Economic Damages to Agriculture from Temperature Increases: Decomposing the Effects of Heat Exposure and Water Stress

Nathan P. Hendricks and Jeffrey M. Peterson

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Abstract

Higher temperatures affect crop production by increasing heat exposure and increasing water stress through greater evapotranspiration demand. Estimating the relative impact of these two mechanisms has important implications for designing appropriate adaptation strategies to climate change. We quantify the economic damages from these two mechanisms separately by estimating the effect of degree days and evapotranspiration on the rental value of nonirrigated cropland. Our results indicate annual damages due to a 2°C increase in temperature of $8.76 billion on nonirrigated cropland in the Corn Belt, Mississippi Delta, and Great Plains. Only about 6.5% of the damages are due to greater water stress. Increased heat exposure causes the largest relative damages in the southern Corn Belt and increased water stress causes the largest relative damages in the semi-arid region of the Great Plains.
Several empirical studies estimate the negative impact of extreme heat on crop yields (e.g., Schlenker and Roberts 2009; Lobell et al. 2011). There are two primary mechanisms by which heat affects crop production: (i) increased heat exposure and (ii) increased water stress. Exposure to extreme heat causes faster crop development which reduces production and extreme heat also has negative impacts during the reproductive stage of crop development (Hatfield et al. 2011). Higher temperatures also increase the evapotranspiration demand for crops and thus cause greater water stress. Understanding the relative impact of these two mechanisms is especially important for assessing appropriate adaptation strategies. We provide new evidence on the impact of higher temperatures on agriculture in the Midwestern United States by separately identifying the economic damages of greater heat exposure through degree days and the damages from water stress through greater evapotranspiration demand.

We adopt the approach of many recent economic studies that estimate the damages from future climate change by estimating the impact of variations in current climate or weather on economic outcomes (Dell, Jones, and Olken 2014). In particular, we estimate a cross-section regression of agricultural rents on nonlinear functions of average weather measures while controlling for soil characteristics. Our econometric strategy exploits the significant precipitation and temperature gradients across the Midwestern United States. We use nonlinear transformations of temperature and precipitation that the agronomic literature suggests are important for crop production rather than reduced form functions of temperature and precipitation. Schlenker, Hanemann, and Fisher (2006) made a significant contribution to the economic literature by proposing the use of growing degree days and extreme degree days to estimate the impact of temperature on land values. We extend this literature by incorporating evapotranspiration into the econometric model.

Evapotranspiration (ET) represents the sum of evaporation and plant transpiration and thus measures the water demand of the atmosphere. Actual ET depends on the particular crops and growing conditions of a region. Including actual ET in an econometric model
creates an endogeneity problem where regions (or years) with lower actual ET have lower returns because stressed crops use less water. To avoid this endogeneity problem we calculate the ET demand for corn under no water stress for every location in our study. Next, we define net precipitation as the expected difference between precipitation and ET for corn under no water stress. We also include off-season precipitation—no greater than the water storage capacity of the soil—in our measure of net precipitation. In water deficit areas, net precipitation takes on negative values, while it has positive values in water surplus regions.

Several recent studies have argued for the importance of including vapor pressure deficit (VPD) as an explanatory factor of crop yields (Roberts, Schlenker, and Eyer 2013; Lobell et al. 2013, 2014). These studies largely argue for the importance of VPD because of its association with water stress. In fact, VPD enters as one of the major factors in the calculation of ET (Allen et al. 1998). An advantage of using ET rather than VPD is that ET expresses the effect of temperature in units of water demand. Thus, it seems natural to use net precipitation as an explanatory factor rather than including ET or VPD as a separate control variable.

Somewhat surprisingly, Schlenker and Roberts (2009) find that changes in precipitation have relatively small impacts on crop yields compared to temperature changes. Lobell et al. (2013) argue that this finding is consistent with agronomic simulation models because temperature changes cause large changes in water stress so a substantial change in precipitation is required to be of comparable magnitude.1 Ortiz-Bobea (2013) argues that previous studies find small effects of precipitation because they neglect to model the timing of precipitation and its impact on soil moisture. A key point though is that estimating the impact of precipitation and temperature separately does not allow identification of the separate mechanisms by which temperature affects production. Using the estimates of the effect of precipitation to calculate the effect of an increase in ET results in double-counting damages because the effect of ET is implicitly captured in the temperature effects.

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1 One difficulty with their discussion is defining what is meant by large changes in temperature versus large changes in precipitation.
Most previous studies assume the effects of precipitation and temperature are additively separable, but some studies also include an interaction term between temperature and precipitation under the assumption that dry areas are most negatively impacted by temperature increases (e.g., Seo et al. 2009; Fezzi and Bateman 2012; Jacoby, Rabassa, and Skoufias 2014). By accounting for a nonlinear function of net precipitation in our model, we capture the inherent interaction between temperature and precipitation. For counties with greater precipitation, the rent function is flatter and an increase in evapotranspiration demand has a smaller effect on rent.

We quantify the damages to agriculture by regressing nonirrigated cash rental rates on nonlinear functions of climate measures while controlling for soil characteristics. Cash rental rates are reported separately for irrigated and nonirrigated land by the National Agricultural Statistics Service (NASS). We construct measures of average climatic conditions in each county using daily data from PRISM Climate Group (2004). Detailed soil characteristics are from the gSSURGO database created by the Natural Resources Conservation Service. We aggregate soil characteristics over the cropland area within each county.

Our approach follows the Ricardian—or hedonic—model pioneered by Mendelsohn, Nordhaus, and Shaw (1994). The Ricardian approach has been widely applied in many different regions of the world (e.g., Polsky 2004; Schlenker, Hanemann, and Fisher 2006; Seo et al. 2009; Massetti and Mendelsohn 2011). The Ricardian model exploits variation in climate across space to analyze the effect of climate differences on the value of agricultural production. The primary advantage of the Ricardian approach is that it accounts for adaptation since farmers in each county have an incentive to adopt the optimal cropping pattern and production practices given their climate. The primary critique of the Ricardian approach is that omitted variables that affect land values may also be correlated with the climate variables. Thus, the regression coefficients on climate variables may simply reflect the in-

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For a comprehensive review of the literature see Mendelsohn and Dinar (2009).
fluence of other characteristics of the regions rather than the true causal effect of climatic differences.

