Bright spots in U.S. corn production

1. Introduction

Nearly 40% of global land is devoted to food production (Foley et al., 2011; Ramankutty, Evan, Monfreda, & Foley, 2008). In the U.S., this number rises to 55%, with two-thirds of all cropland cultivated with corn, wheat, or soy (Bigelow & Bourchers, 2017; USDA NASS, 2019). The yields of these crops have climbed consistently in recent decades, thanks largely to technological innovation—particularly genetic improvements (Cooper, Gho, Leafgren, Tang, & Messina, 2014)— and an increased reliance on off-farm inputs (Burchfield, Matthews-Pennanen, Schoof, & Lant, 2019; Mulvaney, Khan, & Ellsworth, 2009; Pimentel & Burgess, 2014). At the same time, real farmer incomes have declined (Mishra & Sandretto, 2002; Parton, Gutmann, & Ojima, 2007), farm debt has increased (Key, Burns, and & Lyons, 2019), and environmental externalities linked to agricultural intensification have grown (Cardinale et al., 2012; Tscharntke et al., 2012). These challenges will likely be exacerbated by a rapidly changing climate (Schlenker & Roberts, 2009; Zhao et al., 2017; Romero-Lankao et al., 2014) and an estimated doubling of global food demand by 2050 (Ray, Mueller, West, & Foley, 2013; Valin et al., 2014). For agricultural systems to thrive in the future, they must meet human demand while *also* sustaining the environmental resource base and farmer livelihoods (NRC, 2010). The future of agriculture, therefore, lies in identifying the attributes of highly productive agricultural systems and questioning whether and to what extent these attributes can be managed for a sustainable future.

We employ *bright spots analysis* to locate U.S. counties where the yields of corn—the most widely cultivated crop in the U.S.—are surprisingly higher than expected given regional expectations, seasonal weather, and soil suitability. Unlike traditional outlier analysis, this approach locates regions that deviate strongly from expectations *given a set of conditions*. These counties are regional "surprises" that, by definition, achieve unexpectedly high levels of agricultural productivity. We then use multinomial logistic regression to identify the *actionable* factors—or the factors over which agricultural stakeholders can exert a certain level of control—that most strongly predict whether a county is a bright spot. In surprisingly productive regions, we observe higher rates of fertilizer expense, labor expense, irrigation use, and financial support from federal programs. We conclude by questioning whether and to what extent these correlates of productivity can be managed for a sustainable future.

2. Methods

2.1. Bright spot identification

We generated yield expectations at two spatial scales—the U.S. county and the National Conservation Service's Land Resource Regions (Figure 1)—by constructing a null model with random effects at both scales and *nonactionable* factors known to affect agricultural productivity over which farmers have little control. These nonactionable factors consisted of three indicators of seasonal weather exposure and one soil suitability indicator. The three county-level indicators of seasonal weather exposure—growing degree days, stress degree days, and total precipitation—were constructed from gridded daily four-kilometer temperature and precipitation data provided by the PRISM Climate Group for each year included in the analysis. To align daily gridded weather data with county-season yield data, we computed the average daily maximum temperature and precipitation in each county and then summed these daily values for all days in the growing season—defined using the spatially-explicit growing season planting and harvesting dates provided by Ramankutty et al. (2008). To compute growing degree days (GDDs)—an indicator of cumulative temperature exposure—we summed maximum daily temperatures within a crop-specific tolerance

