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Sustainable use of groundwater dramatically reduces maize, soybean, and wheat production

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J.R.L., J.M.W., J.E., G.H., C.P., and A.C.R designed the study. J.R.L., J.M.W., and J.E. ran crop model simulations, and J.R.L. and J.M.W. developed agricultural water supply scenarios. All authors analyzed results. J.R.L. and J.M.W. wrote the manuscript, with help from G.H., C.P., J.E., A.C.R, M.A., and C.H.

This PDF file includes:

Main Text
Figures 1 to 4
Table 1
SI Appendix

Abstract

The current rate of groundwater extraction in the United States is unsustainable, making it essential to understand the impacts of limited water use on food production. Here, we integrate a gridded crop model with satellite observations and water survey data to assess the effects of sustainable groundwater withdrawals on US agricultural production. Using the most optimistic assumptions for groundwater extraction, we find that sustainable groundwater use will decrease US irrigated production of maize, soybean, and winter wheat by 20%, 6%, and 25%, respectively. Using more conservative assumptions of groundwater availability, US irrigated production of maize, soybean, and winter wheat will decrease by 45%, 37%, and 36%, respectively. Model uncertainty was assessed by comparing simulations with independent estimates. Seasonal simulated evapotranspiration in agricultural areas between crop models and satellite based estimates (ALEXI) were in agreement (R^2 = 0.68 across simulations). Additionally, model simulations of total production per county and average yield were strongly correlated with survey data from the United States Department of Agriculture (R^2 ranged 0.82-0.94 for county level production and 0.37-0.54 for yield across crops). These results demonstrate the vulnerability of US agricultural production to unsustainable groundwater pumping, highlighting the difficulty of expanding or even maintaining food production in the face of climate change, population growth, and shifting dietary demands.

Significance Statement

To our knowledge, this study provides the most thorough and realistic continental-scale assessment of US irrigated agricultural sustainability to date. Through our modeling approach, we identify regions that are vulnerable to groundwater supply reductions, as well as the characteristics common across both vulnerable and resilient agricultural districts. The results of this study have several important implications for agricultural stakeholders and policymakers in the United States. First, it quantifies the national production supported by unsustainable groundwater pumping. Second, by identifying vulnerable regions, it highlights areas that can be targeted for enhanced groundwater management and irrigation efficiency initiatives. Finally, the sensitivity of production losses across groundwater supply scenarios provides information about the limitations of each agricultural district and context for climate change impacts assessments.

Introduction

Groundwater extraction in much of the United States (US) is unsustainable(1–4). Combined, the two major aquifers in the US, the Ogallala in the High Plains and Central Valley in California, were depleted by approximately 12.5 km^3 and 3.1 km^3 per year between 2003 and 2013, respectively(5). This depletion is equivalent to 15% of the total groundwater extraction in the US in 2010(1). Between 2010 and 2015, groundwater withdrawals for irrigation increased by 16%(2). Irrigation used 67% of the total US groundwater extraction in 2015(2), and exceeds groundwater recharge across 15% of the contiguous US(3). Groundwater extraction for irrigation must substantially decrease for US agricultural production to be sustainable, but doing so would have a negative impact on both the US and world food supplies. The US is responsible for 36% of the global maize production, 35% of the global soybean production, and 8 % of the global wheat production(4). These crops occupy 52% of the US irrigated agricultural area (maize 22%, soybean 17% and wheat 13%)(2). The tension between increasing food production and using water sustainably raises two critical questions: how much groundwater can be extracted while still irrigating sustainably, and what would the impacts of irrigating sustainably be on agricultural production?

Sustainable groundwater extraction for agriculture can be approximated using the concept of safe aquifer yield. Safe aquifer yield is defined as the estimated sustainable groundwater extraction rate and based on aquifer recharge rates(6). The safe aquifer yield over agriculturally intensive areas can be derived using a water balance approach, where the aquifer recharge rate is calculated from water inflows (precipitation and irrigation return flow) and outflows (runoff, evapotranspiration)(3). Aquifer recharge rates are highly dependent on future precipitation, but future precipitation and drought are difficult to predict(7, 8). Therefore, safe aquifer yields are typically set below recharge rates, and can vary based on approach(3). For example, Miles and Chambet(6) proposed a conservative safe aquifer yield of 10% of recharge, while Hahn *et al.*(9) estimated annual safe aquifer yields between 36% and 75% of recharge for different areas depending on elevation. Here, we define the most optimistic safe aquifer yield as 100% of recharge, and the least optimistic safe aquifer yield as 25% of recharge.

The impacts of reducing groundwater extraction on agricultural production can be addressed using a spatially explicit, process-based crop model. Process-based crop models are capable of simulating the impacts of climate and management practices on agricultural production at field to global scales(10–12). To simulate areas larger than a field, process-based crop models are run over multiple grid cells. For each grid cell, the model evaluates daily weather data, as well as information on soil properties, management, and crop varieties. In this study, we used a parallel and gridded implementation of the Decision Support System for Agrotechnology Transfer software (pDSSAT)(12–14), which contains a collection of process-based crop models. Process-based crop models have been evaluated extensively, in particular within the Agricultural Model Intercomparison and Improvement Project (AgMIP)(10–12, 15).

Irrigation is critical to US agricultural production, yet unsustainable, and the impacts of reducing water use are largely unknown. In this manuscript, we calibrate a gridded, process-based crop model, and use it to assess the effects of sustainable water use on irrigated production of maize, soybean, and winter wheat across the contiguous US (Fig. 1). We further test the sensitivity of these effects to safe aquifer yield to determine the range of possible shifts in production that would result from using water sustainably.

Results and Discussion

National Impacts of Sustainable Agricultural Water Use

We assessed the impacts of sustainable groundwater use on irrigated agricultural production of maize, soybean, and winter wheat in the US by examining the difference in production between pDSSAT simulations with unlimited groundwater and pDSSAT simulations with groundwater reduced to a sustainable level (see Methods). Nationally averaged, production losses for the most optimistic safe aquifer yield (100% recharge) for maize, soybean, and wheat are 20%, 6%, and 25%, respectively, and production losses for the least optimistic safe aquifer yield (25% recharge) for maize, soybean, and wheat are 45%, 37%, and 36%, respectively. The production losses for maize and wheat are higher than soybean for safe aquifer yields of 50% recharge or more, but at the lowest safe aquifer yields soybean production drops dramatically (Table 1).

