2.9%
50^{th}	Apr	.29	(.19)	-.39	(.32)	-.36	(.32)	-.52	(.37)	
	May	.04	(.16)	.21	(.29)	.11	(.38)	.17	(.39)	
	Jun	.00	(.16)	-.94**	(.43)	-.55*	(.33)	.09	(.42)	
	Jul	-.12	(.16)	-.81**	(.33)	-.65**	(.32)	.05	(.40)	
	Aug	-.22	(.20)	-.61	(.40)	-.51	(.35)	-.25	(.37)	
	Sep	-.49***	(.15)	-.49	(.37)	-.24	(.39)	.80**	(.37)	1.4%
25^{th}	Apr	.27	(.19)	-.60*	(.33)	-.23	(.31)	-.22	(.36)	
	May	.13	(.14)	-.05	(.26)	.55*	(.33)	.20	(.30)	
	Jun	.03	(.15)	-.98***	(.34)	-.37	(.26)	-.33	(.36)	
	Jul	-.14	(.14)	-.71***	(.27)	-.31	(.26)	-.22	(.33)	
	Aug	-.21	(.18)	-.66**	(.31)	-.31	(.29)	-.48	(.35)	
	Sep	-.32*	(.18)	-.81**	(.32)	-.40	(.40)	.35	(.38)	.4%
5^{th}	Apr	.04	(.24)	-.53	(.42)	.11	(.37)	.52	(.46)	
	May	-.02	(.21)	-.60	(.41)	.22	(.44)	.08	(.44)	
	Jun	.08	(.22)	-.99**	(.40)	-.40	(.33)	-.29	(.43)	
	Jul	-.25	(.20)	-.97***	(.36)	-.16	(.32)	-.10	(.39)	
	Aug	-.13	(.26)	-.86**	(.42)	-.56	(.37)	-.45	(.48)	
	Sep	-.47*	(.26)	-1.27**	(.56)	-.73	(.54)	-.20	(.51)	.1%

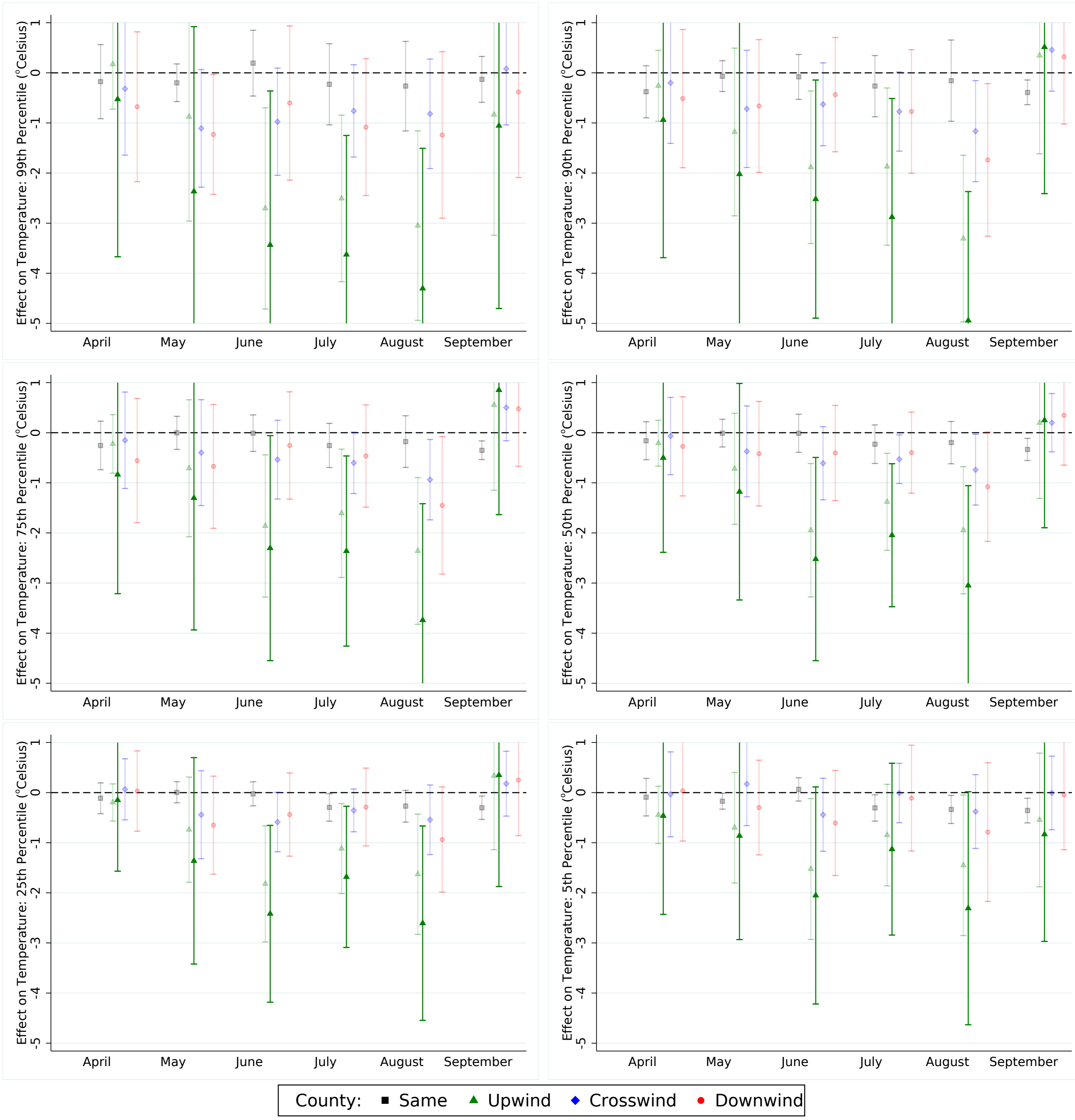
Notes: Table replicates Table 1, but limits the data set to the three southern states (**Texas**, **Oklahoma** and **New Mexico**). Each panel (separated by horizontal lines) presents regression results from a joint regression using 122,484 observations and controls for previous-month precipitation - see specification (5). Units are in $°C/$(fraction of county area that is irrigated). The six panels present results for the 99^{th}, 90^{th}, 75^{th}, 50^{th}, 25^{th} and 5^{th} temperature percentiles for each month between April and September relative to the rest of the year. The four middle columns include information on the fraction of the county that is irrigated for same, up-, cross- and downwind counties. Conley s.e. (in parentheses) are computed using Bartlett kernel and a 1,000km cutoff distance. ***, ** and * denote statistical significance respectively at the 1%, 5% and 10% levels.

Figure A1: Sensitivity to Clustering: Conley Standard Errors



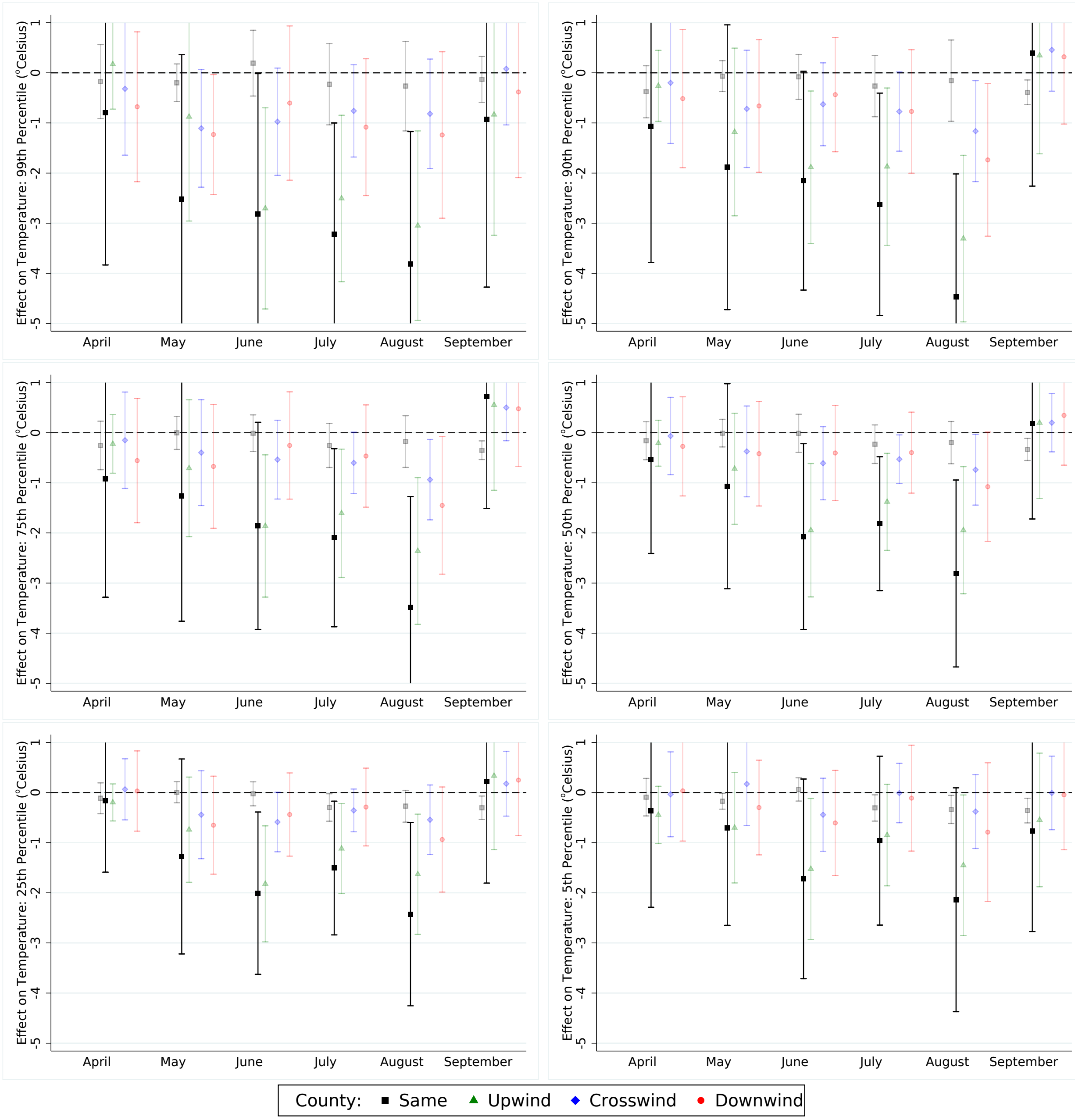
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors make one modification: they use Conley standard errors that account for both serial correlation as well as spatial correlation with a Bartlett kernel and a 1,000km cutoff distance. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A2: Sensitivity to Defining Neighbors: Upwind County Only