49 range (10°C to 30°C for corn) over the growing season for each county in the coterminous U.S.
50 (Cross & Zuber, 1972). To model the effects of heat stress on plant growth (Burchfield et al., 2019;
51 Lobell et al., 2013; Schauberger et al., 2017; Schlenker & Roberts, 2009), we also included a metric of
52 seasonal heat exposure called stress degree days (SDDs) which measures the total accumulated daily
53 degrees above the maximum GDD threshold temperature (30°C for corn). To control for the
54 effects of seasonal precipitation on yields, we computed total precipitation (TP), or the sum of
55 precipitation (in millimeters) throughout the growing season.
56   In addition to these seasonal weather indicators, we extracted to the county level an indicator
57 of the suitability of a region's soils to the cultivation of corn provided by the gSSURGO dataset, the
58 highest accuracy and finest spatial resolution dataset available for U.S. soils (Soil Survey Staff, 2019).
59 This indicator, the National Commodity Crop Productivity Index (NCCPI), integrates soil chemical
60 properties (e.g., pH, cation exchange capacity, organic matter, adverse chemical properties in the
61 root zone), soil water properties (e.g., available water-holding capacity, precipitation recharge, water
62 table recharge), soil physical properties (e.g., bulk density, soil depth), soil climate properties (e.g.,
63 frost-free days, precipitation), soil landscape properties (e.g., slope, depth to water table during
64 growth season), and crisp positive (e.g., soil fabric) and negative soil properties (e.g., surface rock
65 fragments, erosion) to generate a "corn productivity score" that ranges from 0.01 (low productivity)
66 to 0.99 (high productivity) (Dobos, Sinclair, & Robotham, 2012). To align this gridded dataset with
67 the county-level yield data, we computed the average productivity score of the subset of only a
68 county's agricultural lands to the cultivation of corn. We measured corn productivity using county-
69 level yield estimates (bushels/acre) provided by the USDA NASS Survey. The final null panel
70 includes only counties reporting more than two years of corn yields (n = 1896 counties) over recent
71 USDA Census years: 1997, 2002, 2007, 2012, and 2017.
72   Despite the importance of irrigation in explaining yield variability, we did not include it as a
73 predictor in the null model because data suggests that irrigation rates have changed considerably in
74 many counties over the last 20 years. For this reason, we consider irrigation to be an *actionable* factor
75 and include it in the attribute analysis described below. To test sensitivity of our results to this
76 assumption, we ran null models including irrigated extent which produced similar seasonal weather
77 response curves and *bright* and *dark spots* (SI Table 8).
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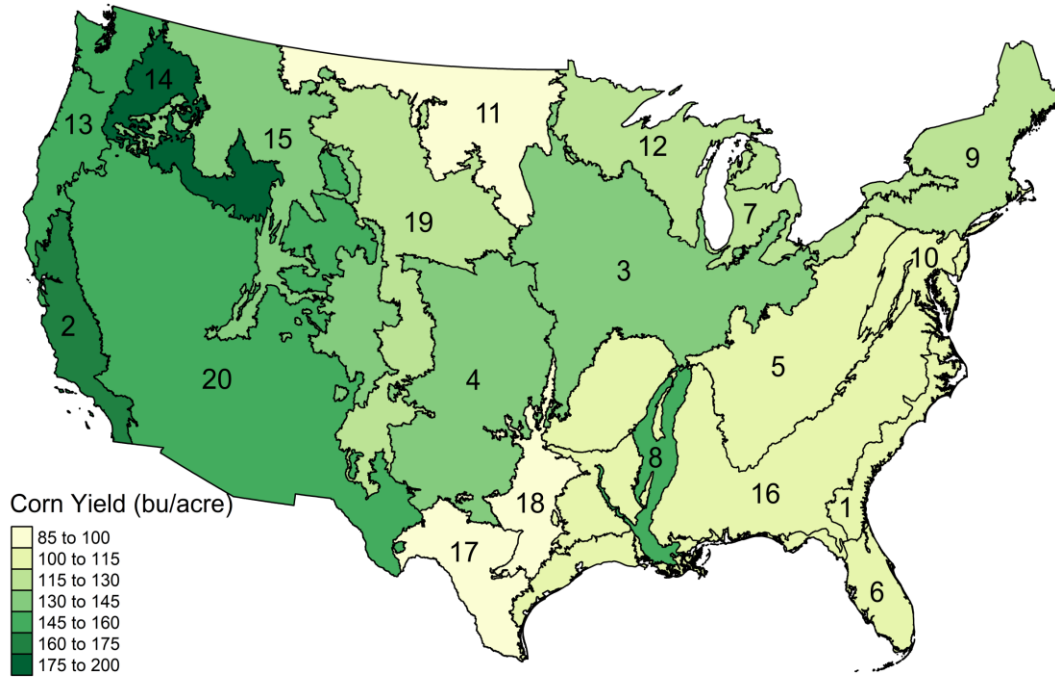
Figure 1: Land Resource Region boundaries and average corn yield (bushels per acre) recorded in USDA Census years between 1997 and 2017. Note that the Florida Subtropical Fruit, Truck Crop, and Range Region (6) and the Northwestern Forest, Forage, and Specialty Crop Region (13) were dropped from the models as less than ten county-year yield observations were available over the period of interest for these regions.