We address the concerns about omitted variables in several ways. First, we use nonirrigated cash rental rates as the dependent variable rather than average land values. Previous studies that use land values from the Census of Agriculture are biased because irrigation is not properly accounted for in the model (Darwin 1999; Schlenker, Hanemann, and Fisher 2005). Second, we restrict our estimation to a set of land resource regions in the Corn Belt, Mississippi Delta, and Great Plains with a similar type of climate and similar crop production practices. Third, we carefully construct a set of detailed soils data to include as controls. We discuss each of these points in more detail later.

We cannot control for unobserved heterogeneity of counties using fixed effects in our study because there is minimal variation in rental rates from year to year due to weather shocks. In contrast, studies that examine the effect of weather shocks on crop yields can use fixed effects to isolate the effect of random weather shocks and obtain a very credible causal estimate. A disadvantage of studies that estimate the effect on crop yields is that they do not account for adaptation to different climatic conditions.

Another critique of Ricardian models is that the estimates may reflect adaptation that occurs over several decades or even centuries and may not be a relevant time scale for adaptation to climate change (Dell, Jones, and Olken 2014). Furthermore, Ricardian estimates do not reflect the cost of adaptation (Quiggin and Horowitz 1999). These are especially important when the estimation sample contains large differences in production practices. These concerns are likely small in our region where the majority of nonirrigated cropland is planted to a few field crops with relatively similar production practices.

1 Conceptual Model

We begin by developing the Ricardian model conceptually in order to examine the implications for functional form. We focus on the role of net precipitation in our discussion since
that is our primary innovation. Consider a stylized model of a farmer’s profit maximization problem, where the farmer allocates crops to his or her land. To simplify the model, we assume no economies of scale and risk neutrality. Since we assume there are no economies of scale, the problem can be written as maximizing profits on a per acre basis. The model considers only rainfed crops, depicting the cropping patterns and rents on nonirrigated land. We consider a model of the farmer’s decision prior to the growing season when acreage decisions are made, so our variables—including net precipitation—represent expected values. To simplify the model, we assume that prices and production are uncorrelated.\footnote{We could relax this assumption and add the covariance between price and production into the profit maximization problem. As long as farm-level crop acreage decisions do not affect the covariance, it would have no effect on our result.}

We denote $\delta_j \in [0, 1]$ as the share of land planted to crop $j$, with $J$ crops considered, $p_j$ as the expected price of the crop, $f_j(\cdot)$ as the expected production function, $\text{netppt}$ as the expected net precipitation, and $\theta$ as a set of other exogenous variables affecting production (e.g., climate and soils). Expected net precipitation is defined as $\text{netppt} = E[ppt - et]$, where $ppt$ is precipitation and $et$ is evapotranspiration (water requirement) for a fixed “reference” crop under no water stress. In water deficit areas $\text{netppt}$ will take on negative values, while it will have positive values in water surplus regions. For simplicity, we have excluded other production inputs from the conceptual model, but farmers are likely to also adjust fertilizer intensity, planting density, and crop varieties depending on expected net precipitation.

The farmer’s maximization problem is written as

$$
\max_\delta \sum_{j=1}^J \delta_j [p_j f_j(\text{netppt}, \theta, \delta) - c_j(\delta)], \quad (1)
$$

subject to

$$
\sum_{j=1}^J \delta_j \leq 1, \quad (2)
$$

and also subject to non-negativity constraints on $\delta_j$. We denote $\delta_j$ as a vector of shares planted to each crop, and $c_j(\cdot)$ as a cost function. The production function depends on acreage planted to each crop due to the possibility of a yield boost from rotating crops and...
the cost of production depends on acreage planted to each crop due to potential input savings from rotating crops and economies of scope (Hennessy 2006; Hendricks, Smith, and Sumner 2014). For simplicity, we model profit maximization as a static problem when in fact it is dynamic due to the incentives to rotate crops. Incorporating the dynamics substantially complicates the model, but the solution to (1) can be thought of as the steady-state solution.

Assuming a competitive market, the cash rental rate for land equals the Ricardian rent, which represents the value of land in its most valuable use net of input costs. The solution to (1) gives a set of optimal crop allocations \( (\delta^*) \) as a function of net precipitation, prices, and other exogenous variables. Substituting these solutions back into the profit maximization problem gives the Ricardian rent for the field,

\[
R(\text{netppt}, p, \theta) = \sum_{j=1}^{J} \delta_j^* \left[ p_j f_j (\text{netppt}, \theta, \delta^*) - c_j (\delta^*) \right].
\]

(3)

The Ricardian rent likely exceeds the envelope of crop-specific rent functions because planting a mix of crops increases value due to the benefits of rotations and economies of scope. In general, economic theory does not provide guidance on the functional form of the rent function.

The purple, gray, and red lines in figure 1 illustrate linear plateau rent functions for different crops. The agronomic literature suggests crop yields are linear in net precipitation (e.g., Fereres and Soriano 2007; Lobell et al. 2013). Thus, crop-specific rent functions are also linear plateau under the restrictive assumption that all other input costs do not differ by net precipitation. The black line in figure 1 indicates the Ricardian rent function where the farmer optimally chooses the mix of crops. Our main point in using linear plateau functions for crop-specific rents is to show that they are consistent with a nonlinear rent function that accounts for changes in the optimal cropping patterns. Moreover, the linear plateau form clearly shows two distinct features of crop specific rent functions: (i) the maximum rent,
given by the height of the plateau, and (ii) the responsiveness of rent to changes in net precipitation, given by the slope of the linear portion.

Figure 1 illustrates two possible functional forms for the rent function. Panel 1a illustrates a concave rent function. The concave functional form is consistent with a model where crops that have a lower rent plateau are more responsive to changes in net precipitation. Panel 1b illustrates the case where the rent function is S-shaped. The S-shaped rent function is consistent with a model where crops that have a lower rent plateau are less responsive to changes in net precipitation. Note that even if the rent function for each crop is concave, the envelope of the crop-specific curves can be convex over a portion of the function. Similar arguments apply for rent as a function of degree days, where economic theory does not provide guidance on the appropriate functional form.

