Future crop yields and water productivity changes for Nebraska rainfed and irrigated crops

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ABSTRACT

We assessed future rainfed and irrigated crop yield and water productivity changes in Nebraska across multiple climate and emission scenarios using an empirical modeling approach. We found rainfed crops showed slightly increased crop water productivity while irrigated crops showed no change or decreased water productivity. Contrary to U.S.-wide studies reporting declines in crop yields, we projected Nebraska crop yields to increase overall with greatest increases in current rainfed fields due to combined effects from maximum and minimum temperatures. However, the increased rainfed yields are not sufficient to fully close the gap between rainfed and irrigated yields.

Abbreviations: USDA: U.S. Department of Agriculture; RegCM4.3: ICTP Regional Climate Model version 4.3; NCEP: National Centers for Environmental prediction; DOE: U.S. Department of Energy; CGCM: Canadian Climate Centre general circulation model; GFDL: Geophysical Fluid Dynamics Laboratory general circulation model; CRCM: Canadian Climate Centre regional climate model; CCSM: National Center for Atmospheric Research general circulation model; HRM3: Hadley Centre's Regional Model 3; HADCM3: Hadley Centre's general circulation model; WRFG: the NCAR Weather Research and Forecasting model; CCCma: Canadian Centre for Climate Modelling and Analysis; CanESM2: Canadian Centre Earth System Model 2; ICHEC-EC: A European community Earth-System Model; IPCC: Intergovernmental Panel on Climate Change; RMSE: Root Mean Square Error

KEYWORDS: Crop yields, water productivity, irrigated crops, rainfed crops, Nebraska

Introduction

How crop yields will change under future climate is a fundamental question for regional and global food security (Lesk, Rowhani, & Ramankutty, 2016; Lobell et al., 2008; Rosenzweig & Parry, 1994). Warmer temperatures and unevenly distributed precipitation could result in large local changes in crop yields. While longer, warmer growing seasons could benefit some crops and regions, crop yields decline when temperature exceeds certain thresholds, and therefore some studies project severe damage to U.S. crop yields under climate change (Lobell & Asner, 2003; Schlenker & Roberts, 2009). Besides reductions in mean yields, one study found that one third of crop yield variability is explained by temperature and precipitation variability (Ray, Gerber, MacDonald, & West, 2015), indicating that variation in yields is at least partially tied to climate variation. Our prior work suggests that future warming and climate variability would increase variability in corn and soy yields in the U.S. Corn Belt (Thompson et al., 2017).

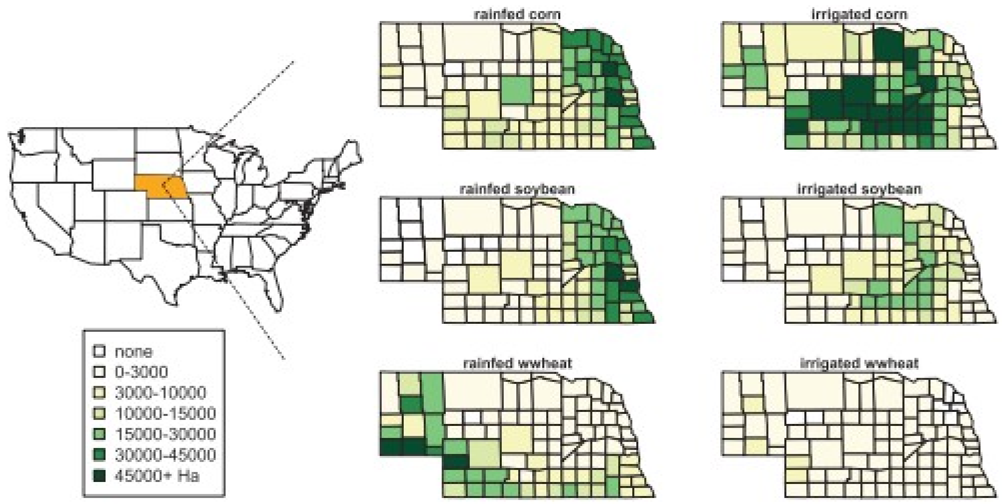

Figure 1. 1982–2012 averaged harvested Hectares of rainfed and irrigated corn, soybean, and winter wheat in Nebraska at the county level (Source data: USDA NASS).