Our null model is specified as:

$$y_{tcr} \sim N(\mu_{tcr}, \sigma^2)$$
$$\mu_{tcr} = \beta_{0cr} + f(\boldsymbol{X}_{tc}) + \beta_1 SOIL_{tc} + \beta_2 TIME_t$$
$$\beta_{0cr} = \gamma_{00r} + u_{0cr} + v_{0cr}$$
$$\gamma_{00r} = b_{000} + v_{00r}$$

where t indexes time, c indexes counties, and r indexes regions. To account for strong spatial autocorrelation in the county yield data, county-level random effects (β_{0cr}) are modeled using a Besag-York-Mollie (BYM) spatial dependency model that includes both random effects (v_{0cr}) and county-level intrinsic conditional autoregressive (iCAR) structured residuals between counties (u_{0cr}). This approach accounts for both random variation in yield across counties and the fact that observations from neighboring counties exhibit higher correlation than more distant regions (Morris et al., 2019). The county-level random effects (v_{0cr}) capture time-invariant factors associated with a county that influence yield and serve as the basis for our identification of bright spots.

In addition to the county-level effects, we estimated random effects (iid) for each Land Resource Region which define *regional* yield expectations (v_{00r}). We focused on regional expectations rather than national expectations because of the tremendous variability in agricultural system characteristics across the U.S. This approach also allows us to identify the most deviant counties in a region given null model covariates while shrinking counties to the regional means (Cinner et al., 2016; Gelman & Hill, 2007). We tested the sensitivity of our models to other regional

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107 definitions including U.S. state boundaries, U.S. EPA Level II Ecoregions, and national average yield
108 and found the null model using Land Resource Regions to consistently be the best performing
109 model (SI Tables 6 and 7).
110   To capture well-established non-linearities in the effects of seasonal precipitation and
111 temperature on yields (Lobell et al., 2013; Schlenker & Roberts, 2009), we modeled the interactions
112 between yields and county-year seasonal weather predictors (GDDs, SDDs, TP) using a first-order
113 random walk function, $f(X_{tc})$. This structure allows the effect of these predictors to vary non-
114 linearly while also accounting for autocorrelation in predictors effects. To avoid overfitting, we
115 modeled soil suitability as a county-level linear control, $SOIL_{tc}$. We also included a dummy indicator
116 for year ($TIME_t$) to capture any dynamics that affect all counties in a particular year such as major
117 market or policy changes.
118   The final null model uses uninformative (reduced precision) prior distributions for linear
119 effects and penalized complexity priors for non-linear seasonal weather predictors. The penalized
120 complexity priors employ a scaling factor to specify priors based on reasonable limits of the data
121 (Simpson, Rue, Martins, Riebler, & Sørbye, 2014). We employed default and recommended settings
122 for penalized complexity priors as provided by Simpson et al (2014). Model fit was evaluated using
123 the deviance information criterion (DIC), the conditional predictive ordinate (CPO), the predictive
124 probability integral transform (PIT), posterior predictive p-values, mean squared error (MSE) and
125 Bayesian R-squared (R2) (Blangiardo & Cameletti, 2015; Gelman, Goodrich, Gabry, & Ali, 2017;
126 Gelman & Hill, 2007). All models were estimated using the R-INLA package (Rue, Matrino, &
127 Chopin, 2009) in R (R Core Team, 2019). Model scripts and additional information on model
128 diagnostics and robustness checks are available at https://github.com/eburchfield/Bright_spots.
129   Following Cinner et al. (2016), we defined *bright* and *dark spots* as the counties in which
130 county-scale random effects ($u_{0cr} + v_{0cr}$) differed by more than 1.5 standard deviations from their
131 regional expected value (v_{00r}). For a county c belonging to a region r:

$$BS_c = |v_{00r} - (u_{0cr} + v_{0cr})| > 1.5[sd_{c' \in r}(v_{00r} - (u_{0c'r} + v_{0c'r}))]$$