The distribution of maize production loss is bimodal (Fig. 2), with some districts and years experiencing near complete production loss (70% – 90%) even at the most optimistic safe aquifer yield, and other districts experiencing more modest losses (10% – 30%). We assess the significance of changes in crop production distributions for districts that experience losses using a two-sided Wilcoxon rank sum test (□ = 0.05). Maize production losses are significant for the 25% ($p = 3.9 \times 10^{-4}$), 50% ($p = 0.0037$), and 75% ($p = 0.019$) recharge scenarios. Soybean production is only significantly lower than the unlimited groundwater use scenario for the least optimistic safe aquifer yield ($p = 0.037$), though even at higher safe aquifer yields some districts experience production losses of 70% – 90%. Consistent with the nationally averaged losses, soybean is particularly sensitive to the safe aquifer yield scenario, with relatively few districts experiencing losses at the most optimistic safe aquifer yield (and therefore not included in Fig. 2), but many more at the least optimistic. In contrast, for districts that experience losses, winter wheat production is significantly different from the unsustainable scenario regardless of safe aquifer yield assumption ($p = 2.8 \times 10^{-4}$ for 25%, $p = 1.5 \times 10^{-3}$ for 50%, $p = 4.9 \times 10^{-3}$ for 75%, $p = 0.02$ for 100%), and changes in the distribution of winter wheat losses are relatively insensitive to safe aquifer yield.

Together, these analyses highlight several key impacts of sustainable water use for irrigated agriculture at the national scale. First, even for the most optimistic safe aquifer yield scenario, there are a substantial number of districts with large (70% – 90%) losses for each crop. Second, in relatively optimistic water restriction scenarios (aquifer yields of 100% and 75% of recharge) the impacts on wheat and maize are large and the impacts on soybean are small. Finally, for the least optimistic safe aquifer yield (25% recharge) soybean losses dramatically increase and maize sustains the largest percentage production loss among the three crops considered.

Geographic Distribution of Sustainable Agricultural Water Use Impacts

Maize production losses are concentrated in southwestern Nebraska, western Kansas, northern Texas, and California for the most optimistic safe aquifer yield, but spread across most of Nebraska, intensify over western Kansas and northern Texas, and expand to the Mississippi Valley for the least optimistic safe aquifer yield (Fig. 3a-b). Production losses for the most optimistic safe aquifer yield overlie the two most stressed groundwater sources in the United States: the Ogallala and Central Valley Aquifers. Qualitatively, these losses agree with future projections of irrigated maize production across the Missouri and California basins under water constraints(16). Irrigated maize production in the Midwest, including Iowa, Illinois, and Indiana, is largely unaffected. As expected, there is a correspondence between production losses and sustainable irrigation fraction (Fig. 4, see Methods), with production losses first appearing in areas with low sustainable irrigation fractions at a safe aquifer yield of 100% of recharge, such as the High Plains and Central Valley, and then expanding to regions such as the Mississippi Valley as decreasing access to recharge (less optimistic safe aquifer yields) lowered sustainable irrigation fractions.

Soybean is mainly grown in more humid eastern areas of the US, including eastern Nebraska and the Mississippi Valley, where there is greater aquifer recharge(3) and groundwater available for irrigation (Fig. 3c-d). Therefore, soybean production is less susceptible to reduced groundwater withdrawals for irrigation at optimistic safe aquifer yields. However, at less optimistic safe aquifer yields, agricultural water demand does exceed recharge, and soybean production is significantly impacted. Accordingly, losses for the most optimistic safe aquifer yield are largely restricted to southern Nebraska, while for the least optimistic safe aquifer yield losses cover extensive areas of eastern Nebraska and the Mississippi Valley. As with maize, irrigated soybean production is largely unaffected in the Midwest and production losses are generally greatest when the sustainable irrigation fraction is less than 0.5 (Fig. 4).

In contrast to soybean, irrigated winter wheat production is located primarily in the more arid regions of the US with lower sustainable irrigation fractions (Fig. 4), and therefore vulnerable to even modest irrigation reductions. For the most optimistic safe aquifer yield, production losses were split between the High Plains states of Nebraska, Kansas, and Texas, and western states of Washington, California, Idaho, and Nevada (Fig. 3e). Irrigated winter wheat is less sensitive to declining safe aquifer yields (i.e., production loss difference between 100% recharge and 25% recharge) than maize and soybean. While losses do intensify in the least optimistic safe aquifer yield, there is a substantial amount of production that is insensitive to even aquifer yields of 25% recharge. This response is clear in Fig. S1c (*SI Appendix*), which shows extensive production classified as red (production lost at 100% of recharge) and dark green (production remaining at 25% of recharge). Fig. 3 and Supplementary Fig. 1c highlight that compared to maize and soybean, fewer new regions of irrigated winter wheat are affected by less optimistic safe aquifer yields, and that the same regions experiencing losses at more optimistic safe aquifer yields are further impacted at less optimistic aquifer yields.

Aggregated across maize, soybean, and wheat, the most sensitive region of the US to groundwater restrictions is the High Plains. Five agricultural districts in this region show substantial yield reductions for all three crops (Fig. 3) at the most optimistic safe aquifer yield: district 11, located in northern Texas; districts 10 and 30 in northwest and southwest Kansas, respectively; and districts 70 and 80 in the south of Nebraska(17). These districts have four common attributes: high irrigated agricultural area (combined the districts represent 11% of national irrigated agricultural area), large proportion of groundwater extraction for irrigation (between 94% and 97%)(1), groundwater extraction rates more than three times the aquifer recharge rates (4.0 times for district 11, 3.6 times for district 10, 3.2 times for district 30, 5.4 times for district 70, and 7.5 times for district 80)(3), and located over the Ogallala Aquifer. This reinforces previous studies that have identified the Ogallala Aquifer as particularly vulnerable to changes in groundwater extraction rates for irrigation(3, 5, 18). California, overlying the Central Valley Aquifer, also experiences large reductions in maize and winter wheat yields; however, specialty crops dominate irrigated agriculture in California, making production of, and therefore production losses of, staple crops smaller than in the High Plains.

The Mississippi Valley, in contrast, is relatively unaffected by sustainable groundwater use. Only four districts in the Mississippi Valley have both substantial corn and soybean production losses at the least optimistic sustainable aquifer yield: district 90 in Missouri, district 30 in Arkansas, and districts 10 and 40 in Mississippi (Fig. 3). At more optimistic safe aquifer yields, production in these districts is practically unchanged (*SI Appendix*, Fig. S1). While these districts also have large overall irrigated agricultural area (combined the districts represent 8% of the national irrigated agricultural area) and utilize most of the groundwater they extract for irrigation (between 87% and 98%)(1), their groundwater extraction rate is less than half of their aquifer recharge rate(3) (0.26 times for district 90, 0.48 times for district 30, 0.36 times for district 10, and 0.4 times for district 40). Finally, across the upper Midwest, including Minnesota, Wisconsin, Iowa, Illinois, Indiana, and Michigan, irrigated production of maize and soybean is largely unaffected (Fig. 3). Agricultural districts in these states are more humid and predominantly rainfed.