2 Econometric Model

The objective of our econometric model is to estimate the Ricardian rent function. We estimate the regression

$$\ln (R_i) = \alpha + f(\text{netppt}_i) + g(GDD_i) + h(EDD_i) + \theta'X_i + \epsilon_i,$$

where $\ln (R_i)$ is the natural logarithm of the nonirrigated cash rental rate for county $i$; $\text{netppt}_i$ is average net precipitation; $GDD_i$ is average growing degrees between 10°C and 30°C; $EDD_i$ is extreme degree days greater than 32°C; $f(\cdot)$, $g(\cdot)$, and $h(\cdot)$ are flexible functional forms; and $X_i$ is a vector of soil characteristics described in the data section. We use the log rental rate as the dependent variable rather than the level of the rental rate because rental rates are skewed—a small number of counties have very high rental rates. The log of rental rates is more evenly distributed than the levels.
Examining the impact on nonirrigated rental rates rather than land values reduces concerns about omitted variable bias.\(^4\) Land values used in previous studies depend on a large number of factors other than agricultural returns, such as real interest rates, real returns on alternative uses of capital, potential for urban development, recreational amenities, and mineral rights (Featherstone and Baker 1987; Just and Miranowski 1993; Plantinga and Miller 2001; Borchers, Ifft, and Kuethe 2014). These alternative drivers of land values bias Ricardian estimates if they are correlated with climate. For example, urban development tends to decrease moving from the eastern United States towards the plains states and precipitation also tends to decrease. Warmer states may also have greater development potential and thus bias the effect of temperature. In addition, land values from the Census of Agriculture reflect the average of nonirrigated and irrigated land values. Schlenker, Hanemann, and Fisher (2005) show that failing to account for irrigation in the model severely biases the estimates. In contrast, our dependent variable does not reflect values from non-agricultural uses of the land or irrigated values.

To further reduce concerns about omitted variables, we restrict our analysis to counties with a majority of their land area in one of six Land Resource Regions—central feed grains, northern lake states, Mississippi Delta, central great plains, western great plains, and northern great plains—but excluding counties in the states of New Mexico, Texas, and Oklahoma (see figure 2).\(^5\) Counties in New Mexico, Texas, and Oklahoma have much larger extreme degree days than other regions yet also have small amounts of annual precipitation, thus including these counties may overestimate the negative effect of extreme degree days. For studies that cover the entire United States, it is arguably difficult to imagine a set of variables that explain the difference between agricultural values in Mediterranean versus continental climates. The Great Plains, Corn Belt, and Mississippi Delta regions considered

\(^4\)Of course, our estimates are closely related to previous studies that use land values assuming that land values represent the net present value of the stream of expected rents and other potential benefits from the land.

\(^5\)Land Resource Regions are defined by NRCS.
in our analysis are relatively homogeneous in that crop production is primarily from grains
and oilseeds.

For our preferred results, we specify \( f(\cdot) \), \( g(\cdot) \), and \( h(\cdot) \) as restricted cubic splines with
four spline knots, where the knots are placed at the 5th, 35th, 65th, and 95th percentiles
of the variable as recommended by Harrell (2001). Alternatively, we could fit a high order
polynomial to the data, but polynomials often do not fit the data well at extremes (Royston
and Altman 1994). Our use of flexible functional forms for the effect of climate on rental
rates is an important distinction of our work. Previous Ricardian models often impose a
quadratic functional form, which restricts the log function to be symmetric and globally
concave or globally convex.

Our econometric model inherently captures the interaction between temperature and
precipitation. An increase in temperature increases evapotranspiration and reduces net pre-
cipitation. The magnitude of the temperature effect depends on the curvature of \( f(\cdot) \) and the
original level of precipitation. For example, in a wetter region \( f(\cdot) \) is likely to be relatively
flat so an increase in evapotranspiration has a small effect on rents.

We investigate what drives the estimated functional form for the climate variables. To get
an idea of the shape of the underlying crop-specific rent functions, we replace the dependent
variable in (4) with the log of expected nonirrigated revenue for different crops. We also
estimate how cropping patterns change with climate by replacing the dependent variable in
(4) with \( \ln \left( \frac{\text{acres}_{ji}}{\text{cropland}_i} \right) \), where \( \text{acres}_{ji} \) is the acreage of crop \( j \) in county \( i \) and \( \text{cropland}_i \) is the
total acreage of nonirrigated cropland in county \( i \). In some cases \( \text{acres}_{ji} = 0 \), so we estimate
the model with Poisson regression rather than OLS regression. We leave all right-hand side
variables the same.

In our econometric analysis, we weight the regressions by total acreage of nonirrigated
cropland in the county and account for spatial dependence in the error term by clustering
standard errors at the state level consistent with Fisher et al. (2012).\footnote{We do not weight the regressions of crop acreage shares.} There are 19 states...
in our sample. Clustering permits any form of spatial dependence between counties within a state, but assumes independence between states. Bester, Conley, and Hansen (2011) have proposed clustering by large spatial blocks as a simple method to account for spatial correlation, relying on the assumption that relatively few observations are near borders that may be correlated with observations in other clusters.

3 Data

Nonirrigated cash rents in 2013 at the county-level are obtained from the National Agricultural Statistics Service (NASS). NASS has reported cash rental rates annually since 2008. We estimate the model using only a cross-section of data in 2013.

Daily precipitation, maximum temperature, and minimum temperature are obtained from PRISM for the period 1981-2010 (PRISM Climate Group). PRISM interpolates data from a large number of weather station networks to a 4km grid covering the contiguous United States. We used the meta-file provided by Wolfram Schlenker and Michael Roberts that links each grid cell to a county and indicates the cropland area within the grid cell.7 From the PRISM data, we calculate growing degree days between 10°C and 30°C and degree days greater than 32°C within the growing season (April 1–September 30). We also calculate cumulative net precipitation that includes in-season and off-season net precipitation. These three measures are calculated for each grid cell, then averaged across cells within each county for each year (weighted by the share of cropland within each grid cell), then averaged over the time period 1981-2010.