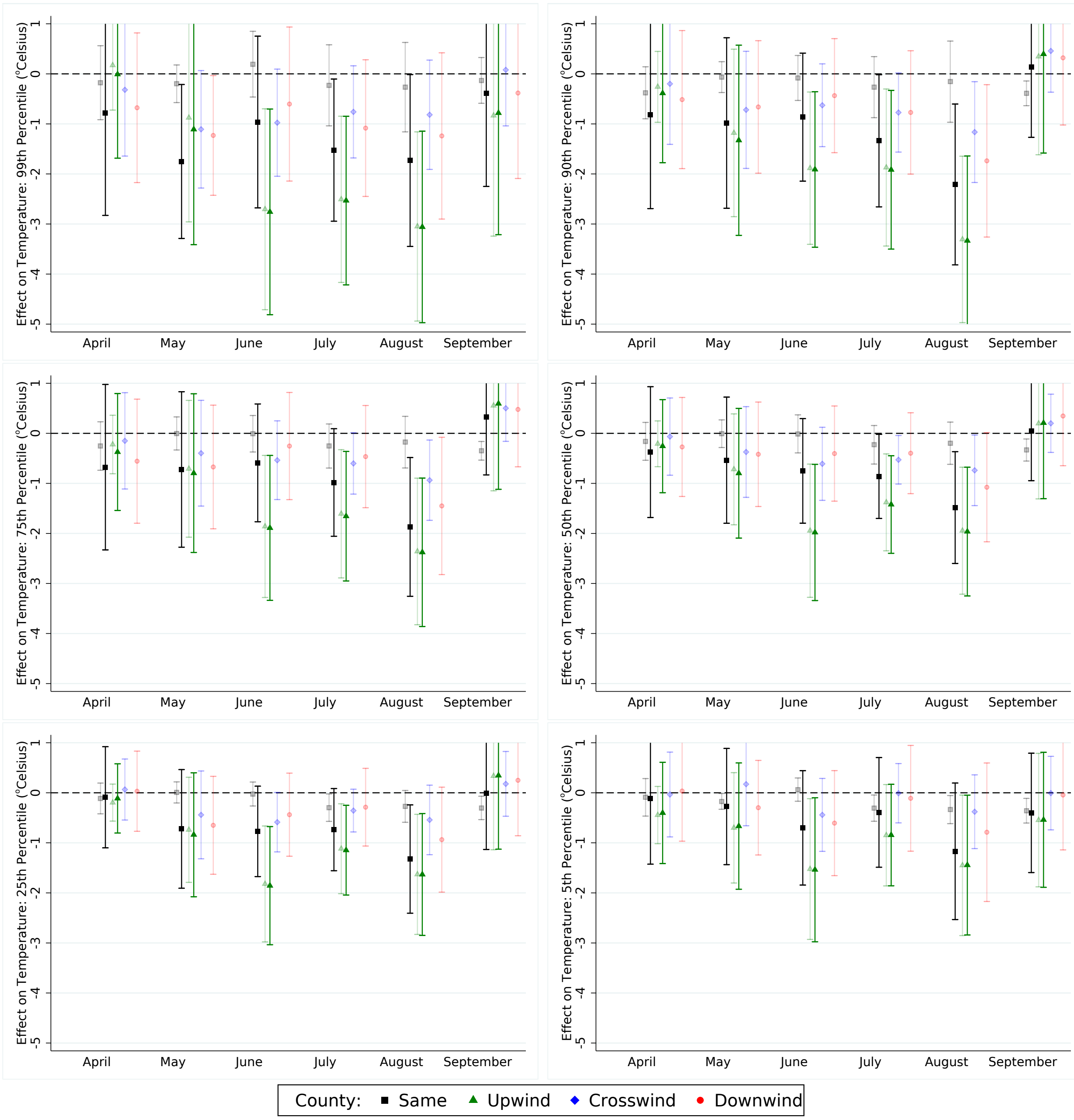
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors varies which variables from surrounding counties are included. In this figure, only data from the upwind county (green line) is included, while the same, crosswind and downwind measures are excluded. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A3: Sensitivity to Defining Neighbors: Same County Only



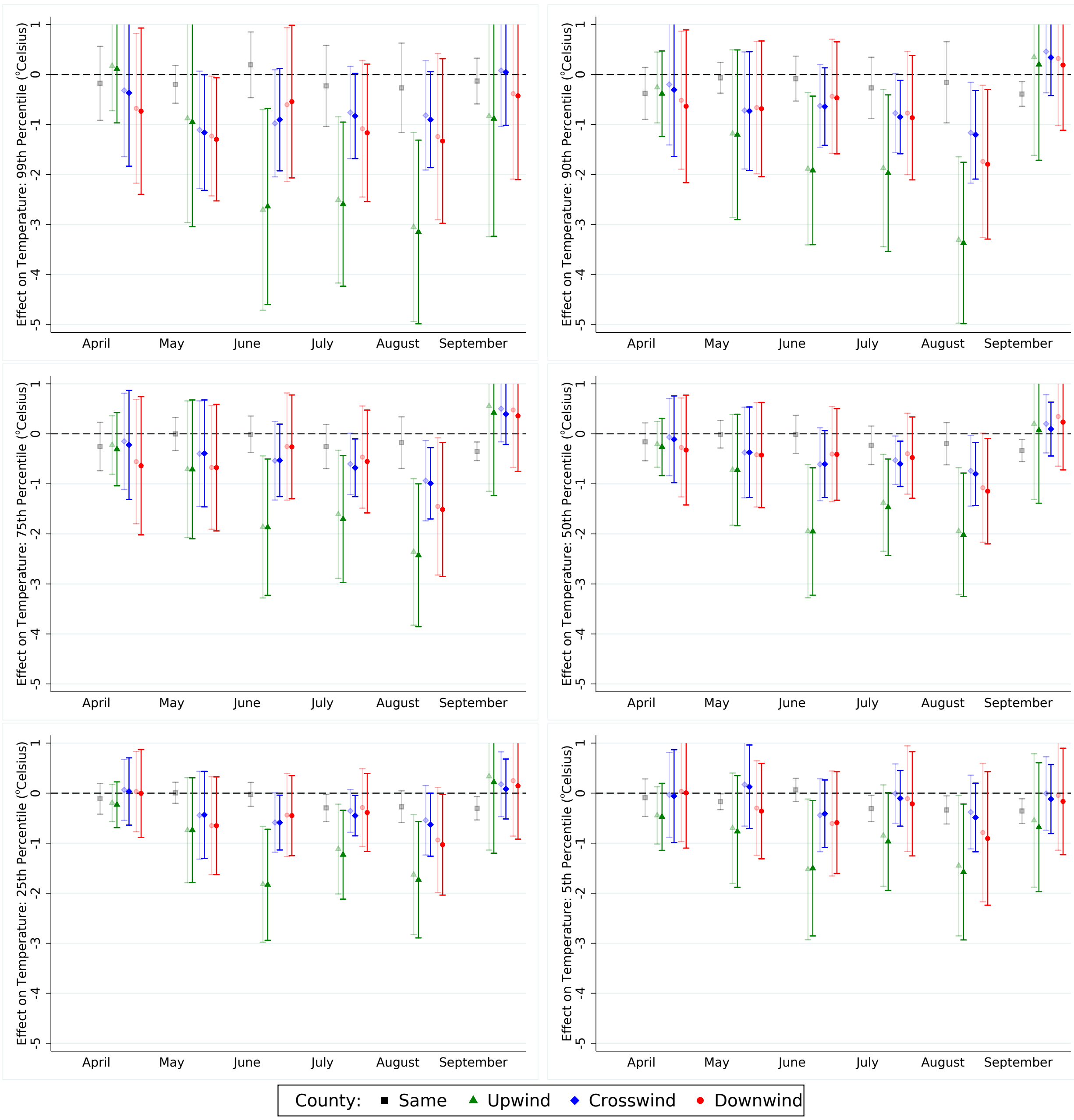
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors varies which variables from surrounding counties are included. In this figure, only data from a county itself (black line) is included, while the upwind, crosswind and downwind measures are excluded. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A4: Sensitivity to Defining Neighbors: Same and Upwind County



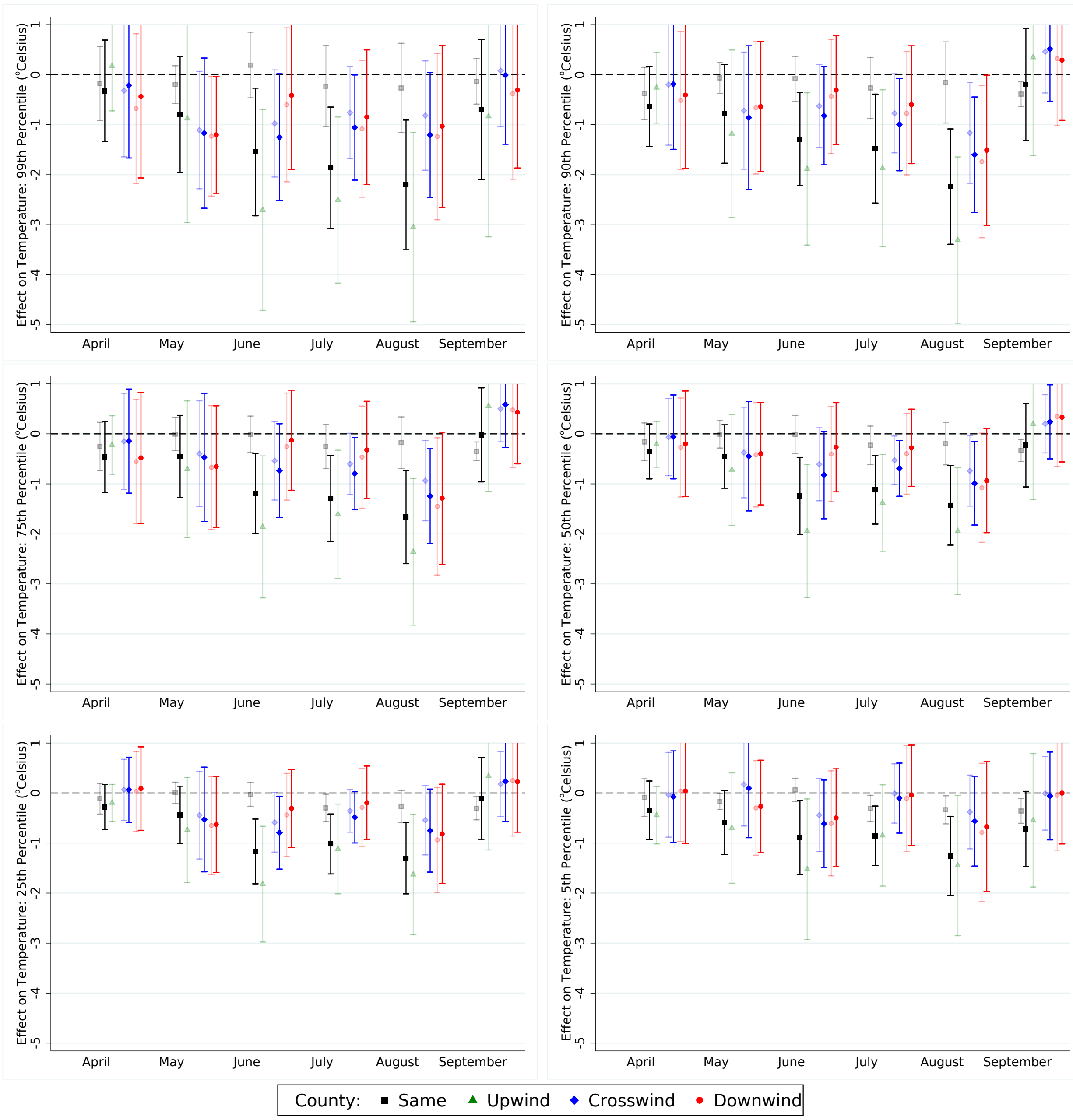
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors varies which variables from surrounding counties are included. In this figure, irrigation from a county itself (black line) as well as its most frequent upwind neighbor (green line) are included, while the crosswind and downwind measures are excluded. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A5: Sensitivity to Defining Neighbors: Neighboring Counties