Conclusion

We show that sustainable agricultural water use, simulated by limiting groundwater use to available recharge, reduces production of irrigated maize, soybean, and winter wheat by 20% – 45%, 6% – 37%, and 25% – 36%, respectively. Winter wheat and maize production are most vulnerable at optimistic safe aquifer yields, while for the least optimistic safe aquifer yields maize is most vulnerable, followed by soybean and winter wheat. The largest production losses occur across the High Plains states, especially Nebraska, western Kansas, and northern Texas. This region is heavily reliant on groundwater from the Ogallala Aquifer, and generally cannot support rainfed agriculture. California, drawing from the Central Valley Aquifer, and other western states also experience reduced production, although they devote less area to maize, soybean, and winter wheat. Production losses extend to the Mississippi Valley, especially for soybean, at less optimistic safe aquifer yields.

We caveat that in our analysis, technology, management, cropping areas, and the fraction of total irrigation water from groundwater are held fixed as water supply is reduced. There are a variety of adaptations such as increased aquifer monitoring and management, irrigation efficiency, crop switching, reduced soil evaporation, and deficit irrigation(19–23), that can decrease agricultural water use. We also focus on staple crops, which account for the vast majority of irrigation across the Central US, but not in the western US where specialty crops are substantial, and often the dominant, users of agricultural water. In addition, international food trade has the potential to offset some of the negative impacts of irrigation water supply shortages(24). We note that agricultural water sustainability is just one facet of an evolving national food production system that is intricately linked to global markets. Climate change will have major impacts on irrigated crop yields through changes in plant water use efficiency(25, 26), temperature(27, 28), and water supply(29). For example, Elliott et al.(30) found greater production losses running global gridded crop models without CO_2 effects than with CO_2 effects, where enhanced levels of CO_2 increased simulated plant water use efficiency. Elliott et al.(30) also identified currently rainfed agricultural areas that had the potential for irrigation, offsetting losses from irrigated regions that were no longer viable, but requiring substantial investment. Finally, Liu et al.(24) found that projections of increased precipitation actually make much of the currently unsustainable irrigated agriculture in the Central US sustainable by the year 2050.

Sustainable irrigated agriculture is vital to ensuring US food security and supporting the broader global food system. Our study highlights the range of potential impacts on irrigated crops in the US from using groundwater sustainably based on a physically constrained set of groundwater availability scenarios. Our safe aquifer yield assumptions, which linearly scale the amount of accessible recharge, could also represent the difference between immediate action to reduce groundwater consumption (most optimistic safe aquifer yield) and delaying action (least optimistic safe aquifer yield) until the viability of irrigation from the Ogallala and Central Valley Aquifers is compromised(18). The latter scenario would not only have a devastating impact on heavily irrigated agricultural regions, and even some areas not usually thought to be groundwater limited, but would also be community-altering, reduce US agricultural productivity, and have serious repercussions for the global food supply.

Materials and Methods

Modeling Approach

We simulated maize, soybean, and wheat yields on a 5 arc-minute grid (approximately 9 km at the equator) on a daily time step over a period of five years (2008 – 2012) using the Cropping System Models (CSMs) CERES-Maize(31, 32), CROPGRO-Soybean(33, 34), and CERES-Wheat(35), respectively. Simulations were conducted on the Dartmouth Discovery Cluster using the Decision Support System for Agrotechnology Transfer (DSSAT), a widely used biophysical modeling platform that contains a suite of CSMs capable of simulating more than 42 crops including all major staple crops(14, 36). The CSMs contained in DSSAT are point-based biophysical models that run on a daily time step and simulate crop growth and development as a function of weather, detailed soil profiles, cultivar specific parameters, and farm management. We ran gridded simulations of DSSAT in parallel using the parallel System for Integrating Impact Models and

Sectors (pSIMS)(12), which has been applied to climate change and sustainability assessments across large regions and the world (11, 30, 37, 38).

Input and Calibration Data

The model input data sources are summarized in Table S1 (*SI Appendix*). Weather data included incoming solar radiation, maximum and minimum temperatures, and precipitation. The soil database contained information for eight soil horizons for each grid, with attributes including bulk density, organic carbon, pH, and water release curve characteristics. The initial conditions and parameters, including crop specific parameters that simulate different cultivars, were similar to Glotter and Elliott(38). Crop specific land use was obtained from the USDA Cropland Data Layer (CDL)(39, 40). USDA-CDL land use data were further classified into irrigated and non-irrigated area using the Moderate Resolution Imaging Spectoradiometer (MODIS) Irrigated Agriculture Dataset for the United States (MIrAD-US)(41). All irrigated grids from each crop were simulated irrigated and rainfed in order to calculate irrigation water use efficiency (see below). The DSSAT irrigation algorithm does account for growing season rainfall throughout the study, as it triggers irrigation based on soil water status (42). However, we did not simulate deficit irrigation strategies in this study.

Model Calibration

We calibrated the model in two steps, first adjusting evapotranspiration (ET) based on an independent ET data source, and then calibrating the yield using county-level measurements from NASS. In DSSAT, ET is computed using an implementation of the FAO-56 crop coefficient equations(43), which estimate crop ET as a crop-type-dependent fraction of the potential ET (PET). To assess the reliability of these estimates, DSSAT ET was compared to remotely sensed ET data from the Atmosphere Land Exchange Inverse (ALEXI) model(44). ALEXI uses the morning surface temperature increase retrieved with the Geostationary Operational Environmental Satellites (GOES) in a surface energy balance algorithm to estimate surface energy and water fluxes at a 5 km resolution over the continental United States. Using a spatial disaggregation technique, ALEXI output has been evaluated with flux tower measurements, yielding typical root mean square errors of 1.0 and 0.4 mm d^{-1} at daily and seasonal time scales, respectively(45). ALEXI output was aggregated over time (growing season) and space (5 arc-minutes) to match pDSSAT growing season simulations. Additionally, since 5 arc-minute cells may contain several sources of ET, including lakes, forest, and various crops, we compared pDSSAT simulations only against aggregated ALEXI cells covered by at least 50% of the crops simulated. We find a relatively small difference (4%) between pDSSAT and ALEXI ET, which suggests that pDSSAT ET is reasonably simulated. While there are uncertainties in the ALEXI ET product, because it does assimilate observed temperature to infer ET, we chose to adjust pDSSAT daily evapotranspiration by 4% through a daily potential evapotranspiration multiplier.

