# Crop switching reduces agricultural losses from climate change in the United States by half

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## Abstract

A key strategy for agriculture to adapt to climate change is by switching crops and relocating crop production. We develop an approach to estimate the economic potential of crop reallocation using a Bayesian hierarchical model of yields. We apply the model to six crops in the United States, and show that it outperforms traditional empirical models under cross-validation. The fitted model parameters provide evidence of considerable existing climate adaptation across counties. If crop locations are held constant in the future, total agriculture profits for the six crops will drop by 31% for the temperature patterns of 2070 under RCP 8.5. When crop lands are reallocated to avoid yield decreases and take advantage of yield increases, half of these losses are avoided (16% loss), but 57% of counties are allocated crops different from those currently planted. Our results provide a framework for identifying crop adaptation opportunities, but suggest limits to their potential.

# 1 Introduction

Extreme temperatures under climate change are predicted to reduce average yields for several of the United States' major crops [1, 2, 3, 4]. However, these impacts can vary across space, with some areas showing benefits from increases in moderate temperatures and increased evapotranspiration under irrigation [5, 6]. As climate shifts, these changes in productivity will drive farmers to change crops and move into new areas [7]. Understanding the extent of these regional changes in agricultural productivity and how they influence future cropping decisions is a central question for the impacts of climate change on agriculture [8, 9]. Crop shifting may be able to attenuate climate impacts, but the potential benefits depend on the distribution of impacts, the total availability of productive land, and costs of switching crops.

In this paper, we explore the potential redistribution of six crops in the United States as an adaptation to climate change. We approach the crop shifting problem as a spatial optimization problem to maximize profits, following Polasky et al. [10] and Devineni and Perveen [11]. Our key innovation consists of providing a new empirical approach which better supports this form of crop shifting analysis, by providing estimates of the potential for crops as they move into new areas.

Empirical agricultural crop models use variation in weather to explain yearly variation in crop yields [5, 12, 13]. Local agricultural management decisions are detailed and dynamic in a way that is unavailable to scientists working at large spatial scales. Econometric techniques allow these unobserved differences between regions to be accounted for with local baselines. However, these techniques have two consequences that undermine their ability to model the crop shifting process. First, they can model changes in yields, but not yield levels, since this information is factored out with region-specific baselines. As a result, crop productivity in regions that are not observed growing the crop cannot be determined. Second, they have a resolution-variance trade-off, whereby interactions terms that allow the relationship between weather and yield to vary by region necessarily reduce the precision of the estimated relationship within each region and may lead to over-fitting.

In this paper, we develop a Bayesian approach which addresses both of these challenges. As with econometric models, yields are predicted with a log-linear model, with terms for the non-linear effect of temperatures, crop water deficits, and a linear technology trend. In our model, the coefficients of the model are allowed to vary for each high-resolution region, represented here with US counties. To constrain this regional variation in parameters and predict parameters in new regions, the expected values of each region's coefficients and of the regional intercept are modeled as a linear combination of a set of spatial covariates in an hierarchical Bayesian model [14, 15]. The method allows "partial pooling", whereby the degree to which regions are pooled to estimate a single national set of parameters is determined by the data: if the data support idiosyncratic regional differences in temperature sensitivity, for example, very little pooling between regions will be used and the parameters for each region will be estimated separately. The covariates used to predict variation in the sensitivity to weather are the annual mean temperature, isothermality (diurnal range divided by annual temperature range), temperature seasonality (standard deviation over months), annual precipitation, precipitation seasonality (coefficient of variation across months), and irrigation fraction by crop (see SI 1-2). Both the region-specific weather coefficients and the model of how those coefficients vary over space are estimated simultaneously. In comparison to a least-squares regression approach, the hierarchical Bayesian approach is more efficient than a two-stage estimation process and allows more regional variation than an regression model with interacted coefficients.

# 2 Results

## 2.1 Spatial variation in climate sensitivity

We fit the Bayesian yield model to yield observations for United States counties from 1949 to 2009 for six crops: barley, corn, cotton, soybeans, rice, and wheat. The covariate model is used to predict weather response functions and yields in new locations for each crop. The coefficients for extreme degree-days, a key driver behind climate impacts, are shown in figure 1 (others are in SI 3).

[Figure 1 about here.]