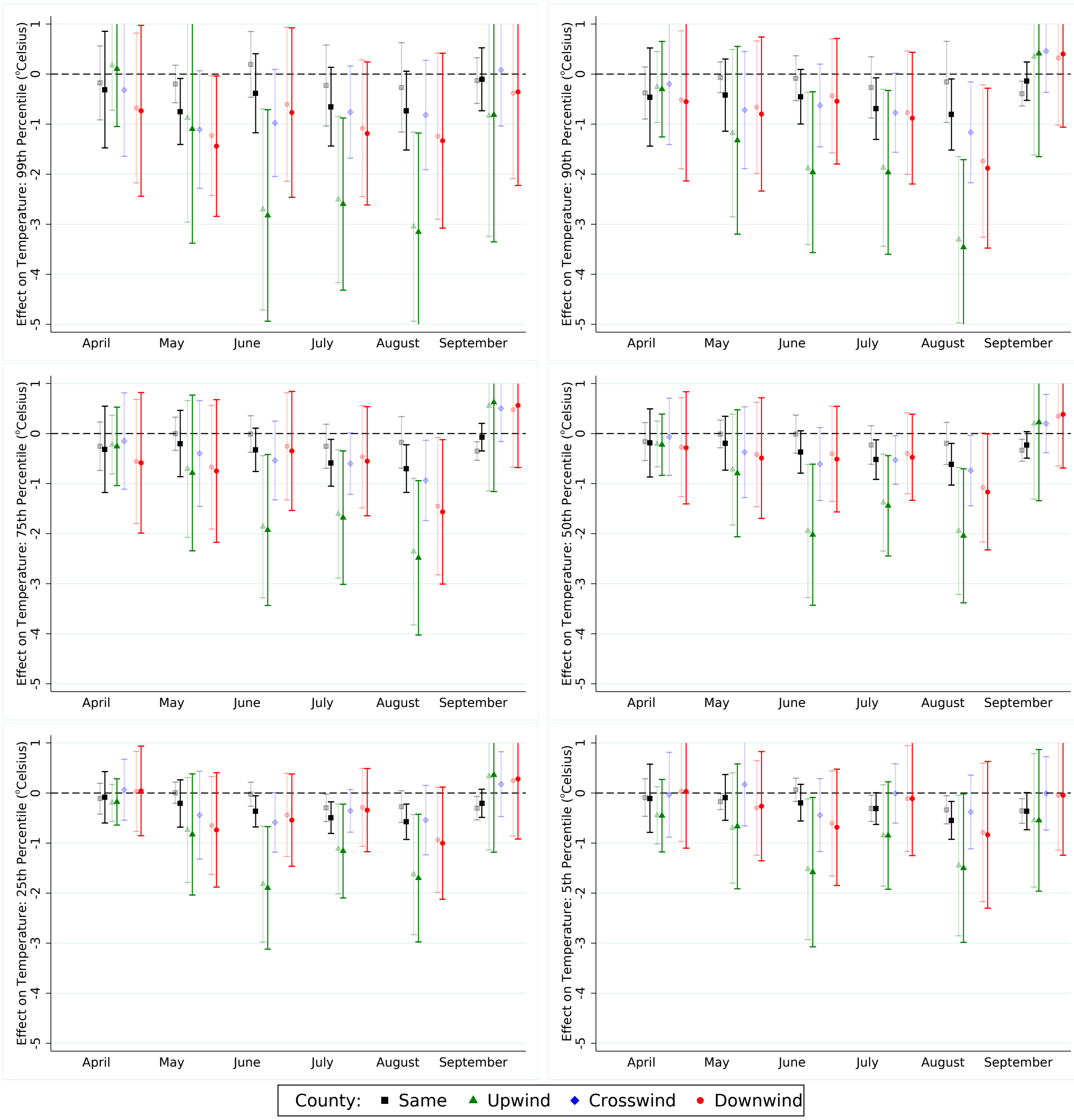
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors varies which variables from surrounding counties are included. In this figure, only measures from neighboring counties are included, while the county itself (black line) is excluded. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A6: Sensitivity to Defining Neighbors: Excluding Upwind Variables



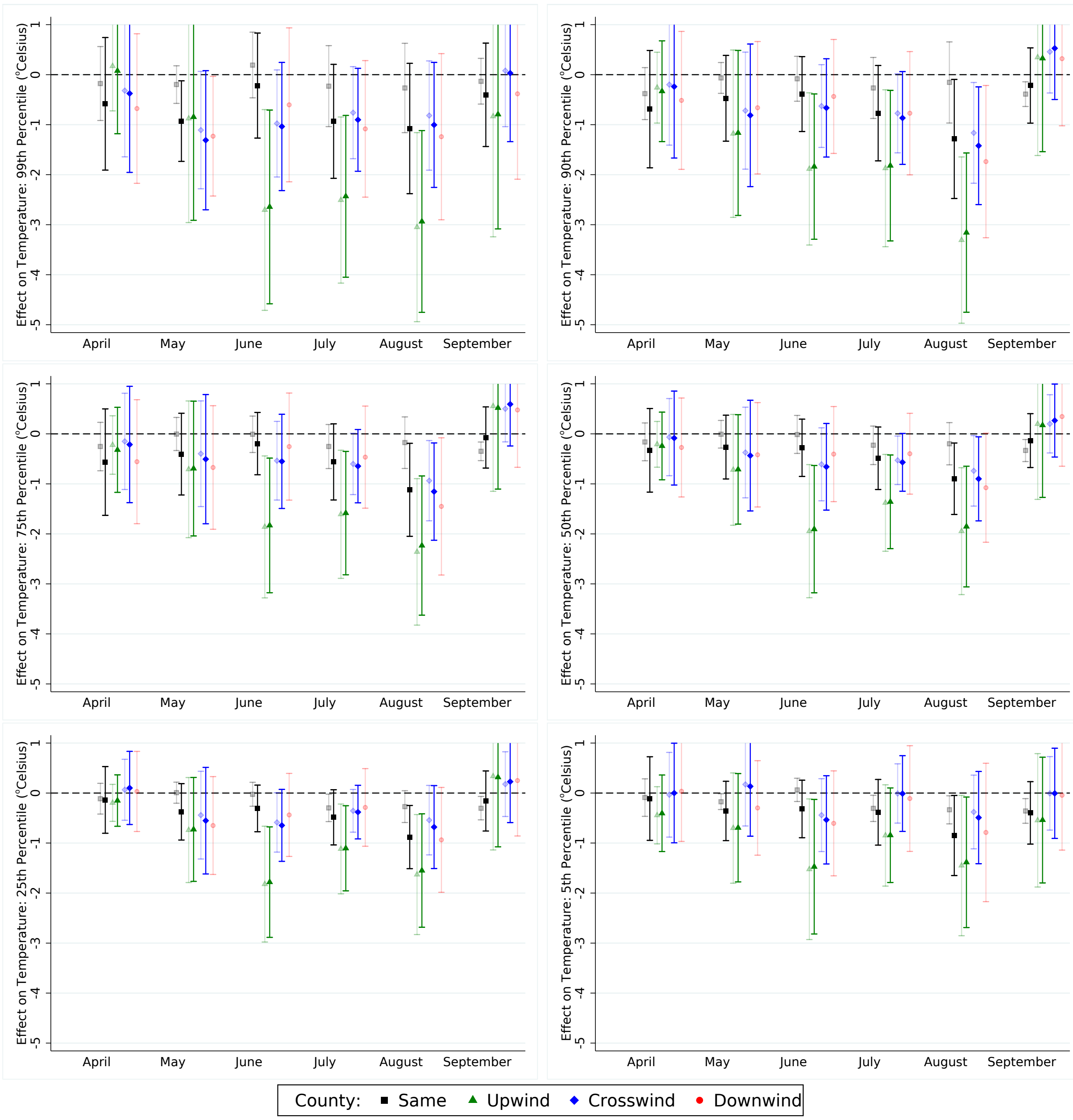
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors varies which variables from surrounding counties are included. In this figure, variables from upwind neighbors are excluded. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A7: Sensitivity to Defining Neighbors: Excluding Crosswind Variables



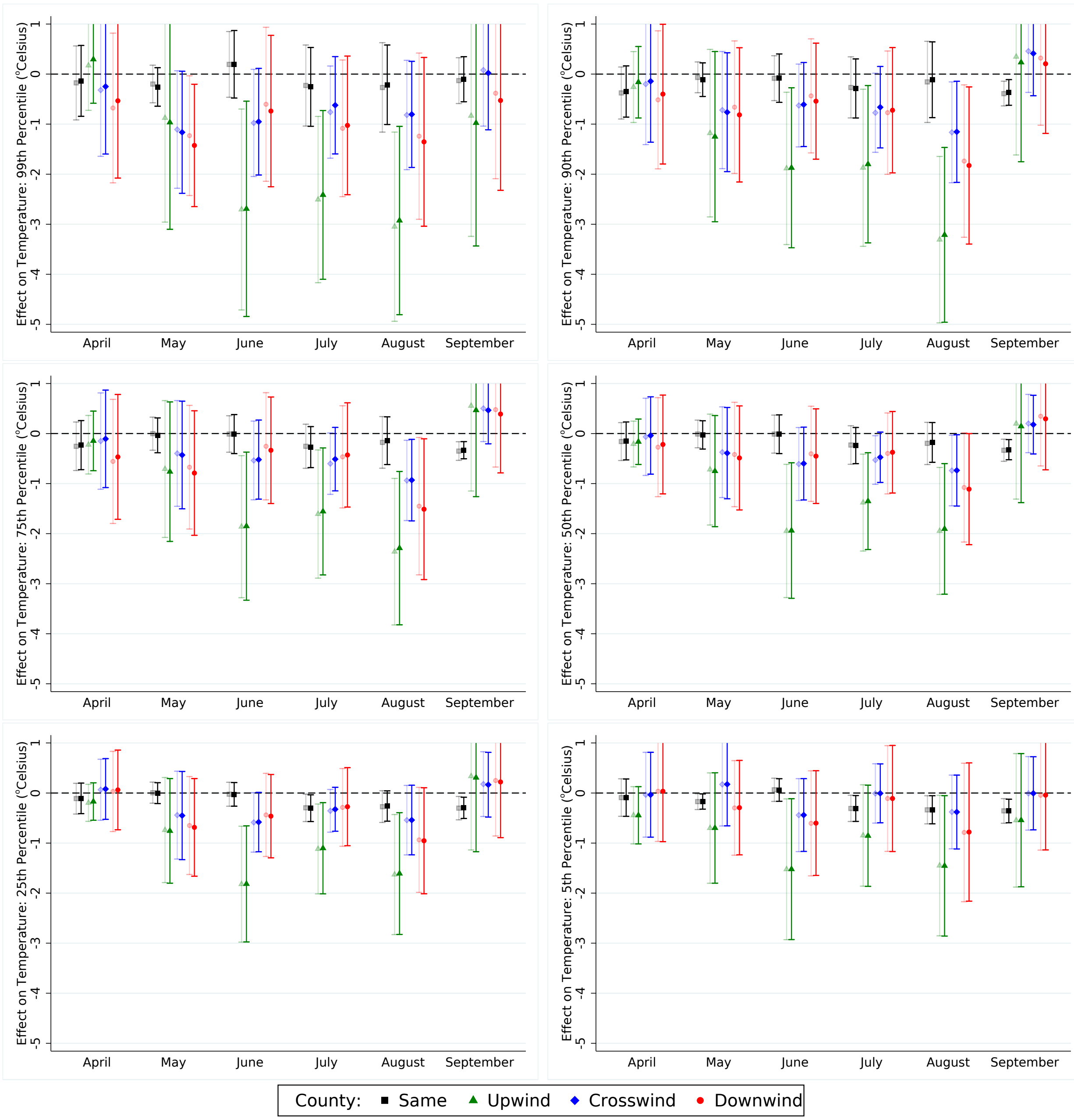
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors varies which variables from surrounding counties are included. In this figure, variables from crosswind neighbors are excluded. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A8: Sensitivity to Defining Neighbors: Excluding Downwind Variables