The benchmark for yield calibration was county level yearly yield data reported by the USDA NASS-Survey (irrigated and rainfed). Crop photosynthesis at the agricultural district level was calibrated to improve model simulations of yield using an ordinary least squares approach. Uncertainty in yield predictions was evaluated using a leave one-out cross validation approach (SI Appendix, Table S2). Next, we evaluated the calibrated model against USDA-NASS Survey county level production. Across the US, the correlation between simulated and observed county level production over both space and time is high for all crops, with R^2 values of 0.94, 0.91, and 0.82 for maize, soybean, and wheat, respectively (SI Appendix, Table S2). Finally, evapotranspiration was re-evaluated against ALEXI (R^2 = 0.68) as it was affected by the calibration of yield.. The calibrated version of pDSSAT predicts both yield and evapotranspiration better than the non-calibrated model. Cropped area within pDSSAT is accurate relative to USDA-NASS Survey data at the county level , with R^2 values for maize, soybean, and wheat of 0.95, 0.96, and 0.88. The correlations between pDSSAT simulations of maize, soybean, and rice yields and NASS measurements over time are 0.54, 0.52, 0.37. The bias in mean yield is below 10% for all crops, with maize simulated best and winter wheat simulated worst (*SI Appendix*, Fig. S3 and Table S2). The performance of pDSSAT is comparable to crop model performance for field-scale agricultural experiments(46, 47).

The modeling approach used to simulate maize, soybean, and wheat across the US is robust for most agricultural districts, with coefficient of determination between simulated and observed county level agricultural production over space and time generally higher than 0.5 for all three crops, both rainfed and irrigated (Fig. 1). Typically, pDSSAT is more accurate for all crops in high producing areas, such as the Midwest and the Mississippi Valley. This increase in accuracy is likely due to the dominance of the crop on the landscape and the spatial resolution of pDSSAT. For intensive agricultural areas, the 5 arc-minute grid cells used for the simulations provide a better representation of the environment in which the crops are growing than in regions where the agricultural area covers a relatively limited fraction of the grid cell(48). The accuracy of simulated production is notably higher for maize than soybean and winter wheat in agricultural districts across the US, with the exception of California. The geographic distribution of the coefficient of determination for soybean is relatively uniform, while correlations for winter wheat are highest in Idaho, California, and the Mississippi Valley, and lowest across southwestern Kansas and northern Texas (Fig. 1).

Calculation of sustainable irrigation water use

Our calculation of sustainable irrigation water use for each crop consisted of two steps. We first determined the sustainable irrigation fraction (*SF*), which is the fraction of the total water used for irrigation (ground and surface) that comes from surface water and sustainable groundwater extraction. We consider any extraction of water in excess of the aquifer sustainable yield to be unsustainable groundwater extraction. The *SF* was calculated at the agricultural district level using the following equation:

$$SF = \frac{SW + GW * \frac{R}{E} * AqY}{SW + GW} \qquad \text{(Eq. 1)}$$

Where *SW* is the district level surface water used for irrigation, *GW* is the groundwater used for irrigation, *R* is the aquifer recharge rate, *E* is the district level total groundwater extraction, and *AqY* is the assumed safe aquifer yield. Aquifer recharge rate estimates were from Reitz *et al.*(3). District level total groundwater extraction, surface water used for irrigation, and groundwater used for irrigation where obtained from the USGS report on estimated water use in the United States(1, 49). All variables were aggregated spatially to the district level on a yearly time step to be used in the model simulations. Since there is substantial uncertainty in future aquifer recharge rates, safe aquifer yield can only be approximated. Therefore, we evaluated the sensitivity of *SF* to safe aquifer yield values between 25% and 100%.

Second, we estimated sustainable irrigation water use (WU_S) by crop and district using the following equation:

$$WU_S = WU_U * SF \qquad \text{(Eq. 2)}$$

Where WU_U is the modeled water use for each crop and district, calculated by running pDSSAT with an assumption of unlimited water supply for each 5 arc-minute grid cell containing any irrigated area by crop. Sustainable irrigation water use was then multiplied by the area of irrigated agriculture for that crop, to aggregate the grid level water use available for each crop to the district level.

Estimation of the groundwater sustainability production losses

Unsustainable production was calculated by multiplying model simulated yield with unlimited water supply by irrigated area in each grid cell, and aggregating irrigated production from all grid cells across each district. Sustainable production was obtained by limiting the irrigated crop production based on WU_S for each safe aquifer yield to only the grid cells with the highest irrigation water use efficiency (IWUE). An example calculation of sustainable production is illustrated in Fig. S4 (*SI Appendix*). Irrigation water use efficiency for each grid was calculated with the following equation:

$$IWUE = \frac{Y_i - Y_r}{I} \qquad \text{(Eq. 3)}$$

Where Y_i is irrigated yield, Y_r is rainfed yield, and I is irrigation amount. DSSAT was run for each irrigated grid, rainfed and irrigated, to obtain Y_i and Y_r. The production loss is the difference between unsustainable and sustainable production.

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Figures and Tables

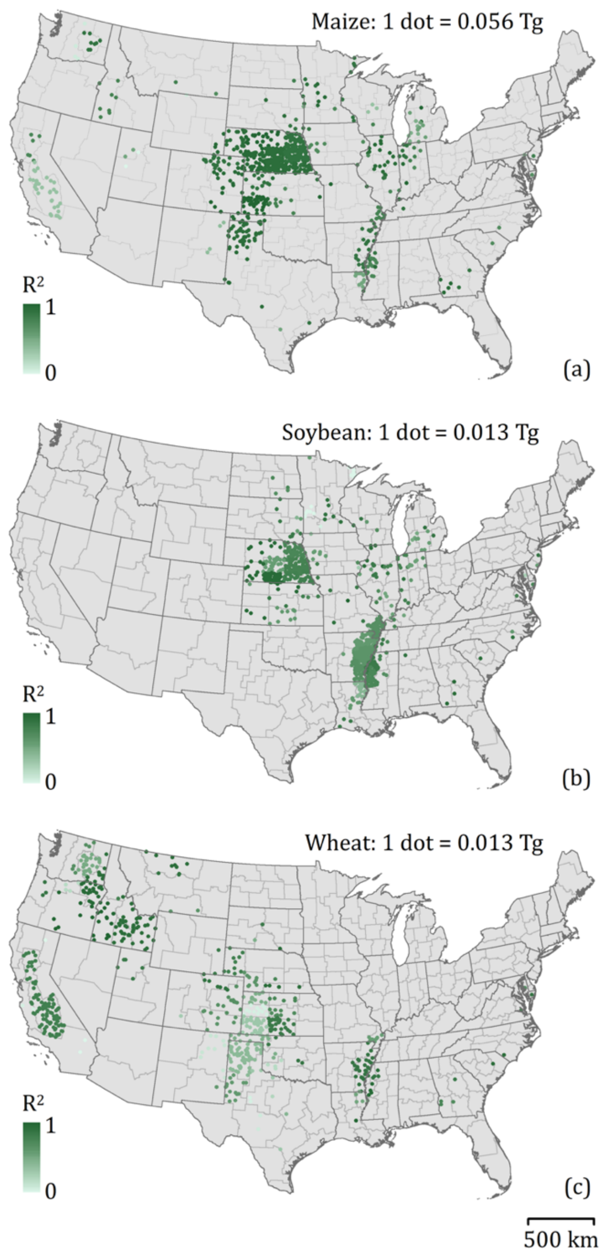

Fig. 1. Crop model evaluation. Coefficient of determination for simulated and observed county level production by agricultural district for maize (a), soybean (b) and winter wheat (c). Color shows correlation, and dot density shows the amount of production in each agricultural district.