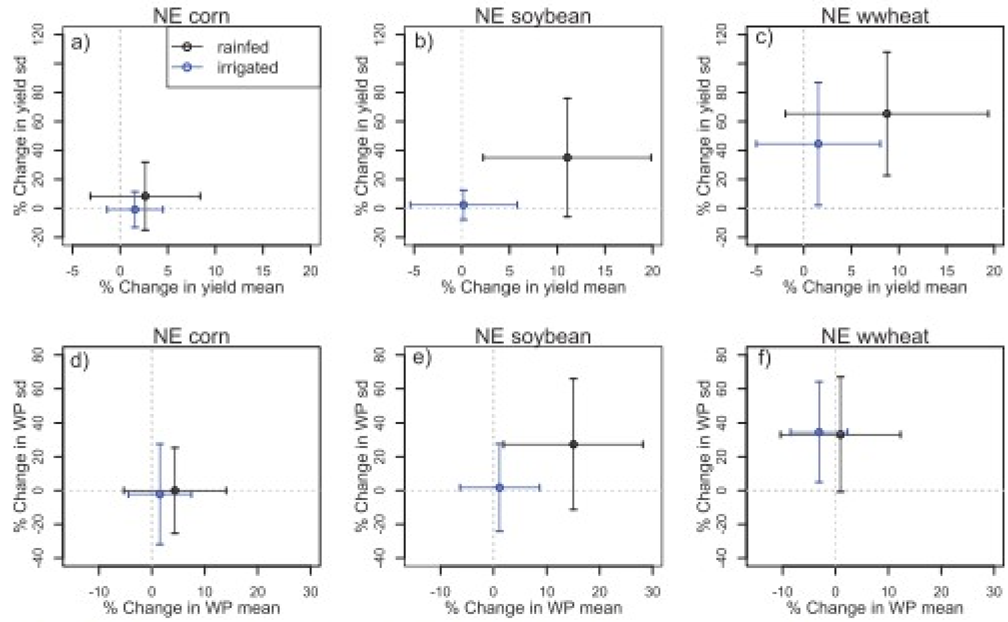

Figure 2. Percentage change in standard deviation (sd) and in mean (a) corn yield, (b) soybean yield, (c) winter wheat yield, (d) corn water productivity, (e) soybean water productivity, and (f) winter wheat water productivity for irrigated (blue) and rainfed (black) fields in Nebraska (NE). The error bars show one standard deviation of the mean across five crop yield models and 10 climate models for three emissions scenarios (6 climate models with A2, 2 with RCP45, and 2 with RCP85).