Some articles find that temperatures greater than 30°C are harmful to crop production, but Lobell et al. (2013) find that this effect is partly due to greater water stress at higher temperatures. We account for the effect of temperature on water stress through the inclusion

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7To be clear, the daily precipitation and temperature data that we use are directly from PRISM. We use a meta-file posted online by Schlenker and Roberts to link each grid cell to a county (available at http://www.wolfram-schlenker.com/). Using their meta-file substantially reduced the effort required to create the county-level data. Prior to 2013, PRISM only released data at the monthly time step. Schlenker and Roberts (2009) created a dataset with a daily time step by interpolating daily data from weather stations to the monthly PRISM grid, but we do not use their weather data in this study.
of evapotranspiration in our model. Ritchie and Nesmith (1991) suggest that temperatures greater than 34°C are harmful for crop production and Deryng et al. (2014) suggest that temperatures greater than 32°C and 35°C are harmful for corn and soybeans, respectively. Thus, we include degree days greater than 32°C to account for the direct effect of heat stress on crop production. We scale growing degree days to hundreds of growing degree days but do not scale extreme degree days.

Cumulative net precipitation is calculated as cumulative precipitation minus cumulative evapotranspiration (ET) for corn under no water stress in the growing season plus the off-season net precipitation that could be stored by the soil. Actual ET depends not only on weather, but also on the land cover, growth stage, and management practices. The concept of “reference ET” was developed as a measure independent of crop characteristics and soil factors. Reference ET is defined as the ET of a well-watered, actively growing grass (Allen et al. 1998). We then use reference ET and coefficients for corn under “standard” growing conditions (i.e., no water stress) from Fipps (2014) to calculate corn-based ET for each county. We calculate ET in the off-season by using the crop coefficient for corn in the first day after planting, which is 25% of reference ET. Net precipitation in the off-season is not allowed to exceed the water storage capacity of the root zone of the soil.

We calculate reference ET using the reduced-set Penman-Monteith method that requires only maximum and minimum temperature data. The full Penman Monteith equation requires additional data on solar radiation, vapor pressure, and wind speed (Allen et al. 1998). In the absence of these additional measures, we follow the method described by Allen et al. (1998) to approximate these measures with temperature data (see our supplementary appendix for details). We calculate extraterrestrial radiation using the latitude of the county and for a given day of the year and approximate solar radiation using the square root of the difference in maximum and minimum temperature to approximate relative sunshine duration. The vapor pressure deficit is calculated by using the minimum temperature to
approximate the dewpoint temperature—the same method used by Lobell et al. (2014). We assume a constant wind speed of 2 meters per second.

Crop-specific ET under “standard” conditions (i.e., no environmental or water stresses) is calculated by multiplying reference ET by a crop-specific coefficient. The crop-specific coefficient varies over the growing season, typically peaking in the middle of the growing season. We do not calculate ET for each county based on the crops that are planted in that county because that would create an endogeneity problem—actual ET is smaller in counties with less acreage in water-intensive crops, which are associated with low rental rates. We calculate corn-based ET under “standard” conditions, since corn is grown in nearly every county in our dataset. The advantage of using corn-based ET versus reference ET is that corn-based ET gives greater weight to ET during the middle of the growing season when most crops are at peak water demand, with wheat being a notable exception.

Several studies have found that vapor pressure deficit is strongly related to crop yields (Roberts, Schlenker, and Eyer 2013; Lobell et al. 2013, 2014). The Penman-Monteith equation in the supplementary appendix shows that ET is a function of the vapor pressure deficit. The correlation coefficient between cumulative ET and average vapor pressure deficit is 0.99 across the counties in our dataset. An advantage of using ET is that it is expressed in units of water demand (inches/day).

We do not use data on the Palmer Drought Severity Index (PDSI) or measures of observed soil moisture because these measures are endogenous across regions. PDSI measures departure of moisture from normal conditions for a given region and soil moisture depends on the particular land cover of a region, thus they do not provide a comparable measure of rainfed water availability across regions. For example, the same amount of precipitation can result in depleted soil moisture in a field of corn but relatively saturated soil moisture in a field of wheat. The value of production, however, may be greater in the field of corn.

We collect detailed soil characteristics from the gSSURGO (Gridded Soil Survey Geographic) database created by NRCS (Natural Resources Conservation Service). We aggre-
gate soil characteristics for each county using only areas classified as cropland by the NLCD (National Land Cover Database).

The following soil characteristics are included as controls in our regression: available water storage, the log of slope, cation exchange capacity (CEC), the proportion of cropland with a pH less than 6, the log of soil permeability, clay content, and silt content. Available water storage is the amount of water that a soil can store within the root zone—measured in inches. We use the log of slope rather than slope because the distribution of slope across counties is skewed, with a few counties highly sloped. Soils with higher cation exchange capacity are less likely to develop nutrient deficiencies (Cornell University Cooperative Extension 2007). We expect cropland with a pH less than 6 will have lower values since they require liming for many crops (Iowa State University 2013). Soil permeability is measured as saturated hydraulic conductivity. Clay and silt content measure the percent of soil components classified as clay or silt.\textsuperscript{8} In contrast to many previous studies, we do not include the land capability classification as a control because the classification depends in part on climatic conditions (Klingebiel and Montgomery 1961).

Summary statistics of the variables used in the regression analysis of nonirrigated rents are provided in table 1. Figure 3 shows maps of cash rental rates in 2013, average net precipitation, average growing degree days, and average extreme degree days. Rental rates are largest in the central Corn Belt. Net precipitation varies primarily east-west and degree days vary primarily north-south.

To investigate what drives the estimated functional forms for climatic variables, we replace the dependent variable with the log of expected nonirrigated revenue for each crop. We obtain county-level yield data from NASS for corn, soybeans, sorghum, and wheat.\textsuperscript{9} NASS reports yield data separately for irrigated, nonirrigated, and the overall average yield. In some counties, NASS only reports the overall average—particularly those with limited irri-

\textsuperscript{8}Soil has three broad components: clay, silt, and sand. We omit sand as the baseline, so coefficients measure the value of greater clay and silt content relative to sand.