The spatial patterns for the effects of extreme temperatures vary by crop. Corn and cotton show less sensitivity to extreme temperatures in the southern US, reflecting adaptation in seed varieties or farming practices to minimize losses. For wheat and barley, adaptation is dependent upon water availability, with higher sensitivity in dry regions. We find that a fairly low degree of partial pooling was applied, so that the estimated parameters for the county-specific models vary considerably. The 95% range of the estimated coefficients on extreme temperatures is 2 (rice) to 12 (cotton) times the standard error of the average coefficient. Much of the variation in coefficients is explained by county mean temperature, suggesting existing adaptation to higher temperatures. The portion of variation in sensitivity of crop yields to extreme temperatures that is explained by mean temperature varies from 8% for soybeans to 63% for cotton. Finally, coefficients vary slowly across space, showing spatial correlations up to 2000 km (see SI 4).

## 2.2 Comparison of crop modeling approaches

To validate the crop models, we compare the coefficients of determination (unadjusted $R^2$) for each crop to the results of a series of panel econometric regressions, mapping out the range between Schlenker and Roberts [5] and an regression-based equivalent to our analysis using covariate interactions. Since we are interested in the ability of the model to predict future years, we also perform cross-validation, by fitting the model to data from 1949 to 1994 and evaluating it on yields during 1995 - 2009. These results are shown in table 1. Spatial patterns of $R^2$ are shown in SI 5, and the regression comparison details are in SI 6.

[Table 1 about here.]

Applied to data from all years, the Bayesian model performs similarly to the most flexible ordinary least squares (OLS) models with linearly varying coefficients. However, these same OLS models are prone to over-fitting, and show large decreases in their $R^2$ under cross-validation. OLS models with constant coefficients across all counties perform better under cross-validation. While the Bayesian models also show reduced predictive capacity under cross-validation, they out-perform all OLS models for four of the crops. In all cases, they have a greater $R^2$ than similarly flexible OLS models. This is due to the idiosyncratic differences between coefficients in different counties that are permitted in the Bayesian model.

## 2.3 Shifting cultivation under climate change

Next, we use the Bayesian model to identify the optimal cultivation patterns now and in the future. We use the yield model with constant error variance (table 1, column 6) to limit the variance in unobserved counties. Since cultivation costs and prices vary across the United States, we use profit (local price in 2010 times predicted yield, minus management costs) in USD acre$^{-1}$ to determine the best crop (see SI 8). Costs and prices are from USDA Economic Research Service [16] for 2010, adjusted when necessary to make the locally optimal crop according to profits match the most widely planted observed crop (see SI 9). Since we do not account for alternative uses of land, we constrain the crops to only be cultivated in the future in areas currently used for at least one of the six crops. Changes in future crop production can also result in general equilibrium effects on prices [9]. Here, we avoid significant price changes by limiting the total land used by each crop to not exceed current nation-wide totals (details in SI 10).

[Figure 2 about here.]

Applied to current climate, crops are grown in characteristic temperature ranges, as shown in figure 2 (top). Barley and rice are mainly grown in cooler counties, while cotton is grown in the warmest areas. However, these suitability envelopes are not exclusive, with some barley and rice grown at higher temperatures. Although the optimization is calibrated to prefer the crop currently most planted in each county, 16% [14 - 18%][1] of counties do experience changes under the optimization, as secondary crops are replaced with the optimal crop, and then these secondary crops are shifted to other counties. This results in a 13% [8 - 37%] increase in total profits (see figure 3). The largest changes result from swaps between soybean and corn, which are commonly grown in rotation (excluding corn-soy swaps, 5% [4 - 6%] of counties show changes).

[1] Ranges in brackets display the 95% credible interval throughout.

We then use a suite of CMIP5 models to project these changes in optimal crops forward under RCP 8.5, and report outcomes in 2050 and 2070 including both climate and statistical uncertainty (figure 2, SI 11). Corn retains its enormous area (by construction, so long as corn profits are positive), but becomes less concentrated in the Midwest. Soybeans show a gradual movement north, replacing spring wheat and barley. The wheat lands of the Great Plains see a gradual hollowing-out, while winter wheat moves up from the south along the Mississippi. Cotton is grown at higher latitudes, becoming the dominant crop in southern California. At the same time, lands in the southern US that are not profitable for any crop expand. These tend to be at the higher end of the temperature distribution, and account for 5% of the included land area by 2070.