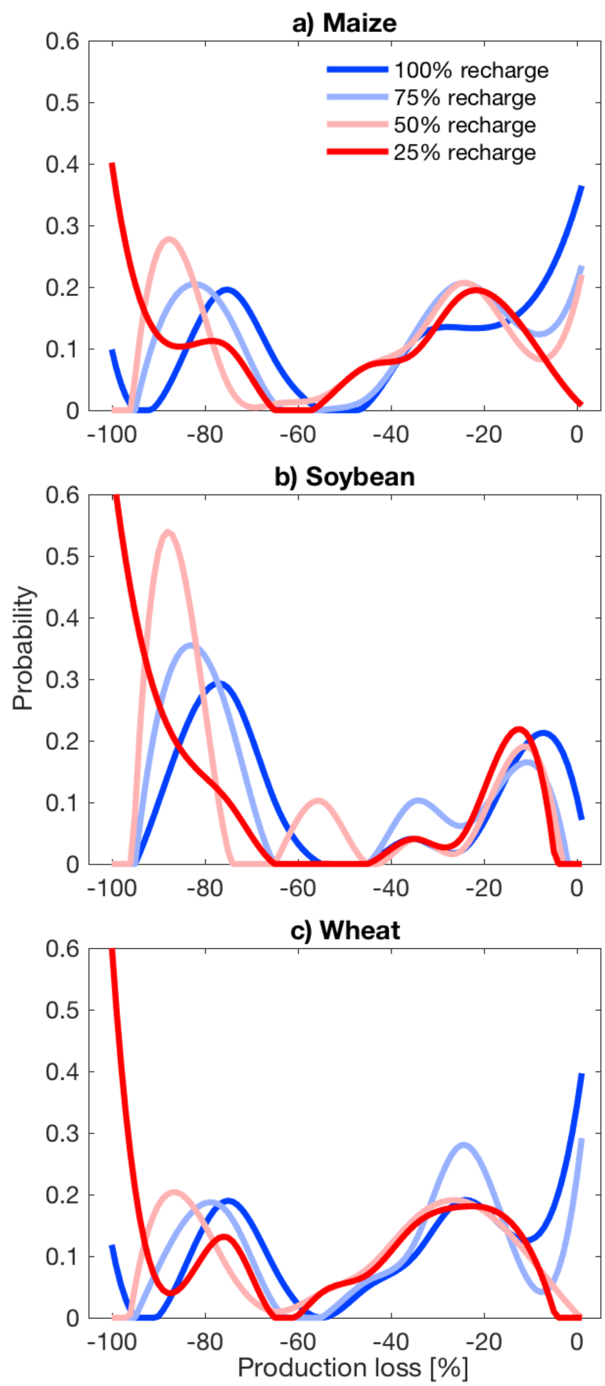

Fig. 2. Production loss from sustainable groundwater use. Production losses across agricultural districts and years for maize (a), soybean (b), and winter wheat (c) with four different assumed safe aquifer yields. Only combinations of districts, years, and safe aquifer yields with a difference between well-watered and sustainable production are shown. Across safe aquifer yields and years, 301, 270, and 287 districts experienced production losses for maize, soybean, and wheat, respectively.