\textsuperscript{9}For wheat, we use the yield of winter wheat or spring wheat depending on which had greater acreage in the county.
gated acreage or limited nonirrigated acreage. For the nonirrigated and overall average yield of each crop in each county, we estimate a linear trend from 1980 to 2013. The predicted yield in 2013 is our measure of the expected yield. If nonirrigated yields were reported for a county, then we use the expected nonirrigated yield. If nonirrigated yields were not reported, then we use the expected overall average yield if less than 10% of the acreage harvested for that crop was irrigated according to the Census of Agriculture in 1997, 2002, 2007, and 2012. We calculate the expected price as the 2009–2013 average of marketing-year average prices from NASS.\textsuperscript{10} Expected revenue is the expected yield times expected price.

We also estimate regressions where the dependent variable is the log share of nonirrigated cropland acreage for corn, soybeans, sorghum, wheat, and fallow.\textsuperscript{11} Data on harvested acreage of each crop and the acreage of fallowed land are from the 2012 Census of Agriculture.\textsuperscript{12} We calculate total nonirrigated cropland acreage as the sum of nonirrigated harvested cropland, failed cropland, and fallowed cropland. This calculation implicitly assumes that minimal amounts of failed and fallowed cropland are irrigated. Unfortunately, the Census does not report crop-specific failed acreage.

4 Results

4.1 Estimates of the Rent Function

Table 2 shows regression results from estimating equation (4). The model explains 84% of the variation in the data. The first nine coefficients in the table give coefficient estimates for the restricted cubic splines of net precipitation, growing degree days, and extreme degree days. These coefficients are difficult to interpret, so we graph the functions in figure 4 by predicting equation (4) across the range of the variable observed in our data and setting all

\textsuperscript{10}We are not attempting to measure the price that farmers expected to receive when they rented land in 2013. Rather, we are simply using an average price to weight the expected yields across each of the crops so that we have a comparable measure of expected revenue.

\textsuperscript{11}For wheat, we use the sum of acreage for winter and spring wheat.

\textsuperscript{12}We use Census data rather than NASS survey data for crop acreage because the Census data provide a much more comprehensive reporting at the county level.
other variables equal to median values. The solid lines in figure 4 shows the predicted value for the cash rental rate, the shaded areas shows the 95% confidence interval of the prediction, and the gray circles plot the observed data. Note that we plot the predicted cash rental rate for ease of interpretation rather than the predicted log rental rate.\textsuperscript{13}

Figure 4a shows that the rent function for net precipitation is not strictly concave. The rent function reaches a maximum at about 6 inches of net precipitation. This is not surprising since 0 inches of net precipitation is the point where growing-season and off-season precipitation equals evapotranspiration demand for corn. Some precipitation is lost to runoff, so it is not surprising that rent is maximized when precipitation exceeds evapotranspiration demand. It is clear from figure 4a that variation in net precipitation across this region has substantial impacts on rent. Rents decline rapidly when net precipitation falls below 0 inches of net precipitation. Predicted rents decline slightly if net precipitation exceeds 6 inches, but the confidence interval becomes quite large in this region since it is near the boundary of our data. As mentioned previously, our model inherently captures the interaction between temperature and precipitation. The rent function in figure 4a implies that an increase in temperature—and thus evapotranspiration—has a smaller effect on rents in counties with large precipitation.

Figure 4b shows predicted rents as a function of growing degree days. The function is clearly not symmetric as a quadratic function would impose. Rents increase rapidly as a function of growing degrees until reaching a maximum at 18.4 hundred degree days. After reaching the maximum, rents stay about constant as a function of growing degree days, consistent with the agronomic literature that temperatures within this range are beneficial.

Figure 4c shows that increases in extreme degree days can have a large impact on rents. Once accumulated extreme degree days increase above 2.3, rents decline rapidly until about 20 extreme degree days. Accumulating greater than 20 extreme degree days has a much smaller effect on rents, although rents are already quite diminished. The functional form

\textsuperscript{13}In order to predict the rental rate, we calculate \( \exp \left( \hat{y} + \hat{\sigma}^2/2 \right) \), where \( \hat{y} \) is the predicted log rental rate and \( \hat{\sigma} \) is the root-mean-squared-error.
implies an increase in extreme degree days has the smallest impact in the coolest regions and the hottest regions. However, an increase in temperature causes the largest increase in extreme degree days in the hottest regions.

The coefficients on soil variables in table 2 all have the expected sign. The available water storage of soils has a substantial impact on rents. For example, soils in Knox County, Missouri have an average available water storage of 6.3 inches compared to 11.2 inches in Fulton County, Illinois. Our regression results suggest that rents are 51 percent lower \((6.3 - 11.2) \times 0.105\) in Knox county due to lower water storage of the soils. Steeply sloped soils and acidic soils (low pH) are valued less while soils with greater cation exchange capacity (CEC) are valued more. Soils are valued more if they are more permeable and have greater clay and silt content, implying that soils with high sand content are valued less.

4.2 Source of Estimated Functional Forms

Next, we evaluate the underlying crop-specific revenue functions that lead to the estimated functional forms for the climate variables. Figure 5 plots the predicted regression curves for the major commodities in this region as a function of each climate variable. Expected revenue does not correspond exactly to the crop-specific rent function because expected revenue does not account for the difference in cost of production across space or crops. The predicted expected revenue curves for some crops do not span the entire range of the climate variables in our sample because NASS did not report nonirrigated yields for these crops where acreage is minimal.

Expected revenue as a function of net precipitation appears to largely be consistent with the standard agronomic models that crop yield responds linearly to evapotranspiration (figure 5a). Crops that have a lower peak expected revenue are also less responsive to changes in net precipitation. For example, sorghum has a lower peak expected revenue than corn,
but the sorghum curve is also flatter.\textsuperscript{14} From our discussion in section 1, this implies that the rent function is S-shaped, consistent with our empirical findings in section 4.1.