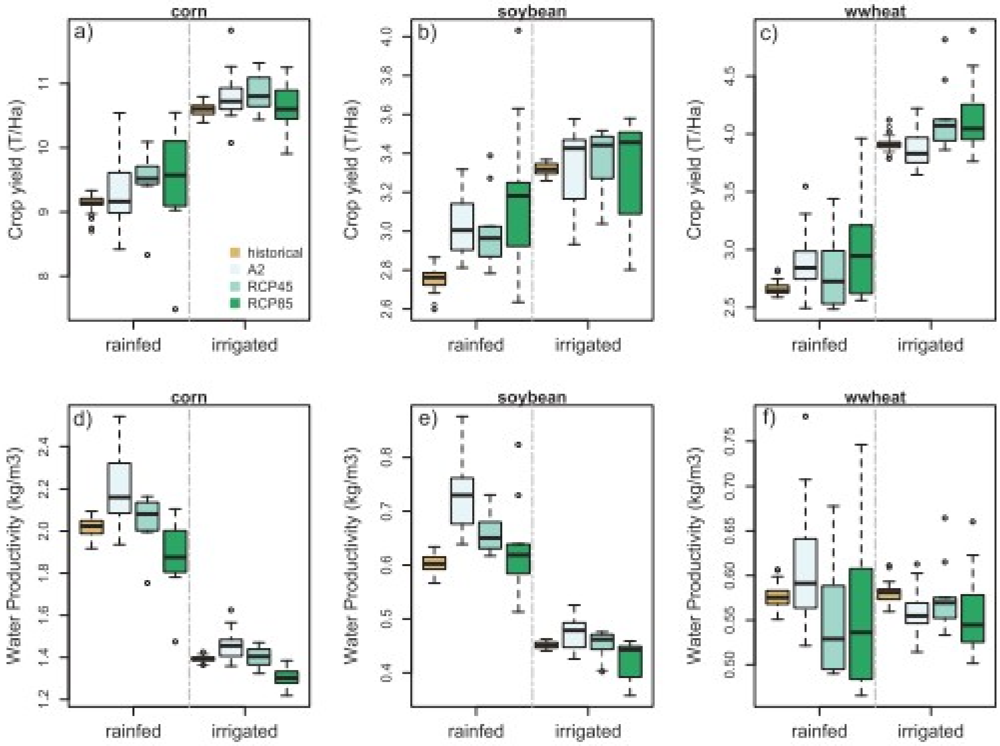

Figure 3. Boxplots for rainfed and irrigated (a) corn yield, (b) soybean yield, (c) winter wheat yield, (d) corn water productivity, (e) soybean water productivity, and (f) winter wheat water productivity under historical and future climate scenarios. Each box represents historical or future annual averaged values across five crop models and six climate models (for historical and A2) or two climate models (for RCP45 and RCP85).

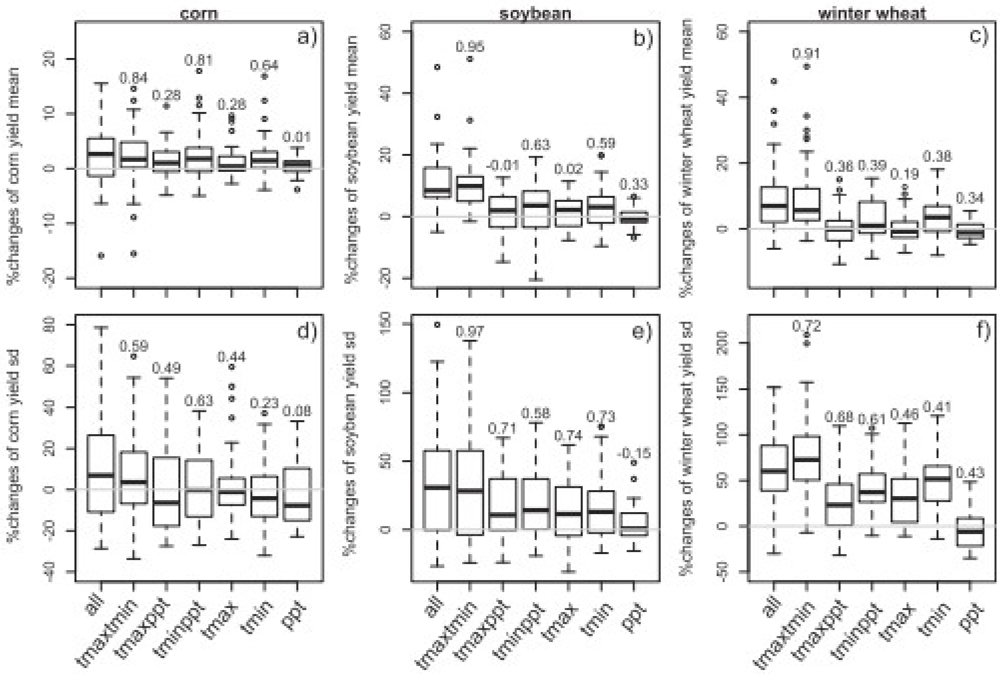

Figure 4. Rainfed crop mean yield and standard deviation changes based on changes in individual or combined climate variables. The values at the top of each box give the correlation between yield changes in the partial models and those using changes in all climate variables.

At the same time, irrigation water demand by crops is expected to increase with warmer temperatures. Two-thirds of global irrigated cropland will possibly suffer from greater irrigation requirements, and Nebraska was predicted to have a 5–15% increase in irrigation requirement with anthropogenic climate change (Doll, 2002). However, ground water depletion is leading to a supply and demand imbalance (Famiglietti & Rodell, 2013). In the U.S. Southern High Plains, 35% of the area will be unable to support irrigation within the next 30 years under current ground water depletion rates (Scanlon et al., 2012). Water limitations have been projected to return 20–60 M ha of irrigated cropland to rainfed cropland globally under representative concentration pathway 8.5 (RCP85), resulting in a further 43% – 112% loss of food production below that due to temperature and precipitation changes only (Elliott et al., 2014).