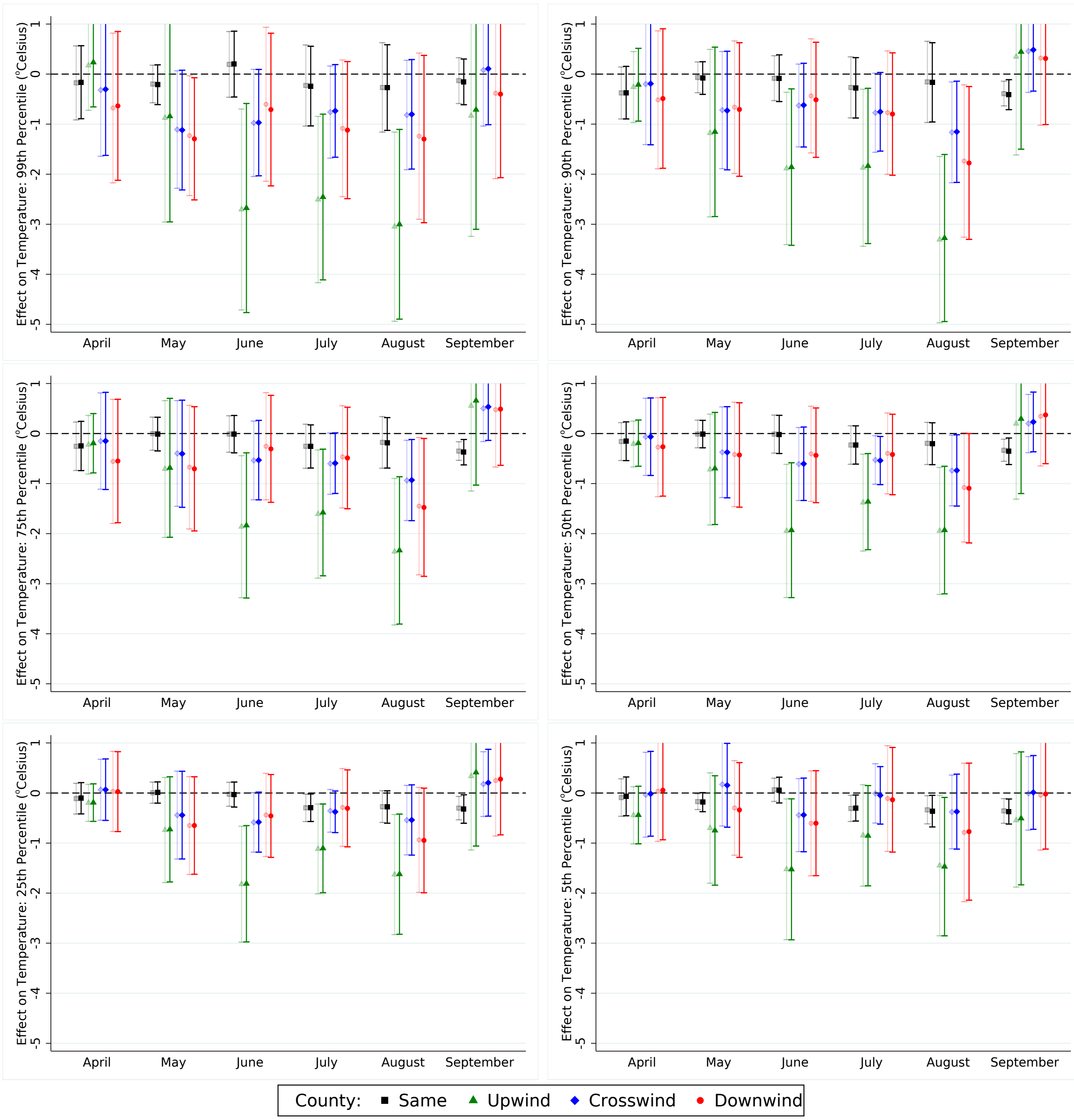
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors varies which variables from surrounding counties are included. In this figure, variables from downwind neighbors are excluded. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A9: Sensitivity to Chosen Control: Excluding All Precipitation Controls



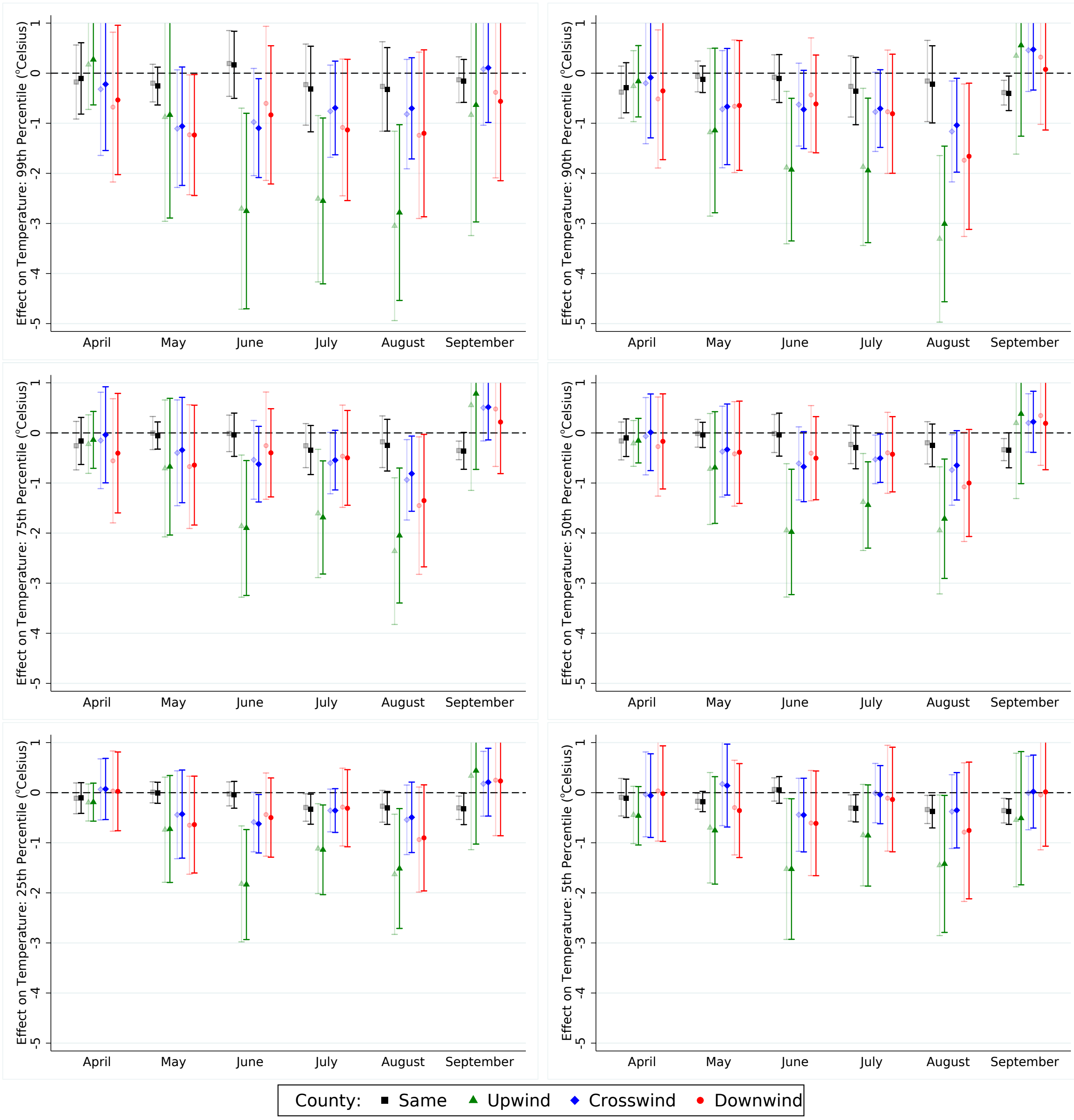
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors make one modification: they exclude all precipitation variables, while the baseline jointly controlled for previous-month precipitation (four variables). Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A10: Sensitivity to Chosen Control: Precipitation Controls by Month



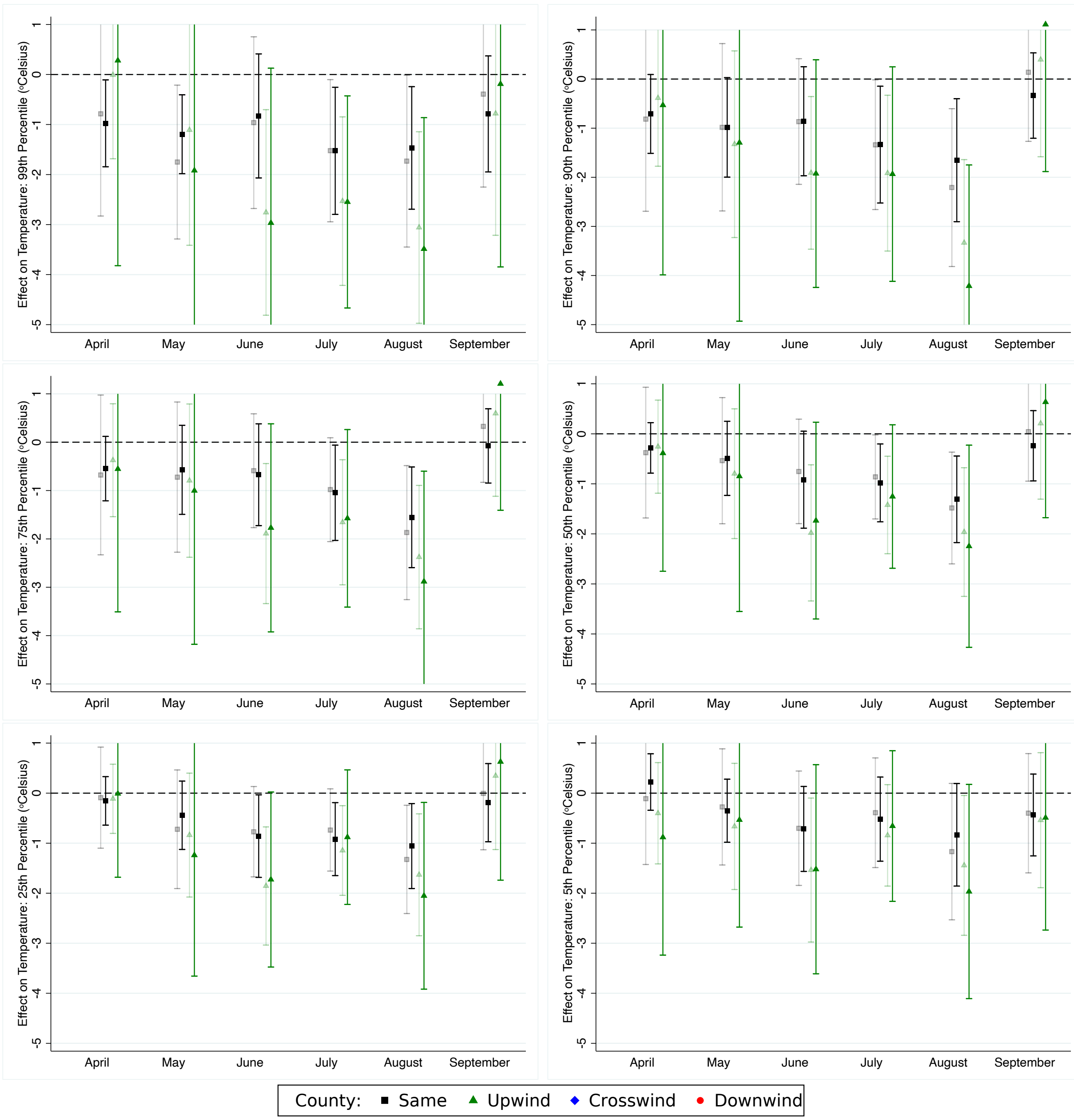
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors make one modification: they allow the effect of the precipitation variables to vary by month (24 variables), while the baseline jointly controlled for previous-month precipitation (four variables). Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A11: Sensitivity to Chosen Control: Including Concurrent Precipitation