Expected revenue for corn and soybeans increases until growing degrees reach about 18 hundred degree days (figure 5b). Expected revenue for wheat does not respond substantially to growing degree days and sorghum revenue increases with growing degree days. Corn and soybean revenues are especially sensitive to exposure to extreme degree days (figure 5c). Thus, the rapid decline in rents as a function of extreme degree days occurs primarily due to the sensitivity of corn and soybean yields to extreme heat. The estimated revenue functions are also consistent with a review of agronomic literature that suggests corn yield is sensitive to heat at a lower temperature threshold (Deryng et al. 2014). It could be that we estimate little impacts of extreme degree days on wheat yields because most extreme degree days are accumulated after wheat harvest. Our results do not imply that heat stress prior to wheat harvest has a small impact on wheat yields.

We also examine how cropping patterns change in response to climate changes (figure 6). We plot the share of cropland fallowed in addition to the share of cropland for each of the four major commodities. In dry regions of the Midwest it is common to leave land fallow occasionally in order to accumulate soil moisture. It is important to note that our predicted curves in figure 6 are for median soil and climate characteristics. Thus, predicted sorghum acreage is often near zero, but the model may predict positive sorghum acreage for counties with different soils and climate than the median.

Figure 6a shows the response of cropping patterns to net precipitation. At high levels of net precipitation, farmers primarily plant corn and soybeans. These crops give the greatest expected return at high levels of net precipitation, but returns also decline the fastest with reductions in net precipitation for these crops. For net precipitation between -5 and 0 inches—where rents are most sensitive to net precipitation—corn and soybeans are still the

\textsuperscript{14} The curve for winter wheat does not appear to peak in the range of yield data that we observe. But we do not observe wheat yields for the highest amounts of net precipitation because profits of other crops dominate wheat.
dominate source of crop production. For low levels of net precipitation (less than -10 inches), farmers have much larger portions of their acreage devoted to wheat and fallow.

Figure 6b shows the response of cropping patterns to growing degree days. Acreage of wheat increases in cooler climates as spring wheat is well-suited to cooler climates. Corn acreage is largest in regions with about the average growing degree days and soybean acreage increases as corn acreage declines in warmer climates. As extreme degree days increase, farmers switch from primarily corn and soybeans to wheat and other crops that are less sensitive to total accumulated extreme degree days (figure 6c).

4.3 Implications for Climate Change Damages

In order to examine the implications for climate change damages, we simulate the effect of an increase in maximum and minimum temperatures of 2°C. We add 2°C to the raw daily PRISM data, recalculate degree days and net precipitation, then aggregate the data to the county level and average across years. On average, the temperature increase causes a reduction of 1.3 inches in net precipitation, an increase of 2.8 hundred growing degree days, and an increase of 17.1 extreme degree days. An increase in average temperature has a much larger effect on extreme degree days in hotter counties and slightly larger effect on evapotranspiration in hotter counties since these measures are nonlinear in average temperature.

We do not model any changes in precipitation, but only a reduction in net precipitation through an increase in evapotranspiration. This is broadly consistent with the most recent climate simulations which indicate that regions between 15 and 45 degrees latitude—including major crop production regions like the United States and Europe—may face reductions in net precipitation in the near term even though precipitation is not likely to change substantially (see figure 7, which we replicate from Kirtman et al. (2013)).

Table 3 reports annual damages from a 2°C increases in temperature and decomposes the effect due to reduced net precipitation and due to increased degree days. We isolate the two effects by simulating the aggregate change in rents if we reduce net precipitation
according to the temperature increase but leave all degree days at their original levels, and vice versa to isolate the impact of degree days. We calculate aggregate damages by multiplying the estimated change in rent in each county by total nonirrigated cropland acreage and then summing across all counties. An increase in average temperature of 2°C leads to annual damages of $8.76 billion on nonirrigated cropland in this region—roughly 32% of current rents. Only about 6.5% of the total damages are due to reduced net precipitation. Our results suggest that little of the negative effect of warming occurs through increasing evapotranspiration demand in contrast to the results from the agronomic simulation model APSIM (Lobell et al. 2013).

The spatial distribution of the damages through the two different mechanisms—net precipitation and degree days—is starkly different (see figure 8). Figure 8a shows that relative damages from reduced net precipitation vary primarily east-west along the precipitation gradient with the largest relative reductions in the semi-arid western counties. Although the overall damages due to reduced net precipitation are much smaller than the damages of degree days, the relative impact can still be substantial in western counties. A value of -0.10 in figure 8a indicates that rents decrease by 10% due to the increase in evapotranspiration demand. Furthermore, the map shows that nearly every county experiences a loss in rent due to reduced net precipitation.

Figure 8b shows that damages from the increase in degree days vary primarily north-south. The largest damages occur in the southern half of the Corn Belt and the Mississippi Delta. A value of -0.50 in figure 8b indicates that rents decrease by 50% due to the increase in degree days. Even though extreme degree days increase the most in southern Kansas, the relative damages are larger in counties with less extreme temperatures. The increase in degree days leads to increases in rents in substantial portions of the northern states due to the beneficial effect of greater growing degree days. Nevertheless, the overall damages are substantial because the largest relative damages occur in the Corn Belt where rents are largest.
The spatial distribution of overall damages—accounting for both mechanisms—is shown in figure 9. The general pattern is similar to the pattern from the increase in degree days in figure 8b. However, reduced net precipitation increases damages especially in western counties and also reduces the benefit of warming in northern counties.

5 Conclusion

We estimate that a 2°C increase in temperature causes annual damages of $8.76 billion to nonirrigated crop production in the Corn Belt, Mississippi Delta, and Great Plains regions. Only about 6.5% of the damages are due to greater water stress from an increase in evapotranspiration demand while the remaining damages are due to greater heat exposure from an increase in extreme degree days. The spatial heterogeneity of the damages differs by the mechanism. Damages from water stress vary primarily east-west while damages from heat exposure vary primarily north-south.