Nebraska is one of the largest agricultural states in the United States. Ninety-three per cent of Nebraska's land area is farms and ranches. Nebraska also has the largest area of irrigated cropland in the United States (3,357,903 ha. in 2013; USDA NASS) thanks to the Ogallala aquifer that extends underneath the state. Farm marketing contributed over $21 billion to Nebraska's economy in 2011 and accounted for 5.8% of the U.S. total farm income (Nebraska Department of Agriculture, 2014). Agriculture in Nebraska also contributes substantially to international markets and the bioenergy industry. For example, 50% of Nebraska's wheat is exported to international markets annually. In 2012, Nebraska ranked second in ethanol production capacity, and over 40% of the state's corn crop was utilized in ethanol production (Nebraska Department of Agriculture, 2014).

Compared to the numerous studies on crop yield changes at continental scales (Lobell et al., 2013, 2014; Naylor, Falcon, Rochberg, & Wada, 2001; You, Rosegrant, Wood, & Sun, 2009), there has been less focus on how climate changes could affect individual localities such as Nebraska's irrigated and rainfed crop yields. Mendelsohn, Nordhaus, and Shaw (1994) and Reilly et al. (2003) both found that future climate change would be harmful to yields in the southern United States due to increasing temperature, and that western arid regions would suffer more than central and eastern Nebraska (Mendelsohn et al., 1994). To facilitate Nebraska water management decisions, it is also important to understand how crop water productivity (kilograms of crop per cubic meter of water input) (Amarasinghe & Smakhtin, 2014) changes with regional climate change, for both rainfed and irrigated crops.

In this paper, we report how projected regional temperature and precipitation changes affect corn, soybean, and winter wheat yields, as well as crop water productivity (water productivity) in Nebraska, distinguishing rainfed and irrigated crops. We focused on these three crops because they are among the top ten commodities in 2011 state cash receipts. Further, temperature and precipitation account for more than 60% of the variation in yields of these crops in our statistical models, indicating that they are sensitive to climate changes. Nebraska has a dry to wet precipitation gradient, extending from west to east, therefore rainfed corn and soybeans are mainly grown in the eastern part of Nebraska (Figure 1). State wide, irrigated corn accounts for 64% of corn yield, while irrigated soybeans account for 38% of soybean yield. Winter wheat is a dryland crop planted mainly in western Nebraska; irrigated winter wheat accounts for only 6% of total yield. We used 31 years of yield (1982–2012) and climate data to develop step-wise, second-order polynomial crop models at the state level for rainfed and irrigated corn, soybean, and winter wheat, and applied them to multiple scenarios of future climate change in Nebraska.

Methods

We took an empirical modeling approach, in which historical crop yield and climate data are used to train a set of statistical crop models, and then the statistical models are used with regional climate change projections to forecast crop yields for the middle of the 21st century. We parameterized the statistical crop models using training data for the years 1982 to 2012. The yield training data are the USDA National Agricultural Statistics Service (NASS) historical crop yields at the county-level (www.nass.usda.gov).[1] We generated the climate training data by running a regional climate model (RegCM4.3; Giorgi et al., 2012) with boundary condition forcing from global reanalysis data (NCEP/DOE Reanalysis 2 product; Kanamitsu et al., 2002).

The time series anomaly for the RegCM4.3/NCEP simulation showed no significant difference with observation-based data.

To quantify the future change in yields, we used historical and future RCM output to drive the parameterized crop models. These RCM outputs were obtained from the North American Regional Climate Change Assessment Program database (NARCCAP) and Coordinated Regional Climate Downscaling Experiment (CORDEX). The NARCCAP (Mearns et al., 2012; Mearns, Gutowski, & Jones, 2007; Mearns et al., 2009) simulations use the IPCC A2 scenarios, and CORDEX (Martynov et al., 2013) uses multiple IPCC Representative Concentration Pathways (RCPs). The NARCCAP simulations were driven by boundary conditions from six alternate global climate model simulations (RegCM with forcing from CGCM and GFDL, CRCM with forcing from CCSM and CGCM3, HRM3 with forcing from HADCM3, WRFG with forcing from CCSM). The CORDEX models used in our study are CCCma-CanESM2 and ICHEC-EC with RCP4.5 and RCP8.5. The simulation years included historical (1968–1998) and mid-century (2038–2069) periods. To correct for differences between the training and hindcast/forecast climate data, we applied a quantile-based bias correction (see details in Thompson et al., 2017).