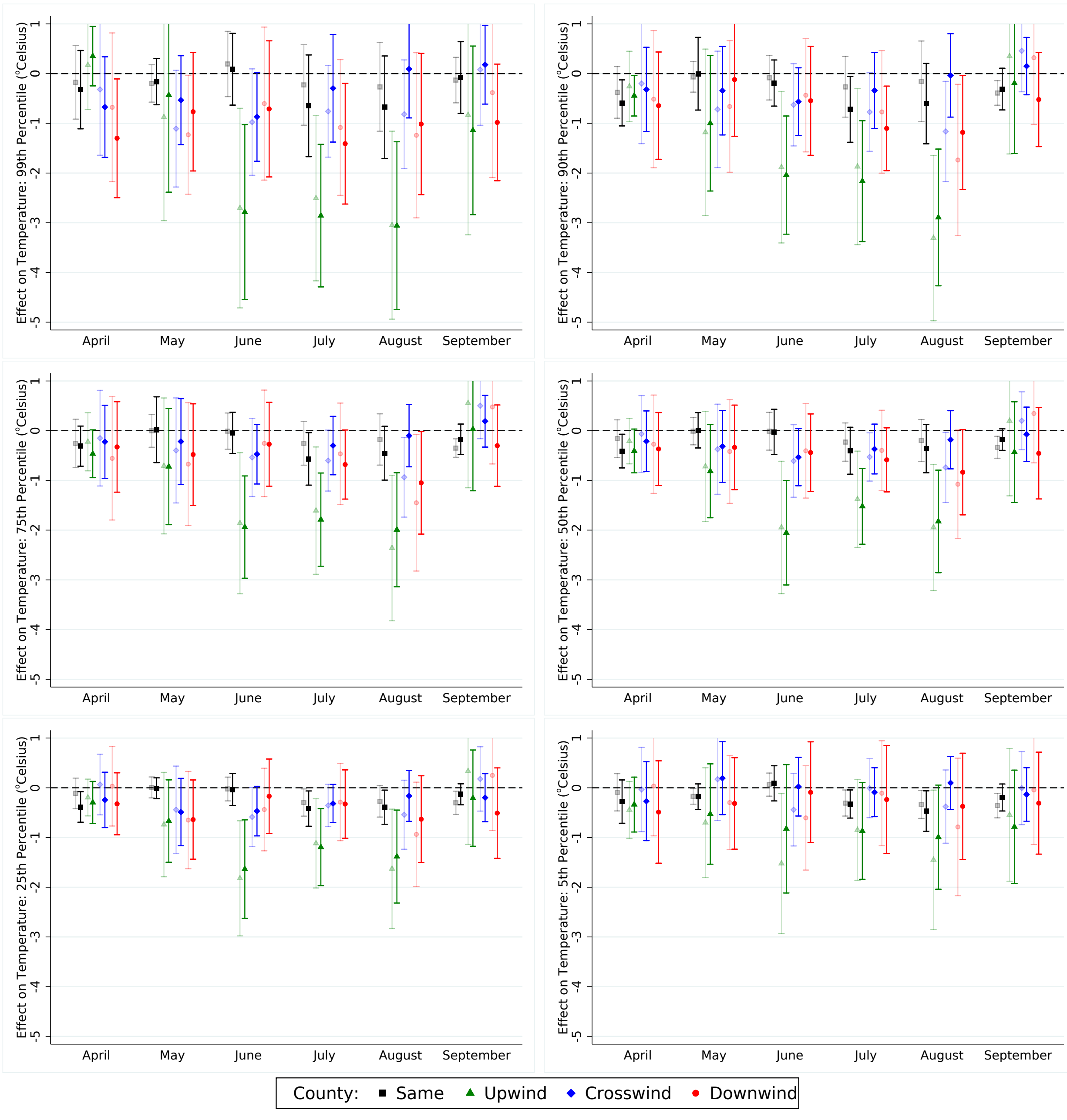
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors make one modification: they additionally include the current month precipitation of the county (same) and allow the effect of the precipitation variables (both the four temporal lags in the four direction as well as the concurrent precipitation in a county) to vary by month 30 variables), while the baseline jointly controlled for previous-month precipitation (four variables). Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A12: Sensitivity to Defining Neighbors: Weighted Average Upwind



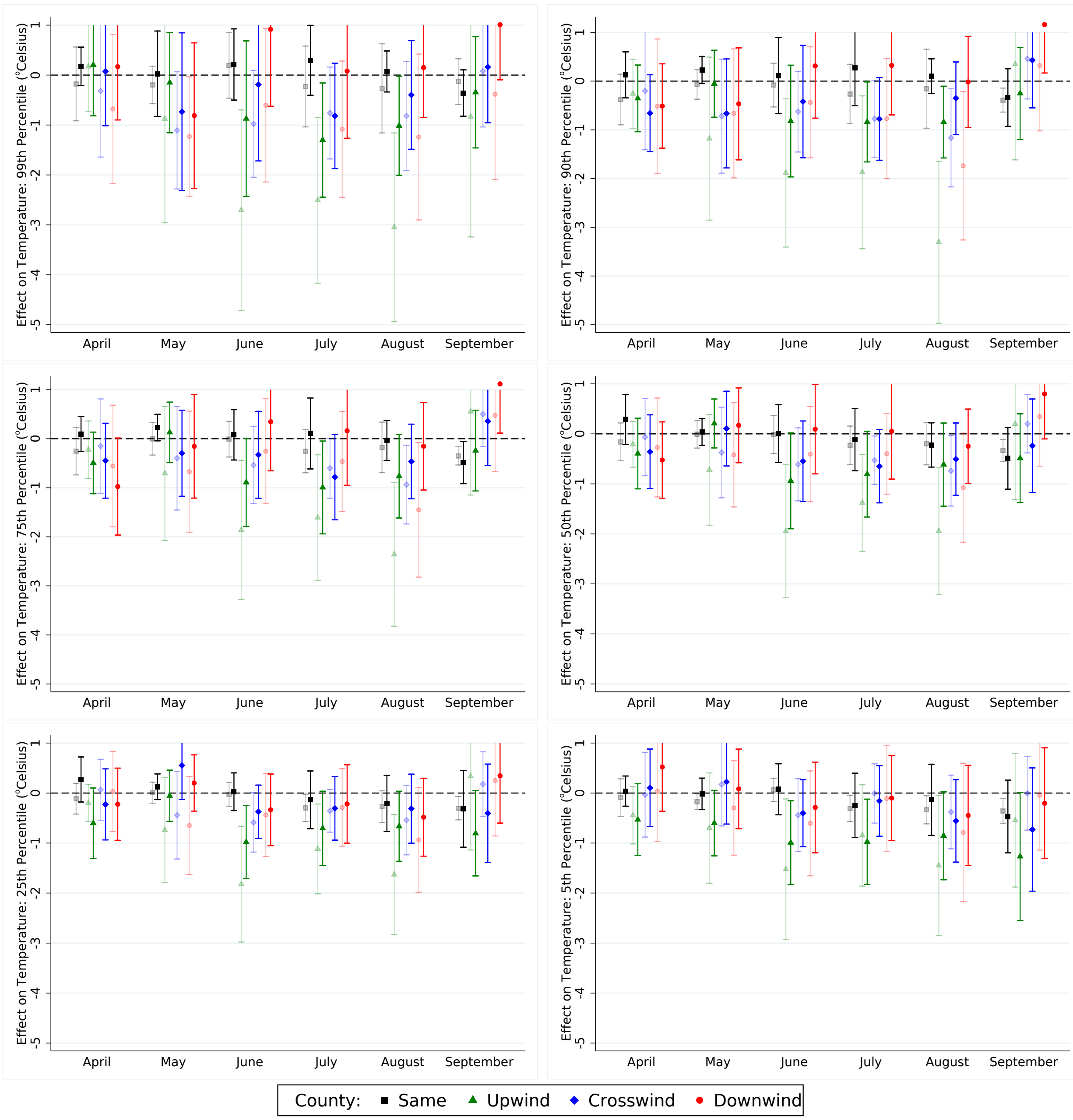
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black) and upwind (green) county for the six months of the growing season relative to the rest of the year. The full-color results from regression in Figure A4 are shown here in faded colors. The second set of estimates in full colors varies how irrigation level from neighboring counties are included. In this figure, upwind irrigation level is the average between irrigation of neighboring counties weighted by the amount of time each of these is upwind. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A13: Sensitivity to Spatial Coverage: Northern Subset



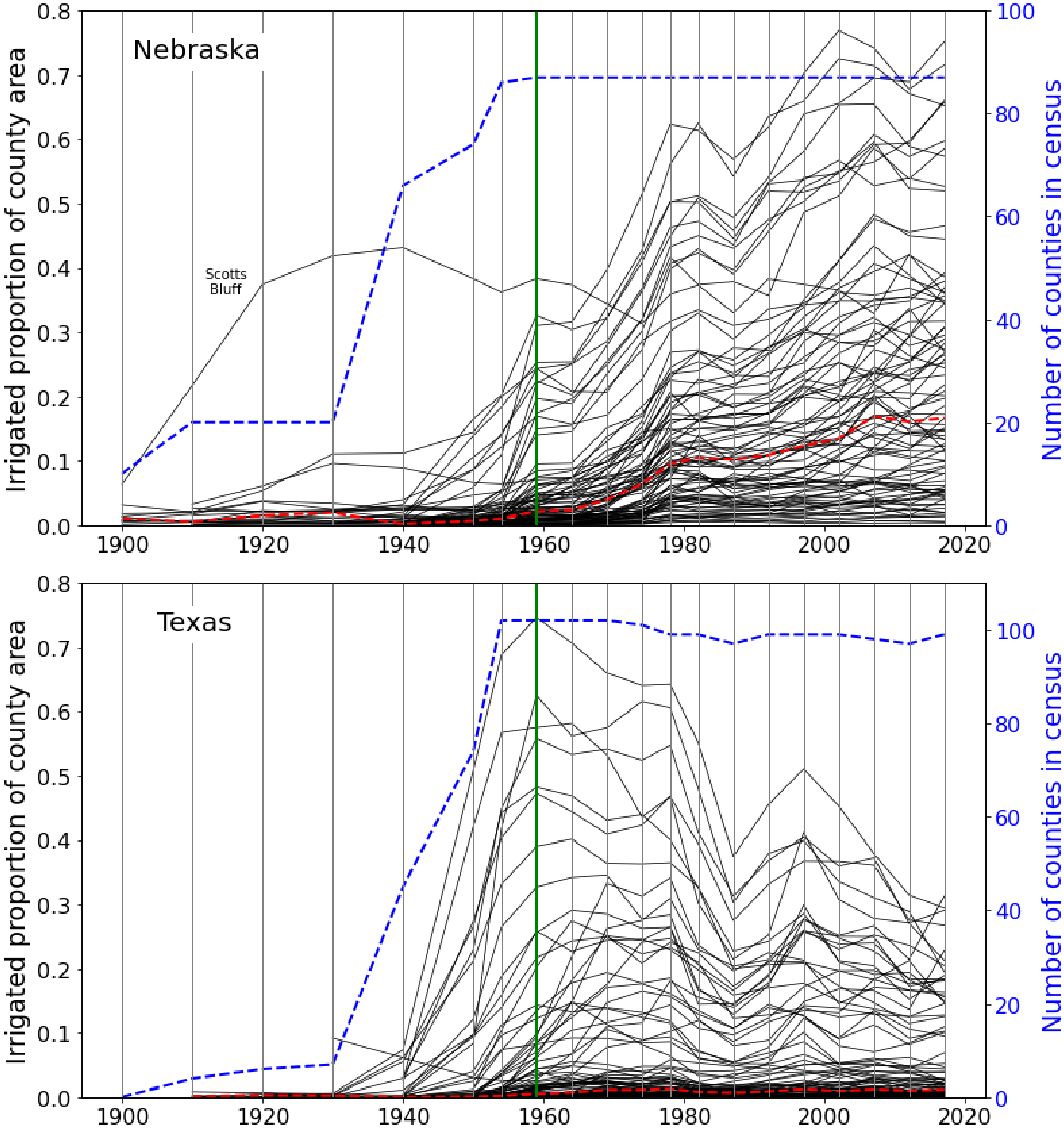
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors limits the data set to the five northern states (**Nebraska**, **Colorado**, **Wyoming**, **South Dakota** and **Kansas**) for a total of 155,610 observations. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A14: Sensitivity to Spatial Coverage: Southern Subset