## 2.4 Economic outcomes of adaptation

Figure 3 (top) shows the amount of switching between crops to maximize profits. Large portions of corn and soybean cultivation continue to swap in 2050, but changes from 2050 to 2070 are more minor. By 2070, 53% [39 - 67%] of counties experience crop switching (36% [21 - 51%] excluding corn-soy swaps). We do not observe an orderly movement to higher latitudes, because of our constraint against crops moving into new areas (see SI 12).

A comparison of the effects of optimization on profits is shown in figure 3 (bottom). In the absence of optimization, total estimated profits fall from \$45.7 [\$44 - 52] billion to \$35.8 [\$24 - 50] billion in 2050 and \$31.4 [\$19 - 48] billion in 2070, a 31% decrease [59%↓ - 5%↑]. With optimization, profits in 2010 were predicted to be able to increase to \$51.8 [\$49 - 63] billion. However, they fall below current profits by 2050 and by 2070, even with further optimization, they fall to \$38.6 [\$28 - 54] billion, still 16% below [38%↓ - 18%↑] observed levels. Relative to the profits of optimally reallocated crops in the current period, percentage losses from climate change are greater, 26% below [45%↓ - 4%↑] the peak.

[Figure 3 about here.]

Behind these profits are both increases and decreases in individual crop production. Production is predicted to be able to increase for most crops under current conditions and optimal planting, ranging from small decreases for soy (2% [4 - 1%]) to large production increases for barley (26% [11 - 44%]). By 2070, however, decreases in total production are shown for barley (9% [22%↓ - 4%↑]), corn (37% [74%↓ - 10%↑]), rice (2% [30%↓ - 37%↑]), and soybeans (6% [16%↓ - 5%↑]) relative to observed production. These are offset by increases from cotton (73% [20% - 192%]) and wheat (2% [26%↓ - 28%↑]). These results do not extrapolate the historical trend in crop yields into the future, to isolate the relative role of climate change (we explore this in SI 13-14).

In the default model, we assume that there are no additional barriers or frictions involved switching crops, and explore the effects of imposing a range of crop switching costs in SI 14. Switching costs of \$180 / acre reduce reallocation changes by half, against average cultivation costs between \$123 / acre (barley) and \$499 / acre (rice). As switching costs increase, optimal losses converge to the losses without crop reallocation. Since optimal profits in 2050 are below current profits, losses will remain under any level of switching costs.

# 3 Discussion

The crop switching projected in this paper would cause disruptions to farmers, food supplies, and environmental habitats. Even if crops are mobile, farmers may not be. In particular, farmers who work on the 5% of cultivated land that becomes economically untenable under our model will need to identify new crops or land uses outside the scope of this study.

Our empirical model only captures adaptation practices currently employed to respond to within-year shocks of high temperatures. Future work is needed to explicitly account for the potential and limits of irrigation expansion, long-term investment in adaptation, and to distinguish the benefits of $CO_2$ fertilization from the long-term trend. While we consider multiple sources of uncertainty in the outcomes, we do not account for risk aversion, unexpected weather shocks, or the multi-year consequences of crop failures.

Our optimization approach assumes perfect knowledge of crop weather responses and that observed weather will correspond to expected climate. As such, our results should be considered a frontier of possibility, assuming that crop yield respond to temperatures in the future as they have in the past. The cropping patterns shown in our current and future results should not be taken as recommendations, since many details at the field and farmer level are not included.

Our results show considerable potential from crop switching to avoid damages from climate change. These changes are driven both by differences in how temperatures may change in different regions as well as differences in the sensitivity of crops to high temperatures. However, the remaining losses imply that crop switching is not a panacea and that new seed varieties and new adaptation practices are needed to support farmers and meet the food demands of the future.


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# Author Contributions

All authors designed and performed the analysis and wrote the text. N.D. performed the Bayesian modeling and J.R. performed the optimizations.

# Competing Interests statement

The authors declare no competing interests.

# Data Availability

The data used in making the charts and tables in this paper is available at DOI `10.5281/zenodo.3889144`.