We developed stepwise, second-order polynomial regression models that also considered interactions between climate variables, while avoiding over-fitting. By including the interaction terms, we expected to better account for extreme events not captured by the second-order terms. Each yield model was composed of three predictor variables with one month for monthly maximum temperature (T_{max}), one month for monthly minimum temperature (T_{min}), and one month for monthly precipitation (Precip). The full equation is given in Equation (1).

$$\begin{aligned} Yield = {} & a_0 + a_1 year + a_2 year^2 + a_3 T_{max} + a_4 T_{max}^2 + a_5 T_{min} + a_6 T_{min}^2 \\ & + a_7 Precip + a_8 Precip^2 + a_9 T_{max} Precip + a_{10} T_{min} Precip + a_{11} T_{max} T_{min} \end{aligned} \qquad (1)$$

Because using the full Equation (1) could result in over-fitting due to the limited number of years (31) used to construct the model, we used the stepwise function in R to automatically build models by adding or removing terms. For each crop, we generated a range of regression models by using permutations of temperature and precipitation from different months. Each regression model uses the best combination of terms based on Akaike information criterion (AIC) selection for a given month of tmax, tmin, and precipitation. Then we selected the best five regression models based on a historical out-of-sample error analysis and these criteria: 1) Any two monthly climate predictors should not be highly correlated over time ($r < 0.3$), 2) no autocorrelation in errors, 3) no heteroscedasticity in errors, 4) RMSE reduced compared to the baseline model (which included 'year' terms only), 5) no negative future yield projections, and 6) $R^2 > 0.6$ for an individual climate predictor and crop yield. We used the five crop regression models to represent different stages important to crop growth rather than using one single regression model with one set of monthly predictors.

We set up and selected statistical models for irrigated crops separately, but excluded precipitation terms from the models. The full model for irrigated crops is:

$$Yield = a_0 + a_1 year + a_2 year^2 + a_3 T_{max} + a_4 T_{max}^2 + a_5 T_{min} + a_6 T_{min}^2 + a_7 T_{max} T_{min} \quad (2)$$

Water productivity measures the efficiency of converting water input into crop yield. Water productivity was calculated as kilograms of crop per cubic meter of water input. The water input for rainfed crops is the growing season (April to September for corn and soybean, October to June for winter wheat) total precipitation. While for irrigated crops, the water input is the growing season total precipitation plus the total irrigation. Using the actual irrigation amount in each year would be ideal but was not possible because these observational data are not available. Instead we used data from a Nebraska irrigation survey in 2013 (USDA NASS), where total growing season irrigation water used for corn, soybean, and winter wheat were 3050 m^3/ha, 2740 m^3/ha, and 2130 m^3/ha respectively. We used the same irrigation rate to calculate both the historical and future water productivity, meaning that interannual variability in historical and future irrigation rate are missing from our water productivity analysis, and change in water productivity is due only to changes in yield and precipitation.

Results

Across multiple future emissions scenarios, a diversity of climate model representations of climate change, and multiple yield model permutations, we found that irrigated crop yields and water productivity are generally less sensitive to climate changes than rainfed crop yields in Nebraska (Figure 2). Averaged across three emission scenarios, the rainfed crop mean yield increased by 3.0%, 11.5%, and 8.7% for corn, soybean, and winter wheat respectively, while irrigated crop yield mean increased by 1.2% and 3.6% for corn and winter wheat, and decreased by 0.1% for soybean. Rainfed crops had an even greater increase in interannual yield variability. The rainfed crop yield standard deviation increased by 11.4%, 31.4%, and 67.0% for corn, soybean, and winter wheat respectively, and while irrigated yield standard deviations increased 51.5% for winter wheat, corn and soybean yield standard deviations changed little (−0.1% and 1.3%).