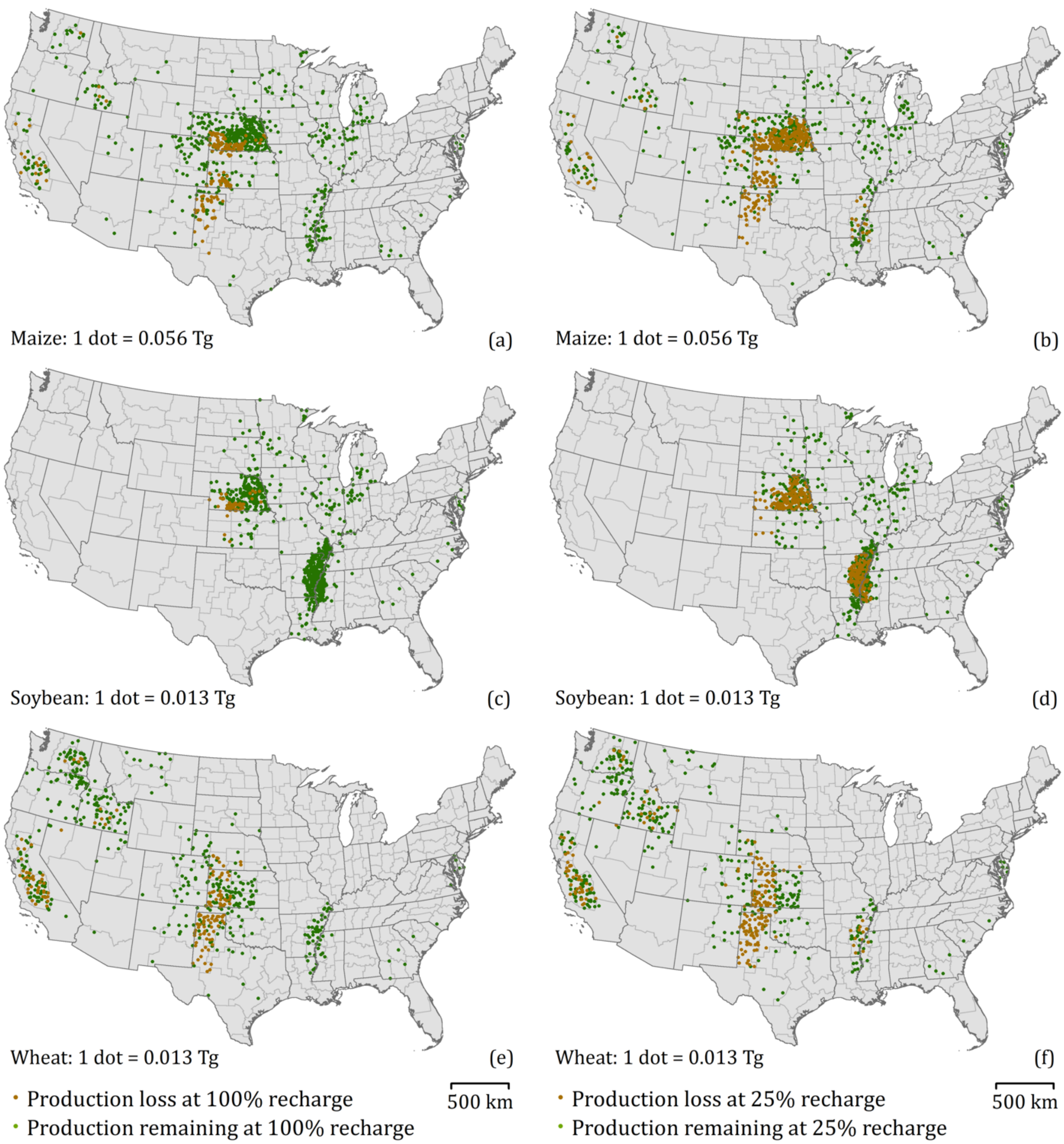

Fig. 3. Distribution of production loss from sustainable groundwater use. Production losses by agricultural district for the most optimistic safe aquifer yield (100% recharge, left) and least optimistic safe aquifer yield (25% recharge, right) for maize (a,b), soybean (c,d), and wheat (e,f). All dots show total irrigated production, brown dots show production lost due to sustainable groundwater use, and green dots show sustainable production remaining.

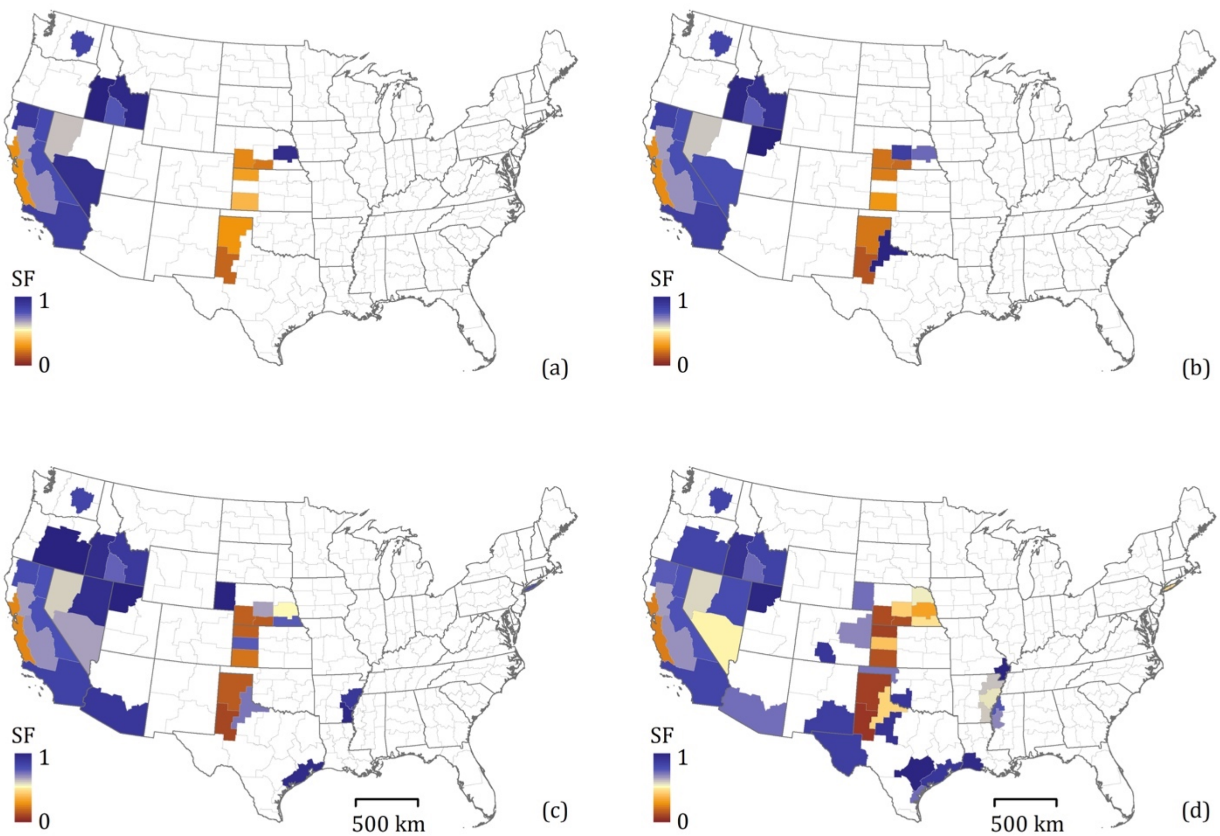

Fig. 4. Spatial distribution of sustainable irrigation fraction. Sustainable irrigation fraction (SF) at 100% recharge (a), 75% recharge (b), 50% recharge (c), and 25% recharge (d). Blank districts have a SF of 1 or more. Values of 1 or more indicate no pressure from agricultural water use on aquifer sustainability, and values of 0 indicate that there is no water available for irrigation because extraction is equal to or higher than recharge.

Table 1. Nationally averaged irrigated production losses from sustainable groundwater use over the simulated period (2008 – 2012). Production from each simulated grid of maize (n = 47100), soybean (n = 33902), and wheat (n = 43180) were aggregated for each sustainable aquifer yield scenario to estimate national production.

	Production Loss		
Sustainable Aquifer Yield	Maize	Soybean	Winter Wheat
100% Recharge	20%	6%	25%
75% Recharge	24%	9%	27%
50% Recharge	31%	15%	30%
25% Recharge	45%	37%	36%

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Supplementary Information for

Sustainable use of groundwater dramatically reduces maize, soybean, and wheat production

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This PDF file includes:

Figures S1 to S4
Table S1 to S2

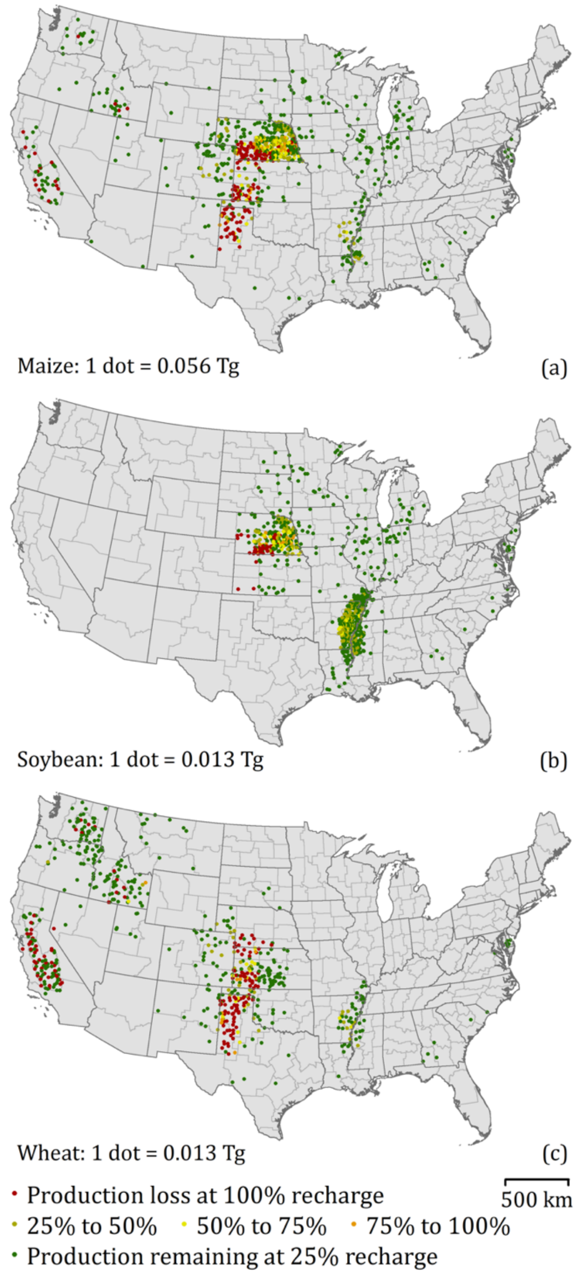


Figure S1. Distribution of production losses from sustainable groundwater use. Production losses by agricultural district for a safe aquifer yield of 100% of recharge, 75% of recharge, 50% of recharge, and 25% of recharge for maize (a), soybean (b), and wheat (c). All dots show unsustainable production, red dots show unsustainable production lost at 100% recharge, orange dots show unsustainable production lost at 75% – 100% recharge, yellow dots show unsustainable production lost at 50% – 75% recharge, chartreuse dots show unsustainable production lost at 25% – 50% recharge, and green dots show unsustainable production remaining due to sustainable water use, by agricultural district.

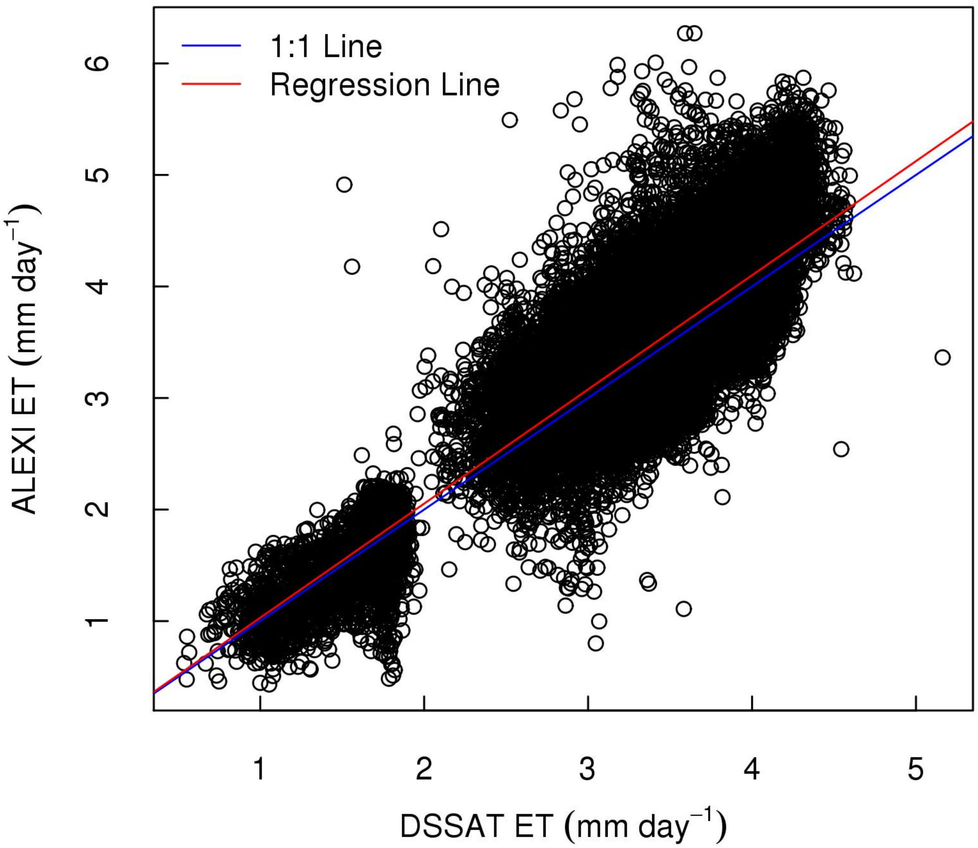


Figure S2. Comparison of simulated and observed evapotranspiration (R^2 = 0.68). Scatter plot of calibrated pDSSAT and ALEXI seasonal evapotranspiration for each grid cell with at least 50% of land covered with maize, soybean, and/or winter wheat.