# Code Availability

All model and display code is available at DOI `10.5281/zenodo.3909637`. The optimization model is constructed using the landuse component of the open-source AWASH water-energy-food model, available at `https://github.com/AmericasWater/awash`.

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Figure 1: **The effect of extreme degree-days on yields, as it varies by county and crop.** The displayed coefficients are for the effect of a 1 standard deviation change in extreme degree-days (EDDs) on log yield, interpretable as the fractional effect on yields. The response to extreme temperatures is predicted even in areas where the crop is not currently grown. Each crop has a different growing season and extreme degree-day (EDD) cut-off, so that model coefficients are normalized by a different standard deviation per crop (240 EDDs / SD for barley, 65 for corn, 40 for cotton, 63 for rice, 64 for soybeans, and 82 for wheat). County outline color indicates the confidence level (solid black outline: $p\text{-value} < 0.05$, thin white outline: $p\text{-value} > 0.33$).

Figure 2: **Optimized crop patterns for each period (across rows), and across temperature (left) and space (right).** When plotted as a distribution across temperature, the climatic annual mean temperature of each county is used, and the distribution is across counties. NA (grey) regions are used where none of the six crops are planted at baseline or where total profits are maximized by leaving land fallow later in the century.

Figure 3: **Adaptation outcomes accounting for crop shifting.** (Top) The portion of area allocated to each crop, under the optimization, in percent labeled boxes. Flows between the allocations show the portion of area previously allocated to the crop on the left, and flowing into its new allocation on the right. The difference between observed and optimized crop allocations (first transition) is due to replacing secondary crops with primary crops. (Bottom) Profits under observed and optimized crop allocations for the current climate (first box), 2050, and 2070. The first bar in each columns gives estimates of profits without relocation of crops, and the second bar is with optimization. Error bars show 95% credible intervals.

| | OLS | | | | Bayesian | |
|---|---|---|---|---|---|---|
| Intercepts: | Uniform | County | Linear | County | Partially pooled | |
| Coefficients: | Uniform | Uniform | Linear | Linear | Partially pooled | |
| Error variance: | Uniform | Uniform | Uniform | Uniform | County | Uniform |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Estimated and evaluated on all years | | | | | | |
| Barley | 0.36 | 0.71 | 0.57 | 0.75 | 0.74 | 0.75 |
| Corn | 0.48 | 0.76 | 0.65 | 0.78 | 0.81 | 0.82 |
| Cotton | 0.32 | 0.64 | 0.55 | 0.70 | 0.68 | 0.69 |
| Rice | 0.75 | 0.84 | 0.81 | 0.84 | 0.85 | 0.85 |
| Soybeans | 0.47 | 0.72 | 0.65 | 0.76 | 0.78 | 0.79 |
| Wheat | 0.42 | 0.71 | 0.56 | 0.73 | 0.76 | 0.76 |
| Estimated on 1949 - 1994, evaluated on 1995 - 2009 | | | | | | |
| Barley | -0.11 | 0.43 | 0.20 | 0.45 | 0.48 | 0.46 |
| Corn | -0.09 | 0.20 | 0.07 | -1.05 | 0.27 | 0.17 |
| Cotton | 0.07 | 0.31 | 0.14 | -37.50 | 0.21 | 0.12 |
| Rice | 0.20 | 0.37 | 0.12 | -1.59 | 0.19 | 0.14 |
| Soybeans | 0.26 | 0.47 | 0.39 | -16.27 | 0.53 | 0.48 |
| Wheat | 0.16 | 0.49 | 0.31 | 0.47 | 0.51 | 0.50 |

Table 1: **Comparison of the predictive power of OLS and Bayesian yield models.** Table cells show $R^2$ by crop and model specification, using all data (top) and under cross-validation on 1995 - 2009 (bottom). In all cases, $R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y}_i)}$, where $y_i$ is the observed log yield for county-year $i$. $\hat{y}_i$ is the point estimate for OLS and the posterior prediction for the mean MCMC parameter draw for the Bayesian model, and $\bar{y}_i$ is the average across all observations of $y_i$. The first four columns are ordinary least squares (OLS) specifications, variously including region-specific intercepts and covariate interactions. The last two columns are for the Bayesian model, either allowing each county to have a different variance (5) or constraining all to have the same variance (6).