Due to the small changes in irrigated corn and soybean yields, their water productivity did not change much (1.5% and 1.2% for mean water productivity, −2.2% and 1.7% for its standard deviation). Rainfed corn and soybeans showed a greater increase (or less decrease) in mean and standard deviation of water productivity (4.4% and 15% for mean water productivity, −0.1% and 27.3% for water productivity standard deviation).

For winter wheat, the water productivity standard deviation increased similarly for rainfed (33%) and irrigated (34%) fields. The increase in winter wheat mean yield did not result in a large increase in mean water productivity, with the irrigated winter wheat mean water productivity decreasing by 3.1%, and rainfed winter wheat mean water productivity increasing by only 1%.

Even though the rainfed crops had greater yield increases than irrigated crops, rainfed crop yields were still projected to be less than irrigated crop yields (Figure 3). Future irrigated corn, soybean, and winter wheat yields were 10.7 T/ha, 3.5 T/ha, 3.8 T/ha, and rainfed yields were 9.2 T/ha, 3 T/ha, 2.8 T/ha averaged across all scenarios. In fact, future rainfed crop yields did not exceed historical irrigated crops yields. At the same time, future rainfed crops had greater water productivity than future irrigated crops, except for winter wheat. Future rainfed corn, soybean, and winter wheat water productivity were 2.1 kg/m^3, 0.7 kg/m^3, 0.6 kg/m^3, and irrigated water productivities were 1.4 kg/m^3, 0.5 kg/m^3, 0.6 kg/m^3 averaged across all scenarios.

The crop yield and water productivity projections differed among the three emission scenarios. RCP85 showed the highest future rainfed crop yields (9.5 T/ha, 3.2 T/ha, 3.0 T/ha) and also resulted low water productivity (1.87 kg/m^3, 0.63 kg/m^3, 0.56 kg/m^3) for corn, soybean, and winter wheat. For irrigated crops, RCP85 did not result in the highest crop yield, and generated the lowest water productivity for corn (1.3 kg/m^3), soybean (0.42 kg/m^3), and winter wheat (0.56 kg/m^3). A2 showed a slightly greater increase in rainfed crop yields and had the highest water productivity. Irrigated corn and soybean also showed the highest water productivity under the A2 emission scenarios.

To understand the individual and combined effects of the climate variables on yield changes, we applied the future values of the individual and combined temperature and precipitation variables one at a time, while keeping other variables at the historical values. For rainfed crops, we found T_{max} and T_{min} together generated yields that most closely matched the full projections (Figure 4). Mean rainfed yield changes projected using only T_{max} and T_{min} were highly correlated with mean yield changes projected using all climate factors for corn (0.84), soybean (0.95), and winter wheat (0.91). T_{max} and T_{min} together also predicted yield standard deviation changes well; the correlation with the full projected yield standard deviation changes were 0.59 for corn, 0.97 for soybean, and 0.72 for winter wheat, suggesting that changes in T_{max} and T_{min} not only determined the magnitude of mean yield changes, but also determined a large fraction of the interannual variation. For irrigated crops, T_{min} or T_{max} alone did not show strong correlation with the full projection, where the full projection used the combined effects of T_{max} and T_{min} (Equation (2)).

Discussion

Nebraska has the largest acreage of irrigated cropland in the United States (3,357,903 ha. in 2013; USDA NASS). Understanding how irrigated crop yields change in response to a range of climate scenarios is essential to anticipating changes in food security and the agricultural economy of the state. Using an empirical modeling approach, we showed that irrigated crops are less sensitive to climate changes than rainfed crops. On average, across emission scenarios and climate models, rainfed crops showed a greater increase in both mean yield and interannual variability in yield, as did crop water productivity. The crop yield and water productivity projections differed among the three emission scenarios. However, all emission scenarios produce a wider range of future crop yield and water productivity values than the historical period, suggesting increasing uncertainty in future yield projections. When looking at the averaged results, RCP85 showed the highest future rainfed crop yields but also low water productivity, while A2 showed a slight increase in rainfed crop yields but had the highest water productivity.