There are several important caveats to our analysis. First, our estimates of the damages are valid for the prices used when farmers negotiated 2013 cash rental rates. If climate change reduces global crop production, then prices may increase—even in real terms—and we underestimate the damages. Second, while our estimates reflect adaptation, they do not reflect the cost of adjustment (Quiggin and Horowitz 1999). Third, our estimates do not reflect the effects of CO₂ fertilization on plant productivity, although the effect may be smaller than once thought (Long et al. 2006). Fourth, our estimates quantify the effect of changes in average climatic conditions but do not quantify the effect of changes in the variability of weather.

Our primary contribution is to separately quantify the damages from temperature increases due to the underlying mechanisms, which is important for designing adaptation strategies. For example, if heat exposure is the primary driver of damages, then emphasis should be placed on developing heat tolerant crop varieties. If water stress is the primary driver of damages, then emphasis should be placed on drought resistant crop varieties. Where
water supplies are sufficient, irrigation development can mitigate water stress—and perhaps mitigate heat exposure to some extent as well. Our results indicate that the appropriate adaptation strategy varies spatially and our estimates of the damages quantify the potential benefit from adaptation. Overall, we find that primary emphasis should be placed on adapting crop production to greater heat stress.
References


Cornell University Cooperative Extension. 2007. “Cation Exchange Capacity (CEC).” Fact Sheet No. 22, Department of Crop and Soil Sciences, Cornell University.


### Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>sd</th>
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<tbody>
<tr>
<td>Cash Rent ($/acre)</td>
<td>122.15</td>
<td>83.97</td>
</tr>
<tr>
<td>Log of Cash Rent</td>
<td>4.48</td>
<td>0.88</td>
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<tr>
<td>Net Precipitation (in)</td>
<td>-4.75</td>
<td>5.88</td>
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<td>Hundreds of Growing Degree Days (GDD)</td>
<td>16.72</td>
<td>3.43</td>
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<tr>
<td>Extreme Degree Days (EDD)</td>
<td>16.18</td>
<td>20.73</td>
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<tr>
<td>Available Water Storage (in)</td>
<td>8.91</td>
<td>1.66</td>
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<tr>
<td>Log of Slope</td>
<td>1.12</td>
<td>0.56</td>
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<td>CEC</td>
<td>19.67</td>
<td>5.19</td>
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<tr>
<td>pH Less than 6</td>
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<td>Log of Permeability</td>
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<tr>
<td>Percent Clay</td>
<td>26.97</td>
<td>6.87</td>
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<tr>
<td>Percent Silt</td>
<td>44.76</td>
<td>12.54</td>
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Table 2: Regression Results for the Ricardian Rent Function

<table>
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<tr>
<th>Coefficients</th>
<th>Value</th>
<th>Standard Error</th>
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<tr>
<td>Net Precip Spline 1</td>
<td>0.061**</td>
<td>(0.012)</td>
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<tr>
<td>Net Precip Spline 2</td>
<td>-0.012</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Net Precip Spline 3</td>
<td>-0.282*</td>
<td>(0.138)</td>
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<tr>
<td>GDD Spline 1</td>
<td>0.295**</td>
<td>(0.053)</td>
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<tr>
<td>GDD Spline 2</td>
<td>-0.474**</td>
<td>(0.114)</td>
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<tr>
<td>GDD Spline 3</td>
<td>1.046**</td>
<td>(0.360)</td>
</tr>
<tr>
<td>EDD Spline 1</td>
<td>0.006</td>
<td>(0.031)</td>
</tr>
<tr>
<td>EDD Spline 2</td>
<td>-1.577**</td>
<td>(0.467)</td>
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<tr>
<td>EDD Spline 3</td>
<td>2.265**</td>
<td>(0.637)</td>
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<td>Available Water Storage</td>
<td>0.105**</td>
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<td>Log of Slope</td>
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<td>Log of Permeability</td>
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<td>Intercept</td>
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<td>$R^2$</td>
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Standard errors in parentheses
* p<0.10, ** p<0.05
Table 3: Annual Damages from a 2°C Increase in Maximum and Minimum Temperatures

<table>
<thead>
<tr>
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<th>Change in Rent ($ billion)</th>
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<tr>
<td>Through Net Precip Only</td>
<td>-0.55</td>
</tr>
<tr>
<td>Through Degree Days Only</td>
<td>-8.30</td>
</tr>
<tr>
<td>Total</td>
<td>-8.76</td>
</tr>
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</table>
Figures

Figure 1: Illustration of the Rent Function for Net Precipitation

(a) Globally Concave Rent Function

(b) S-Shaped Rent Function
Figure 2: Counties included in Analysis and Land Resource Regions
Figure 3: Maps of Nonirrigated Cash Rental Rates in 2013 and Climate Variables

(a) Nonirrigated Cash Rents

(b) Net Precipitation

(c) Hundreds of Growing Degree Days

(d) Extreme Degree Days
Figure 4: Prediction of Cash Rental Rate and 95% Confidence Interval with Median Soils

(a) Net Precipitation

(b) Hundreds of Growing Degree Days

(c) Extreme Degree Days
Figure 5: Prediction of Expected Revenue by Crop with Median Soils

(a) Net Precipitation

(b) Hundreds of Growing Degree Days

(c) Extreme Degree Days
Figure 6: Prediction of Nonirrigated Cropland Share by Crop with Median Soils

(a) Net Precipitation

(b) Hundreds of Growing Degree Days

(c) Extreme Degree Days
Figure 7: The Effect of Climate Change on Precipitation (a) and Precipitation minus Evaporation (b)

Note: This figure is replicated from figure 11.13 on p. 985 of Kirtman et al. (2013) with the following caption: “CMIP5 multi-model projections of changes in annual and zonal mean (a) precipitation (%) and (b) precipitation minus evaporation (mm day$^{-1}$) for the period 2016–2035 relative to 1986–2005 under RCP4.5. The light blue denotes the 5 to 95% range, the dark blue the 17 to 83% range of model spread. The grey indicates the 1σ range of natural variability derived from the pre-industrial control runs (see Annex I for details).”
Figure 8: Relative Change in Rent from a 2°C Increase in Maximum and Minimum Temperatures through Changes in Net Precipitation only or Changes in Degree Days only

(a) Effect through Change in Net Precipitation Only

(b) Effect through Change in Degree Days Only
Figure 9: Relative Change in Rent from a 2°C Increase in Maximum and Minimum Temperatures through Changes in Net Precipitation and Changes in Degree Days
Supplementary Appendix

The Penman-Monteith method is widely regarded as the standard method for calculating reference evapotranspiration, but requires data for minimum and maximum temperature, solar radiation, vapor pressure, and wind speed. However, Allen et al. (1998) describe methods of approximating solar radiation, vapor pressure, and wind speed in the absence of observed measures. In this appendix, we give a brief description of those approximations that we use.