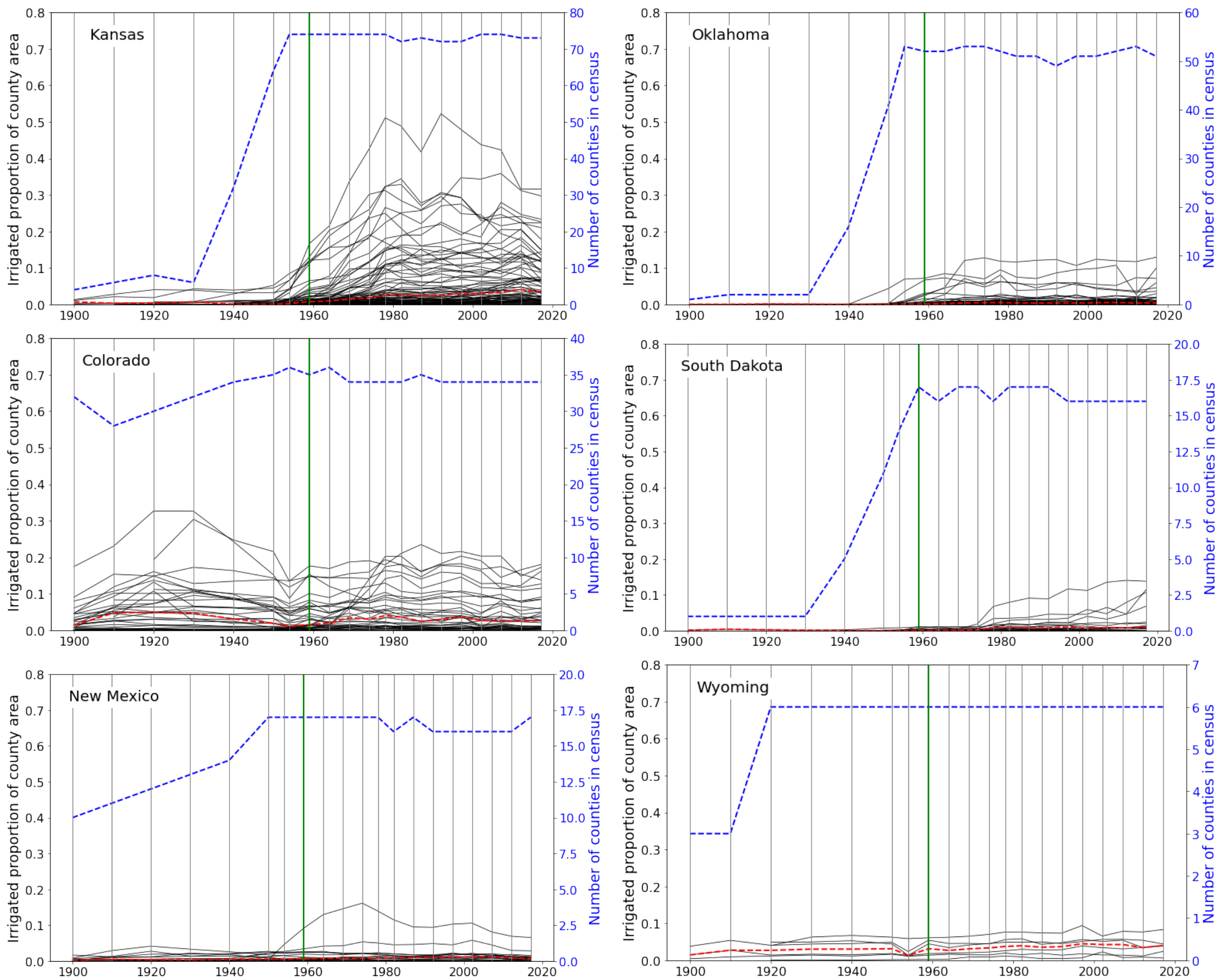
Notes: Each panel shows the estimated effects and 95% confidence intervals of irrigation in the same (black), upwind (green), crosswind (blue) and downwind (red) county for the six months of the growing season relative to the rest of the year. The results from the baseline regression in Figure 3 are shown in faded colors - see Figure 3 for details on the baseline model. The second set of estimates in full colors limits the data set to the three southern states (**Texas**, **Oklahoma** and **New Mexico**) for a total of 122,484 observations. Units are in °C/(fraction of county area that is irrigated). 95% confidence intervals (vertical bars) are based on the regression that twoway-clusters errors by county and year. For clarity the y-scale is limited to $[-5, 1]$ and some confidence bands might be truncated.

Figure A15: Irrigation Trends in Nebraska and Texas 1900-2017



Notes: Panels display the fraction of a county that is irrigated over the time period 1900-2017 in black (left y-axis). The total number of counties with available information about irrigated acres are shown as dashed blue lines (right y-axis). The top panel uses data from Nebraska, the bottom panel uses data from Texas. The median proportion of irrigated county area is indicated by dashed red lines. Vertical lines represent years with an agricultural census, among which the year 1959 (in green) marks the start of the period of interest.

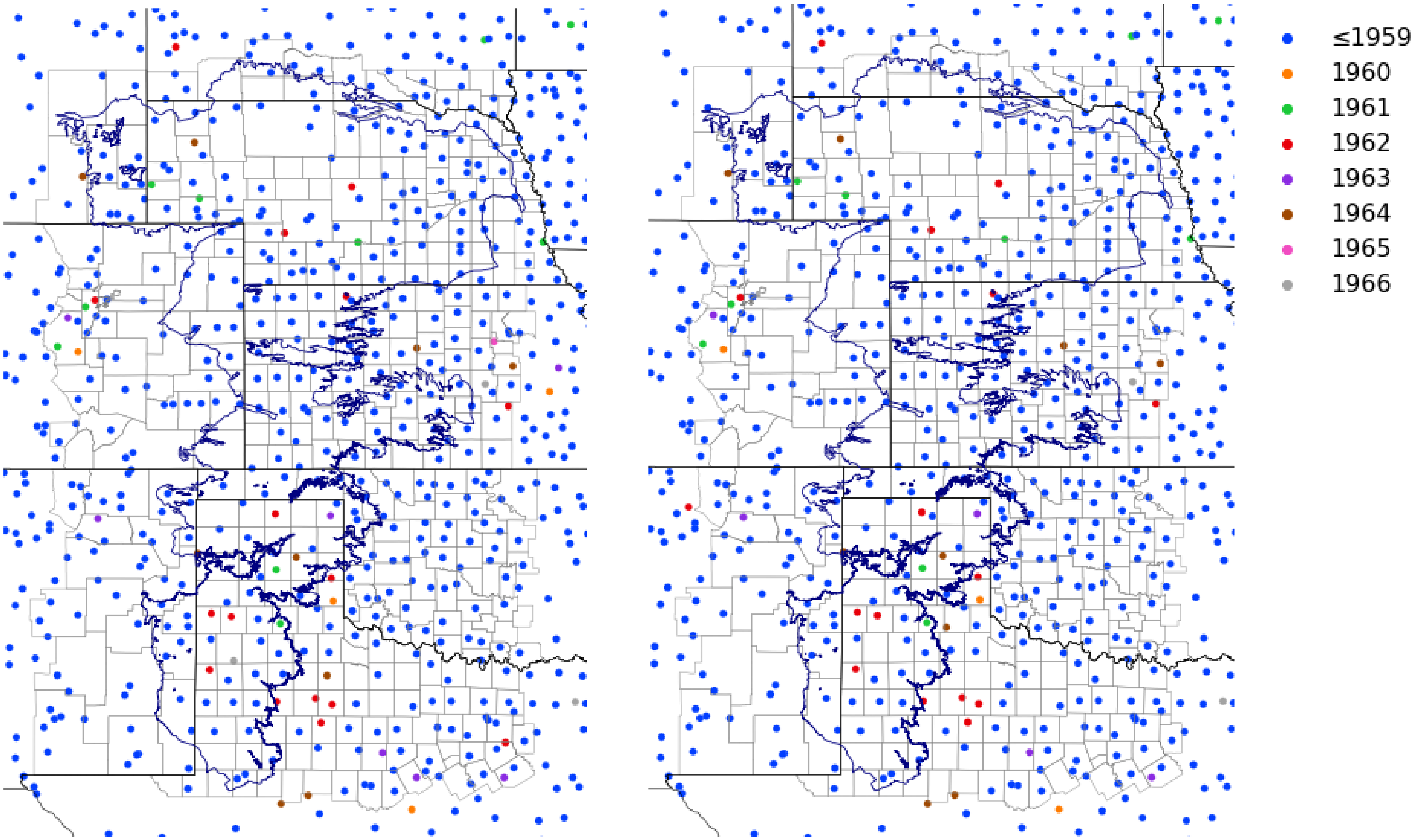
Figure A16: Irrigation Trends in Remaining States 1900-2017



Notes: Figure replicates Figure A15 for the remaining six states. Panels display the fraction of a county that is irrigated over the time period 1900-2017 in black (left y-axis). The total number of counties with available information about irrigated acres are shown as dashed blue lines (right y-axis). The median proportion of irrigated county area is indicated by dashed red lines. Vertical lines represent years with an agricultural census, among which the year 1959 (in green) marks the start of the period of interest.

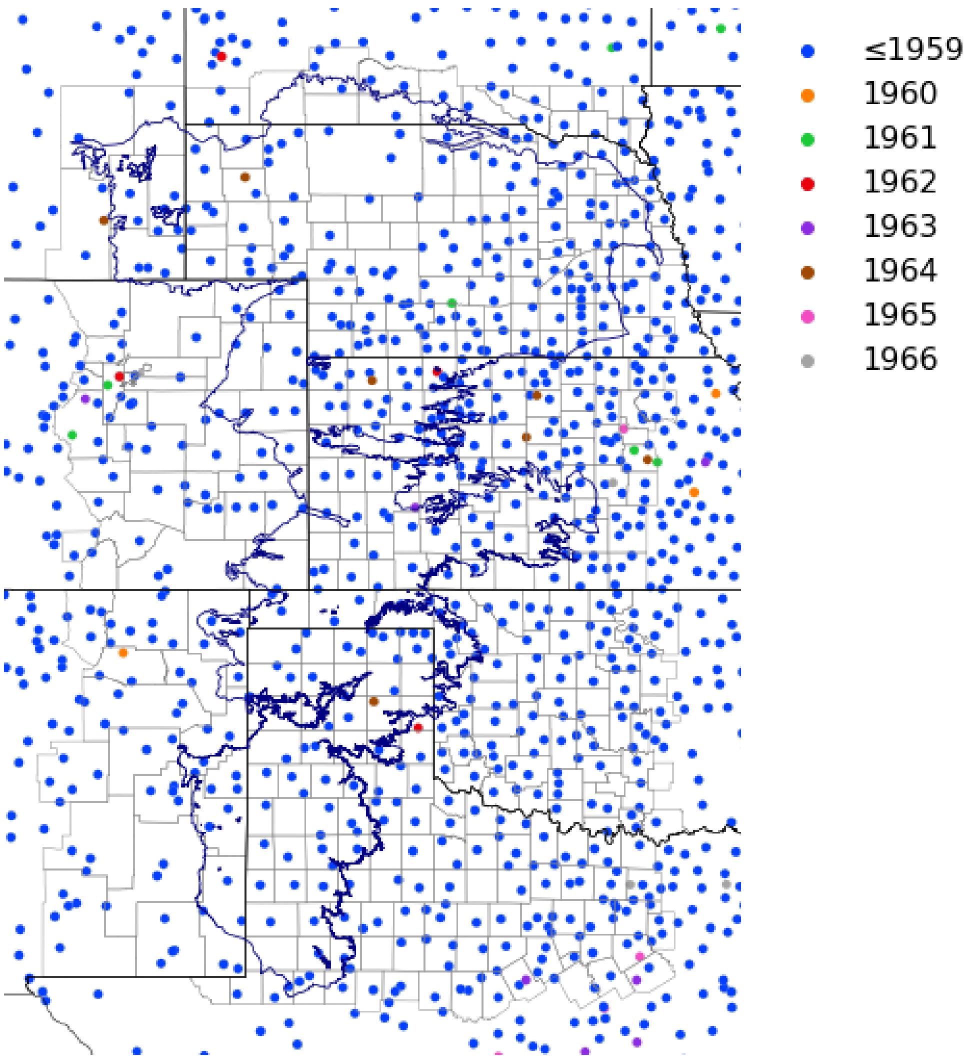
Figure A17: Location of Weather Stations With Temperature Readings