Despite the lower sensitivity to climate change, irrigated crops still showed much higher crop yields than rainfed crops. The high irrigated yield coupled with the large water inputs in irrigated cropland often resulted low water productivity. Among the three crops, we found that irrigated winter wheat is the only crop with water productivity similar to its rainfed counterpart. However, the current irrigated winter wheat area is very small compared with that of irrigated corn and soybean. Our results suggest a benefit of conserving water while maintaining high yields if the irrigated winter wheat area were expanded.

Many studies have shown that future climate could reduce the United States crop yield due to the warmer climate and an earlier but warmer growing season. The magnitude of the decrease varies with emission scenario and the future period of focus. For example, averaged corn, soybean, and cotton yield in US have been projected to decrease by 30–46% before the end of the 21st century under the lowest (B1) warming scenario, with severe decreases (63–82%) under the rapid warming scenario (A1FI) (Schlenker & Roberts, 2009). Declines have been expected to be smaller mid-century (2030–2050), when US corn yields are projected to decrease by 18% (Urban, Roberts, Schlenker, & Lobell, 2012). We selected five crop models with the best estimation of the yield and used seven climate models and three emission scenarios to capture large uncertainties in crop yield projections. In our projections, we found corn, soybean, and winter wheat yields in Nebraska could actually increase on average, especially for the rainfed crops. Differences between state-level and national-level yield change projections suggest large regional variations in yield sensitivity within the US and highlight a need for sate-level decision making to consider regionally specific yield projections.

With a set of sensitivity analyses, we determined that T_{max} and T_{min} together played the most important role in increasing rainfed crop yield. One reason might be that the current locations where rainfed corn and soybean are grown are fairly wet regions in eastern Nebraska, where summer precipitation is not historically limiting. These regions averaged 800 – 900 mm annual precipitation (1982–2012), and future precipitation projections did not vary much from the historical means (< 1 mm/month). When the statistical models were trained with the high historical precipitation, the role of small future precipitation variations was not as important as the larger temperature variations (up to 6°C/month).

Conclusions

In summary, our statistical crop models for corn, soybean, and winter wheat in Nebraska, revealed that irrigated crops are less sensitive to climate changes than rainfed crops, benefitting less from warmer temperatures, but also suffering less from increased interannual variability in yield. For the rainfed crops, combined changes in T_{max} and T_{min} drove the increased mean yield and variability. Therefore, while increased rainfed yields are not sufficient to fully close the gap between rainfed and irrigated yields, maintaining – rather than expanding – the current level of irrigation in Nebraska could allow an increase state-wide crop production thanks to increases in rainfed yields.

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Notes

1. Abbreviations used in the text: USDA: U.S. Department of Agriculture; RegCM4.3: ICTP Regional Climate Model version 4.3; NCEP: National Centers for Environmental prediction; DOE: U.S. Department of Energy; CGCM: Canadian Climate Centre general circulation model; GFDL: Geophysical Fluid Dynamics Laboratory general circulation model; CRCM: Canadian Climate

Centre regional climate model; CCSM: National Center for Atmospheric Research general circulation model; HRM3: Hadley Centre's Regional Model 3; HADCM3: Hadley Centre's general circulation model; WRFG: the NCAR Weather Research and Forecasting model; CCCma: Canadian Centre for Climate Modelling and Analysis; CanESM2: Canadian Centre Earth System Model 2; ICHEC-EC: A European community Earth-System Model; IPCC: Intergovernmental Panel on Climate Change; RMSE: Root Mean Square Error

References

Amarasinghe, U. A., & Smakhtin, V. (2014). Water productivity and water footprint: Misguided concepts or useful tools in water management and policy? *Water International*, 39(7), 1000–1017.

Doll, P. (2002). Impact of climate change and variability on irrigation requirements: A global perspective. *Climatic Change*, 54(3), 269–293.

Elliott, J., Deryng, D., Mueller, C., Frieler, K., Konzmann, M., Gerten, D., … Wisser, D. (2014). Constraints and potentials of future irrigation water availability on agricultural production under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 111(9), 3239–3244.

Famiglietti, J. S., & Rodell, M. (2013). Water in the balance. *Science*, 340(6138), 1300–1301.