The Penman-Monteith method to estimate reference evapotranspiration $ET_0$ is (Allen et al. 1998)

\[
ET_0 = 0.408\Delta (R_n - G) + \gamma \frac{900}{T_{avg} + 273} u (e_s - e_a) \\
\Delta + \gamma (1 + 0.34u)
\]

(A5)

where $R_n$ is net radiation, $G$ is soil heat flux density, $T_{avg}$ is mean daily air temperature in Celsius, $u$ is wind speed, $e_s$ is mean saturation vapor pressure, $e_a$ is actual vapor pressure, $\Delta$ is the slope of the vapor pressure curve, and $\gamma$ is the psychrometric constant.

The soil heat flux for daily calculations of evapotranspiration is small, so we set $G = 0$ (Allen et al. 1998). We do not have wind speed data, so we assume $u = 2$ m/s as recommended by Allen et al. (1998). The psychrometric constant $\gamma$ is a function of atmospheric pressure, and thus elevation above sea level. Evapotranspiration is larger at higher altitudes since there is less atmospheric pressure. The psychrometric constant can be calculated as

\[
\gamma = 0.000665 \times 101.3 \left( \frac{293 - 0.0065z}{293} \right)^{5.26}
\]

(A6)

where $z$ is the elevation above sea level in meters. We assume a constant elevation of 400 meters since this has a small impact on ET in our region.
Vapor Pressure Deficit

Mean saturation vapor pressure \( (e_s) \) is calculated as the average of saturation vapor pressure and maximum and minimum temperatures

\[
e_s = \frac{1}{2} \left[ 0.6108 \exp \left( \frac{17.27 T_{\text{max}}}{T_{\text{max}} + 237.3} \right) + 0.6108 \exp \left( \frac{17.27 T_{\text{min}}}{T_{\text{min}} + 237.3} \right) \right]. \tag{A7}
\]

Ideally, the actual vapor pressure \( (e_a) \) would be calculated as the saturation vapor pressure at the dewpoint temperature or derived from data on relative humidity. In the absence of this data, Allen et al. (1998) suggest using the minimum temperature as an approximation for the dewpoint temperature. Therefore, actual vapor pressure is calculated as

\[
e_a = 0.6108 \exp \left( \frac{17.27 T_{\text{min}}}{T_{\text{min}} + 237.3} \right). \tag{A8}
\]

The vapor pressure deficit \( (e_s - e_a) \) is simply the difference between mean saturation vapor pressure and actual vapor pressure which simplifies to

\[
e_s - e_a = \frac{1}{2} 0.6108 \left[ \exp \left( \frac{17.27 T_{\text{max}}}{T_{\text{max}} + 237.3} \right) - \exp \left( \frac{17.27 T_{\text{min}}}{T_{\text{min}} + 237.3} \right) \right]. \tag{A9}
\]

The slope of the vapor pressure curve \( (\Delta) \) evaluated at mean temperature is calculated as

\[
\Delta = \frac{4098 \left[ 0.6108 \exp \left( \frac{17.27 T_{\text{avg}}}{T_{\text{avg}} + 237.3} \right) \right]}{(T_{\text{avg}} + 237.3)^2}. \tag{A10}
\]

Radiation

The extraterrestrial radiation \( (R_a) \) is a function of the latitude and the time of year and is calculated as

\[
R_a = \frac{24 \times 60}{\pi} 0.0820 d_r \left[ \omega_s \sin (\varphi) \sin (\delta) + \cos (\varphi) \cos (\delta) \sin (\omega_s) \right] \tag{A11}
\]
where $\varphi$ is the latitude measured in radians. Latitude measured in decimal degrees is converted to radians as $\text{Radians} = \frac{\pi}{180} \text{decimal degrees}$. The other parameters needed to calculate $R_\text{a}$ are defined as follows:

$$d_r = 1 + 0.033\cos\left(\frac{2\pi}{365}J\right), \quad (A12)$$

$$\delta = 0.409\sin\left(\frac{2\pi}{365}J - 1.39\right), \quad (A13)$$

and

$$\omega_s = \arccos\left(-\tan(\varphi)\tan(\delta)\right), \quad (A14)$$

where $J$ is the number of the day in the year (i.e., 1 to 365 or 366). Given $R_\text{a}$, we can calculate the clear-sky solar radiation as

$$R_\text{so} = \left(0.75 + 2 \times 10^{-5}\right)R_\text{a} \quad (A15)$$

Ideally, solar radiation ($R_\text{s}$) would be measured directly or inferred from measures of relative sunshine duration. In the absence of these measures, we follow Allen et al. (1998) and estimate solar radiation as

$$R_\text{s} = 0.16\sqrt{T_{\text{max}} - T_{\text{min}}}R_\text{a}. \quad (A16)$$

The square root of the temperature difference is a proxy for cloud cover.

Given measures of $R_\text{s}$ and $R_\text{so}$, we can estimate the net radiation $R_\text{n}$ as the difference between incoming net shortwave radiation ($R_{\text{ns}}$) and outgoing net longwave radiation ($R_{\text{nl}}$)

$$R_\text{n} = R_{\text{ns}} - R_{\text{nl}}, \quad (A17)$$

where
\[ R_{ns} = (1 - 0.23) R_s \quad \text{(A18)} \]

and

\[ R_{nl} = 4.903 \times 10^{-9} \left[ \frac{(T_{max} + 273.16)^4 + (T_{min} + 273.16)^4}{2} \right] (0.34 - 0.14 \sqrt{e_a}) \left( 1.35 \frac{R_s}{R_{so}} - 0.35 \right) . \quad \text{(A19)} \]