Panel A: Maximum Temperature **Panel B: Minimum Temperature**



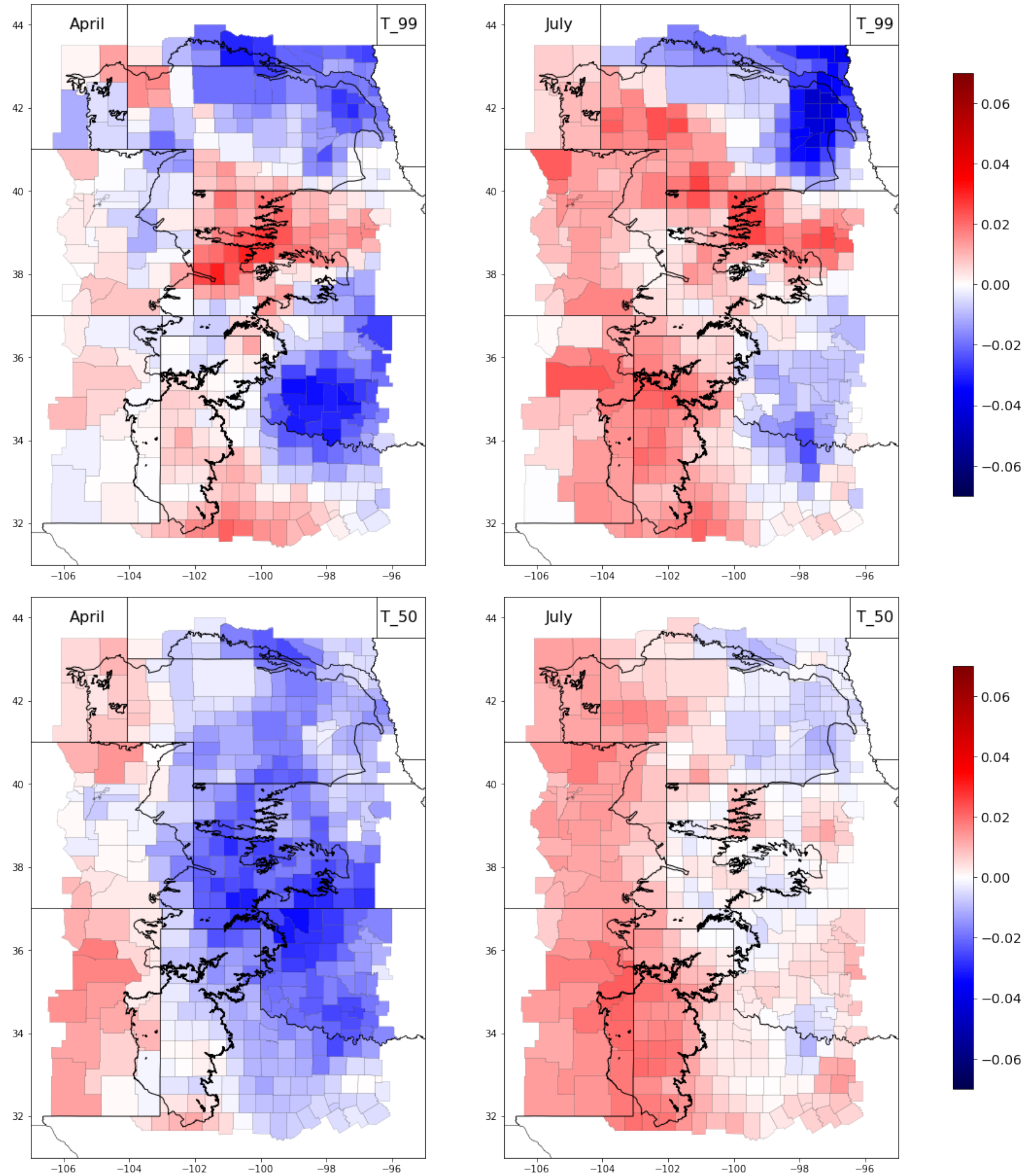
Notes: Figure displays the location of the weather stations used in the interpolation of maximum temperature (Panel A) and minimum temperature (Panel B) as circles, which are colored by the first year the station reported data (see right legend). Outlines of state borders, Ogallala aquifer and counties of interest are added in black, blue and gray respectively.

Figure A18: Location of Weather Stations With Precipitation Readings



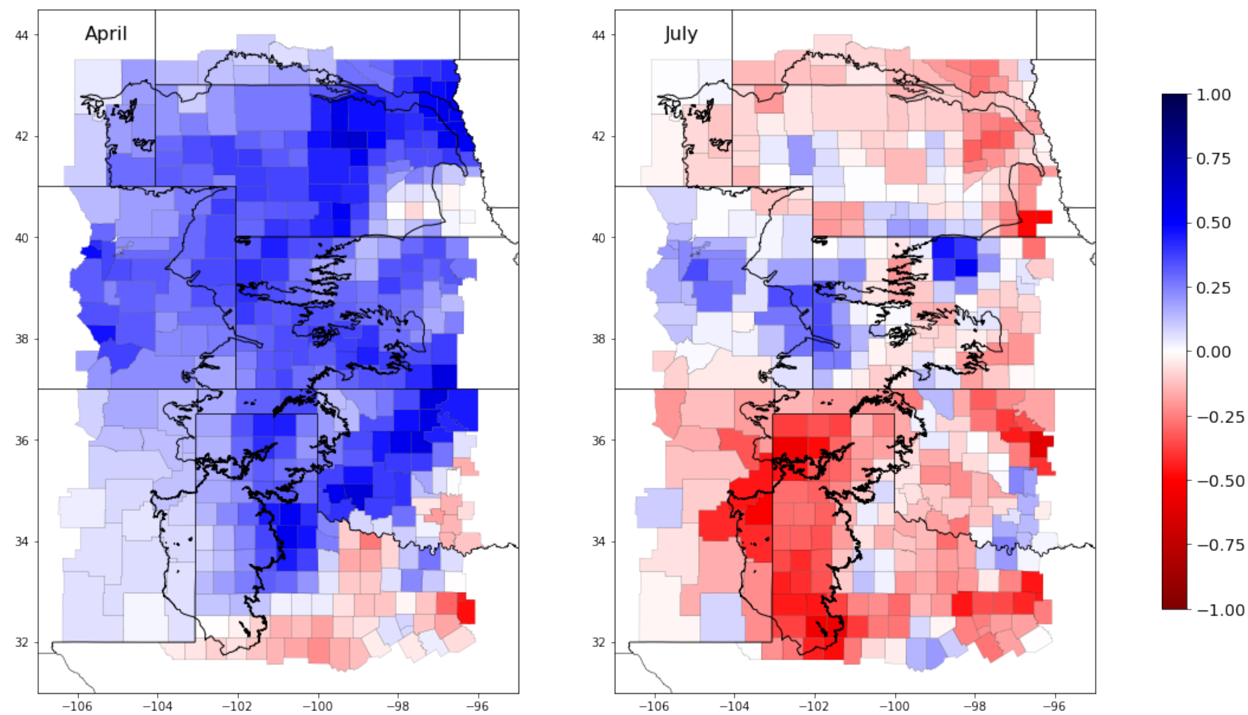
Notes: Figure displays the location of the weather stations used in the measurement of precipitation as circles, which are colored by the first year the station reported data (see right legend). Outlines of the state borders, Ogallala aquifer and counties of interest are added in black, blue and gray respectively.

Figure A19: Observed Trends in Selected Temperature Percentiles in April and July



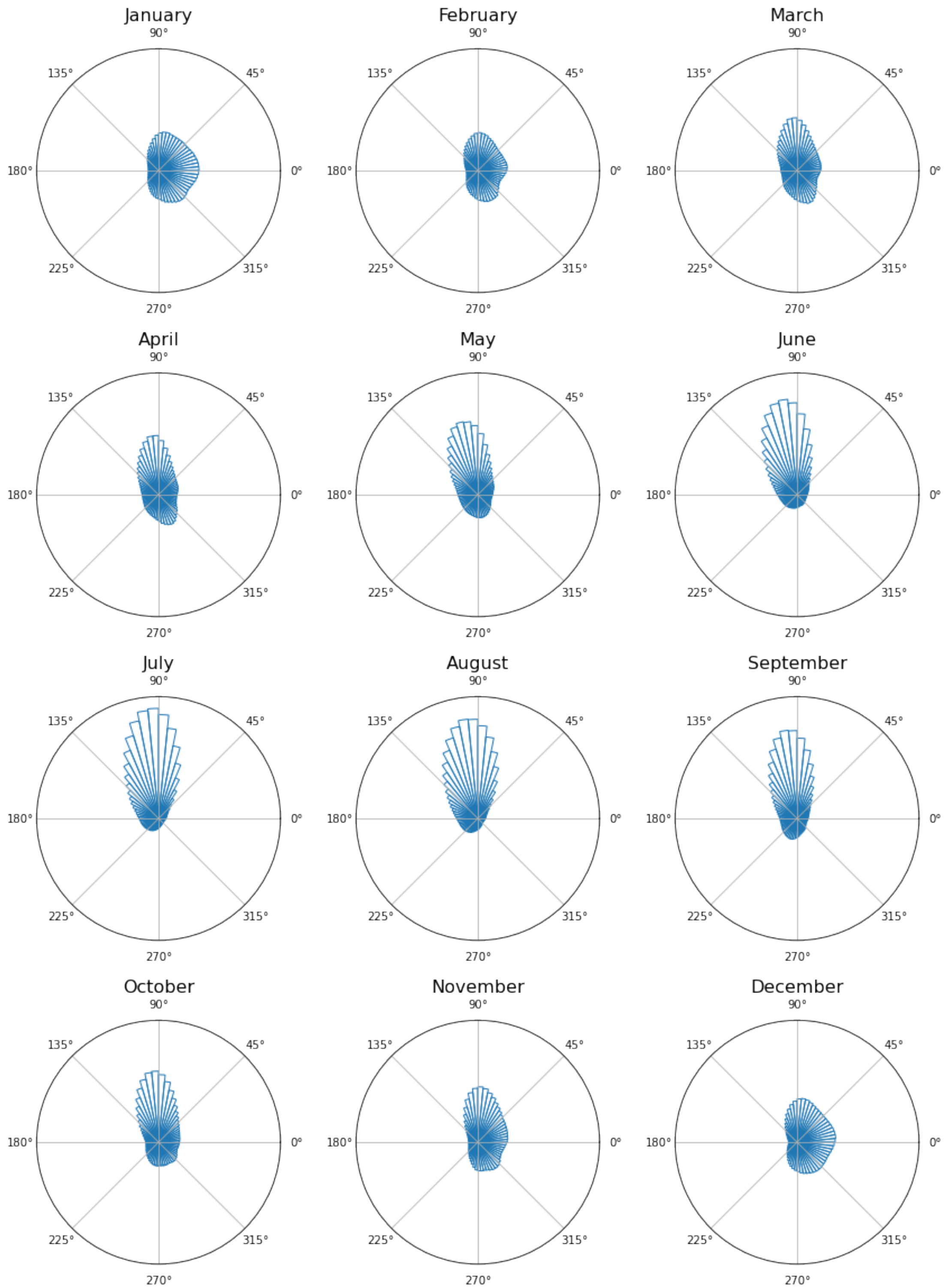
Notes: Panels display observed temperature trends for the 393 counties covering the Ogalalla aquifer. The left column shows results for April, the right column for July. The top row shows the trend for the 99$^{\text{th}}$ percentile and the bottom row shows the trend for the 50$^{\text{th}}$ percentile. Counties having experienced an average cooling (warming) over the 1959-2017 period are colored in blue (red). The color bar is on a common scale and given in units of $^{\circ}C/y$.