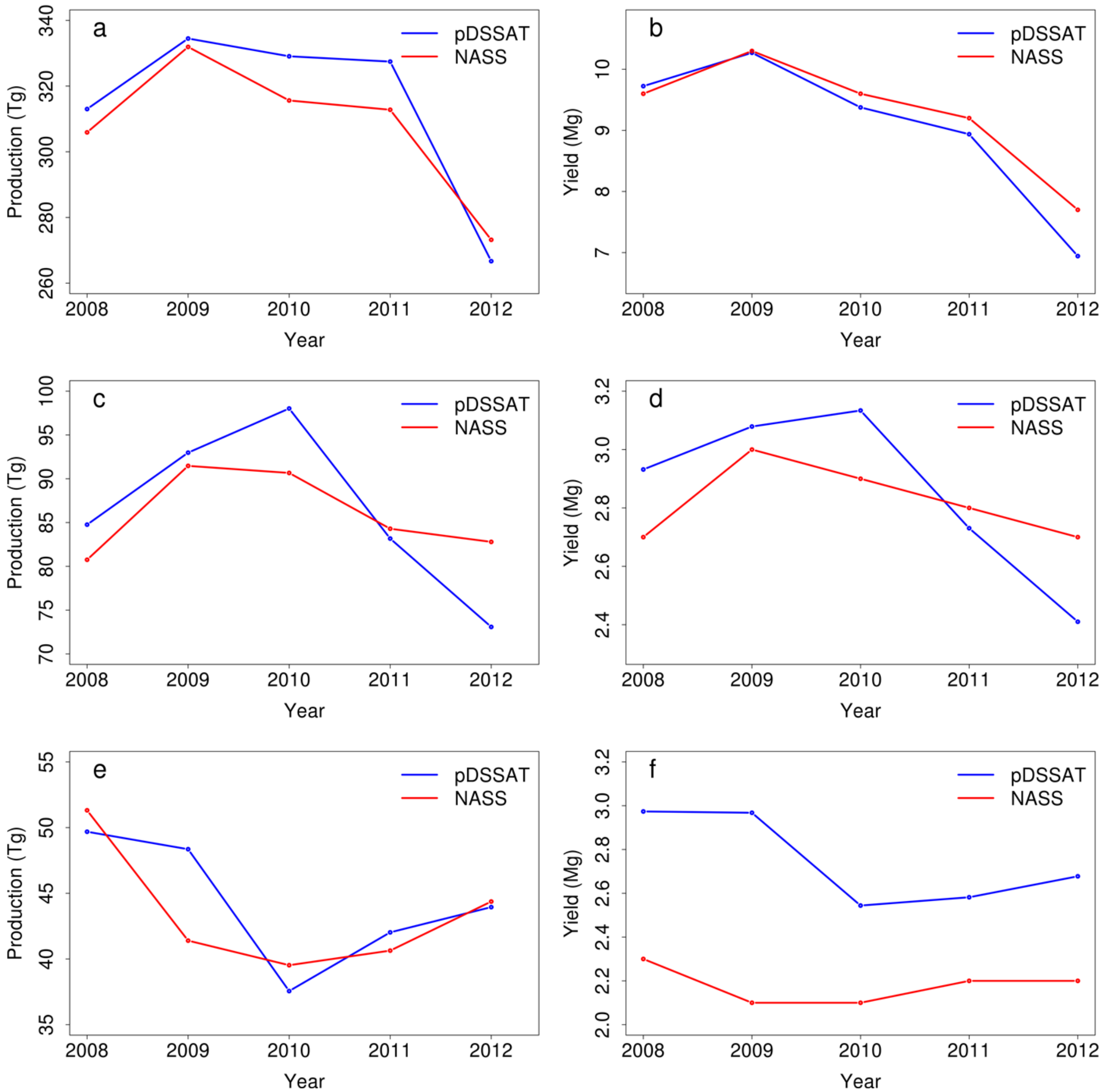
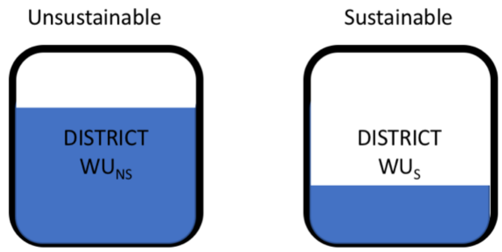


Figure S3. Simulated and observed national production and yield. Time series of irrigated and rainfed national production (left) and yield (right) for maize (a, b), soybean (c, d), and winter wheat (e, f).



Grid	Prod	WU	WUE
G_1	P_1	WU_1	WUE_1
G_2	P_2	WU_2	WUE_2
G_3	P_3	WU_3	WUE_3
G_4	P_4	WU_4	WUE_4
G_5	P_5	WU_5	WUE_5
G_6	P_5	WU_6	WUE_6

DISTRICT $WU_S = WU_1 + WU_2 + WU_3$

Grid	Prod	WU	WUE
G_1	P_1	WU_1	WUE_1
G_2	P_2	WU_2	WUE_2
G_3	P_3	WU_3	WUE_3

$SP = P_1 + P_2 + P_3$
SP: SUSTAINABLE PRODUCTION

Figure S4. Schematic of simulating sustainable production. Unsustainable water use (WU_U) was calculated by aggregating the simulated water used from pDSSAT by district. This number was then multiplied by the sustainable fraction to obtain the sustainable water use (WU_S) for each district. Agricultural production in each district was then restricted to the grid cells that could be supplied with WU_S, prioritizing grid cells with the greatest water use efficiency (WUE).

Table S1. Data sources used to force pDSSAT, evaluate pDSSAT, and simulate sustainable agricultural production.

Data Type	Institution	Spatial Resolution	Temporal Resolution	Reference
Soil	Yat-sen University	30 arcseconds	NA	*Shangguan, Wei, et al. Journal of Advances in Modeling Earth Systems*6.1 (2014): 249-263
Weather	NASA	1000 m	1 day	*Thornton, P. E., et al. (2017).* Available at: https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1328
Crop Specific Land Use	USDA	30 m	1 year	*Boryan, C. et al. Geocarto Int.* **26,** 341–358 (2011).
Irrigation Land Use	USGS	250 m	5 years	*Pervez, Md Shahriar, and Jesslyn F. Brown. Remote Sensing 2.10 (2010): 2388-2412.*
Aquifer Recharge Rate	USGS	800 m	1 year	*Reitz, Meredith, et al. JAWRA Journal of the American Water Resources Association 53.4 (2017): 961-983.*
Evapotranspiration	USDA ARS	2.7 arcminutes		*Anderson, Martha C., et al. Journal of Geophysical Research: Atmospheres* 112.D10 (2007).
Initial Crop Parameters	University of Chicago	5 arc minute	1 year	*Glotter, Michael, and Joshua Elliott. Nature plants 3.1 (2017): 16193.*
Yield and production	USDA-NASS	County, National	1 year	Available at: https://quickstats.nass.usda.gov

Table S2. Crop model evaluation against USDA NASS observed data for maize, soybean, and winter wheat, and ALEXI for evapotranspiration.

Variable	CROP	Mean Observed	RMSE	RRMSE	Percent Bias	R^2
Production (Gg per County)	Maize	172	62	36%	1%	0.94
	Soybean	56	19	34%	0%	0.91
	Wheat	29	25	84%	2%	0.82
Yield (kg ha^{-1})	Maize	7980 ± 685[a]	1828 ± 172	23% ± 3%	-2% ± 5%	0.54 ± 0.04
	Soybean	2624 ± 108	550 ± 38	21% ± 2%	5% ± 7%	0.52 ± 0.08
	Wheat	3477 ± 157	1136 ± 52	33% ± 2%	-5% ± 9%	0.37 ± 0.09
Area (km^2 per county) [d]	Maize	186	52	28%	4%	0.95
	Soybean	199	40	20%	-1%	0.96
	Wheat	95	72	76%	15%	0.88
ET (mm day^{-1})	Combined	3.56	0.40	11%	-3%	0.68

[a] Standard deviation from the mean from leave one out cross validation analysis.