Giorgi, F., Coppola, E., Solmon, F., Mariotti, L., Sylla, M. B., Bi, X., … Brankovic, C. (2012). RegCM4: Model description and preliminary tests over multiple CORDEX domains. *Climate Research*, 52(1), 7–29.

Kanamitsu, M., Ebisuzaki, W., Woollen, J., Yang, S. K., Hnilo, J. J., Fiorino, M., & Potter, G. L. (2002). NCEP-DOE AMIP-II Reanalysis (R-2). *Bulletin of the American Meteorological Society*, 83(11), 1631–1643.

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), 84–87.

Lobell, D. B., & Asner, G. P. (2003). Climate and management contributions to recent trends in US agricultural yields. *Science*, 299(5609), 1032.

Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P., & Naylor, R. L. (2008). Prioritizing climate change adaptation needs for food security in 2030. *Science*, 319(5863), 607–610.

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., & Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change*, 3(5), 497–501.

Lobell, D. B., Roberts, M. J., Schlenker, W., Braun, N., Little, B. B., Rejesus, R. M., & Hammer, G. L. (2014). Greater sensitivity to drought accompanies maize yield increase in the US midwest. *Science*, 344(6183), 516–519.

Martynov, A., Laprise, R., Sushama, L., Winger, K., Separovic, L., & Dugas, B. (2013). Reanalysis-driven climate simulation over CORDEX North America domain using the Canadian regional climate model, version 5: Model performance evaluation. *Climate Dynamics*, 41(11–12), 2973–3005.

Mearns, L. O., Arritt, R., Biner, S., Bukovsky, M. S., McGinnis, S., Sain, S., … Snyder, M. (2012). The North American regional climate change assessment program overview of phase I results. *Bulletin of the American Meteorological Society*, 93(9), 1337–1362.

Mearns, L. O., Gutowski, W., Jones, R., Leung, L.-Y., McGinnis, S., Nunes, A. M. B., & Qian, Y. (2009). A regional climate change assessment program for North America. *Eos, Transactions American Geophysical Union*, 90(36), 311.

Mearns, L. O., Gutowski, W. J., & Jones, R. (2007). *The North American regional climate change assessment program dataset*. Boulder, CO: National Center for Atmospheric Research Earth System Grid data portal.

Mendelsohn, R., Nordhaus, W. D., & Shaw, D. (1994). The impact of global warming on agriculture: A ricardian analysis. *The American Economic Review*, 84(4), 753–771.

Naylor, R. L., Falcon, W. P., Rochberg, D., & Wada, N. (2001). Using El Nino/Southern oscillation climate data to predict rice production in Indonesia. *Climatic Change*, 50(3), 255–265.

Nebraska Department of Agriculture. (2014). *Nebraska agriculture*. Retrieved from http://www.nda.nebraska.gov/publications/ne_ag_facts_brochure.pdf

Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nature Communications*, 6. doi:10.1038/Ncomms6989

Reilly, J., Tubiello, F., McCarl, B., Abler, D., Darwin, R., Fuglie, K., … Rosenzweig, C. (2003). US agriculture and climate change: New results. *Climatic Change*, 57(1–2), 43–69.

Rosenzweig, C., & Parry, M. L. (1994). Potential impact of climate-change on world food-supply. *Nature*, 367(6459), 133–138.

Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L., & McMahon, P. B. (2012). Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. *Proceedings of the National Academy of Sciences of the United States of America*, 109(24), 9320–9325.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 106(37), 15594–15598.

Thompson, W., Gerlt, S., Campbell, J. E., Kueppers, L. M., Lu, Y. Q., & Snyder, M. A. (2017). A cost of tractability? Estimating climate change impacts using a single crop market understates impacts on market conditions and variability. *Applied Economic Perspectives and Policy*, 39(2), 346–362.

Urban, D., Roberts, M. J., Schlenker, W., & Lobell, D. B. (2012). Projected temperature changes indicate significant increase in interannual variability of U.S. maize yields. *Climatic Change*, 112(2), 525–533.

USDA NASS. *United States department of agriculture national agricultural statistics*. Retrieved from http://www.nass.usda.gov/

You, L. Z., Rosegrant, M. W., Wood, S., & Sun, D. S. (2009). Impact of growing season temperature on wheat productivity in China. *Agricultural and Forest Meteorology*, 149(6–7), 1009–1014.