Figure A20: Observed Precipitation Trends in April and July



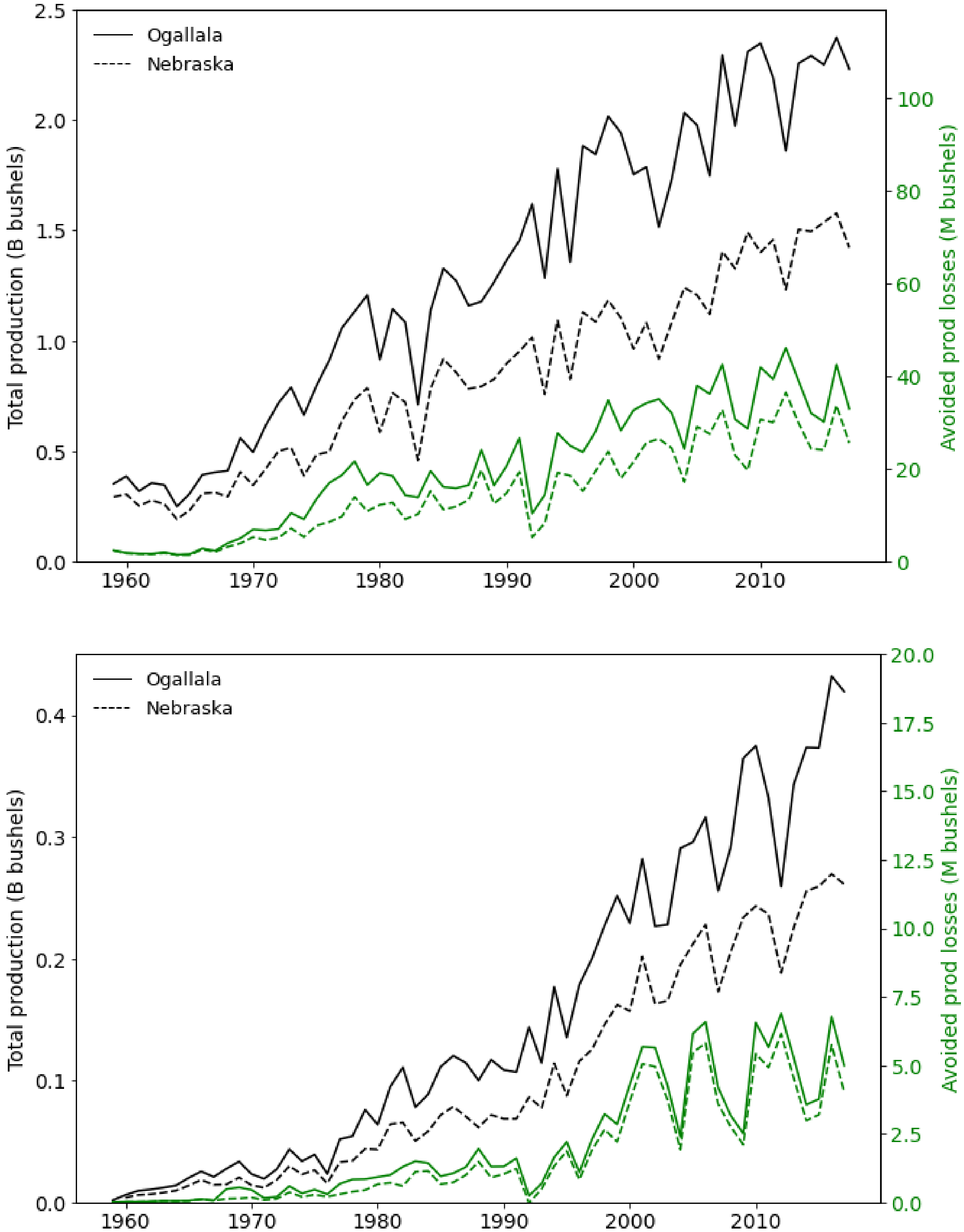
Notes: Panels display observed precipitation trends for the 393 counties covering the Ogalalla aquifer. The left column shows results for April, the right column for July. Counties having experienced an average increase (decrease) over the 1959-2017 period are colored in blue (red). The color bar is on a common scale and given in units of mm/y.

Figure A21: Distribution of Hourly Wind Directions 1979-2017



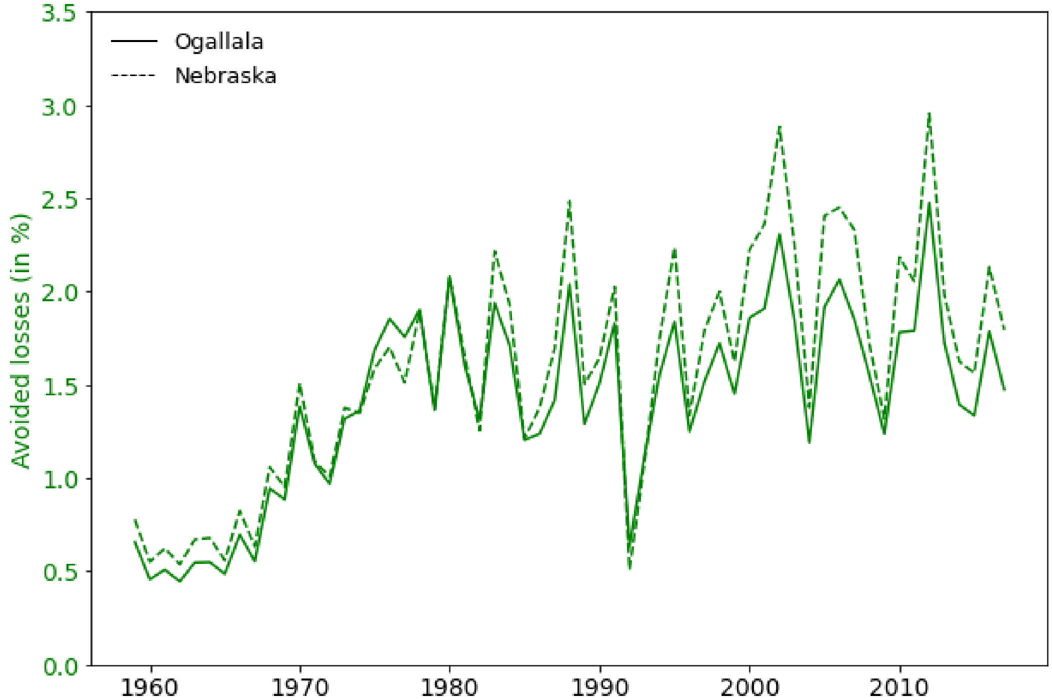
Notes: Polar distributions (by month) of hourly wind directions for counties covering the Ogallala for the years 1979-2017. Contrary to the usual convention for wind roses, we orient directions in agreement with (not against) the wind flow.

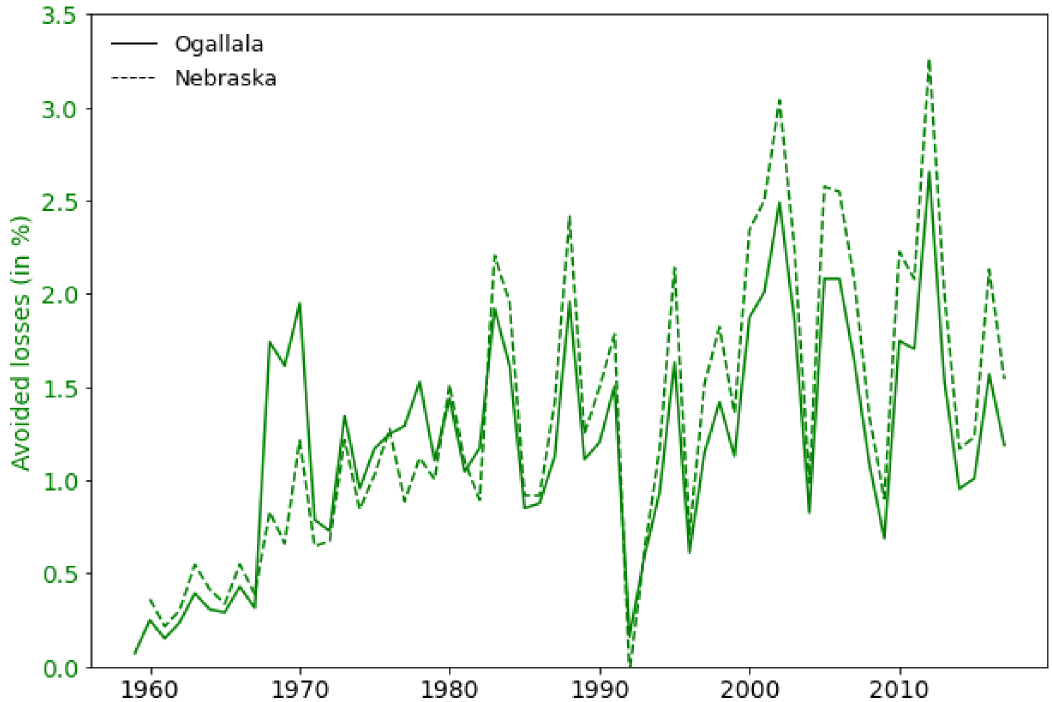
Figure A22: Production and Avoided Yield Losses Due to Cooling-by-Irrigation



Notes: Top panel is for corn and bottom panel is for soybeans. Total production (in billion bushels) are shown as black lines (left y-axis). Avoided losses via the cooling externality due to irrigation in upwind counties (in million bushels) are shown as green lines (right y-axis). Solid lines show the results for counties covering the Ogallala aquifer, while dashed lines are for counties in Nebraska.

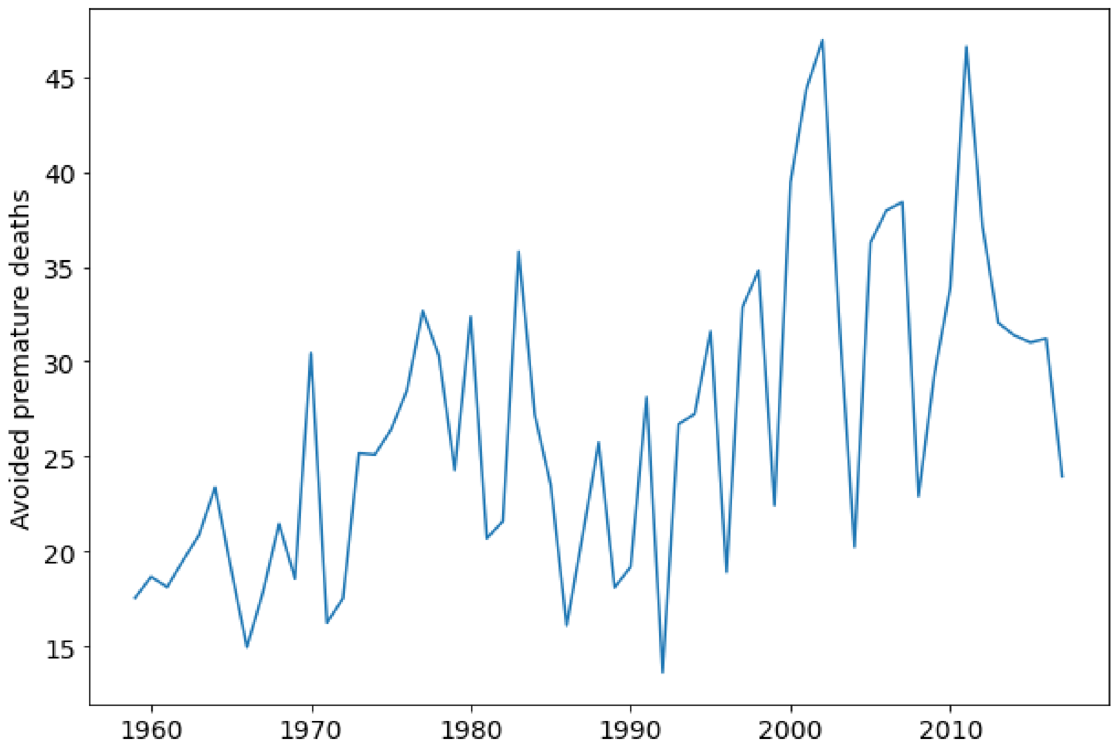
Figure A23: Fraction of Agricultural Production Saved by Cooling-by-Irrigation





Notes: Proportion of avoided losses in total corn (**top panel**) and soybean (**bottom panel**) production via the cooling externality induced by irrigation in upwind counties since 1959, for the region of interest (solid line) and Nebraska (dashed line).

Figure A24: Avoided Premature Deaths Due to Reduced Heat Through Irrigation



Notes: Evolution of the number of avoided premature deaths due to the externality induced by irrigation in upwind counties for the region of interest excluding Dallas (TX), Tarrant (TX) and Oklahoma city (OK) counties.