135 County-level bright and dark spots are, therefore, counties that, given the null model covariates,
136 deviate from regional yield expectations significantly more or less than other counties deviate from
137 their regional expectations over the five years included in our analysis.

139 **2.2. Bright spot attributes**
140   Though these *nonactionable* factors strongly influence where and how farmers cultivate
141 different crops, there are many other *actionable* factors actively managed by humans to create or
142 support desirable cultivation conditions. These include the use of on-farm inputs, participation in
143 federal programs, farm characteristics, and land use decisions (Figure 2). Perhaps the most important
144 of these actionable factors are **on-farm inputs**. Over the period from 1960 to 2018, application
145 rates of synthetic nitrogen fertilizer increased from 17.0 to 83.6 pounds per acre/year (USEPA
146 ROE, 2018). Over the same period, pesticide expenditures experienced a fivefold increase, with
147 recent annual U.S. expenditures over $12 billion (Fernandez-Cornejo et al., 2014). Corn has been the
148 top pesticide-using crop in the U.S. since the 1970s; today, over 90% of U.S. corn is treated with
149 pesticides (Fernandez-Cornejo et al., 2014). Irrigation is another crucial input to production, with
150 irrigated land in the U.S. increasing from 37 million acres in the 1960s to 55.9 million acres in 2018.
151 Today, irrigated acreage comprises 28% of all harvested cropland and generates roughly half of the
152 total value of U.S. crop sales (USDA ERS, 2019). Over the last century, farms have also become far
153 less reliant on physical labor as an input to production, largely due to the rapid advances in

154 mechanization (Mazoyer & Roudart, 2017). On-farm labor has decreased from 9.93 million
155 farmworkers in 1950 to 2.31 million farmworkers in 2019 (USDA ERSa; USBLS, 2019). **Financial**
156 **support** for agricultural production through direct payments from federal programs to farmers has
157 also increased in recent decades (Annan & Schlenker, 2015), providing an important source of
158 income stabilization and financial incentive for retiring land from production for many farmers.
159   In addition to on-farm inputs and financial support, **farm characteristics** influence the on-
160 farm adoption of new technologies and practices that influence agricultural yields. For example,
161 research suggests that the adoption of agricultural best management practices increases as farmer age
162 decreases (Prokopy et al., 2008), rates of tenancy decrease (Soule, Tegene, & Wiebe, 2000), and
163 access to education and extension increase (Baumgart-Getz, Prokopy, & Floress, 2012); however,
164 the direction of these effects is not always clear, and often contradictory across analyses (Knowler &
165 Bradshaw, 2007). Though farmer characteristics such as age and gender are not directly actionable
166 by farmers, policies and programs can target specific groups of farmers to increase access to
167 information or to support their production.
168   Finally, changes in **land use** can alter the provisioning of ecosystem services essential to
169 agricultural production (Duarte, Santos, Cornelissen, Ribeiro, & Paglia, 2018; Shackelford et al.,
170 2013). Increased configurational and compositional complexity of an agricultural landscape is
171 associated with greater pollinator movement and plant reproduction (Hass et al., 2018; Garibaldi et
172 al., 2011), bird and arthropod diversity (Fahrig et al., 2015; Sirami et al., 2019), water quality (Gergel,
173 Turner, Miller, Melack, & Stanley, 2002), and higher yields (Burchfield, Nelson, & Spangler, 2019).
174 Though individual farmers may not have the capacity to manage these landscape dynamics, shifts in
175 regional agricultural policy and markets can shape the crops that are cultivated and the ways in
176 which land is managed (Boody et al., 2005); therefore, we designate these landscape characteristics as
177 *actionable.*
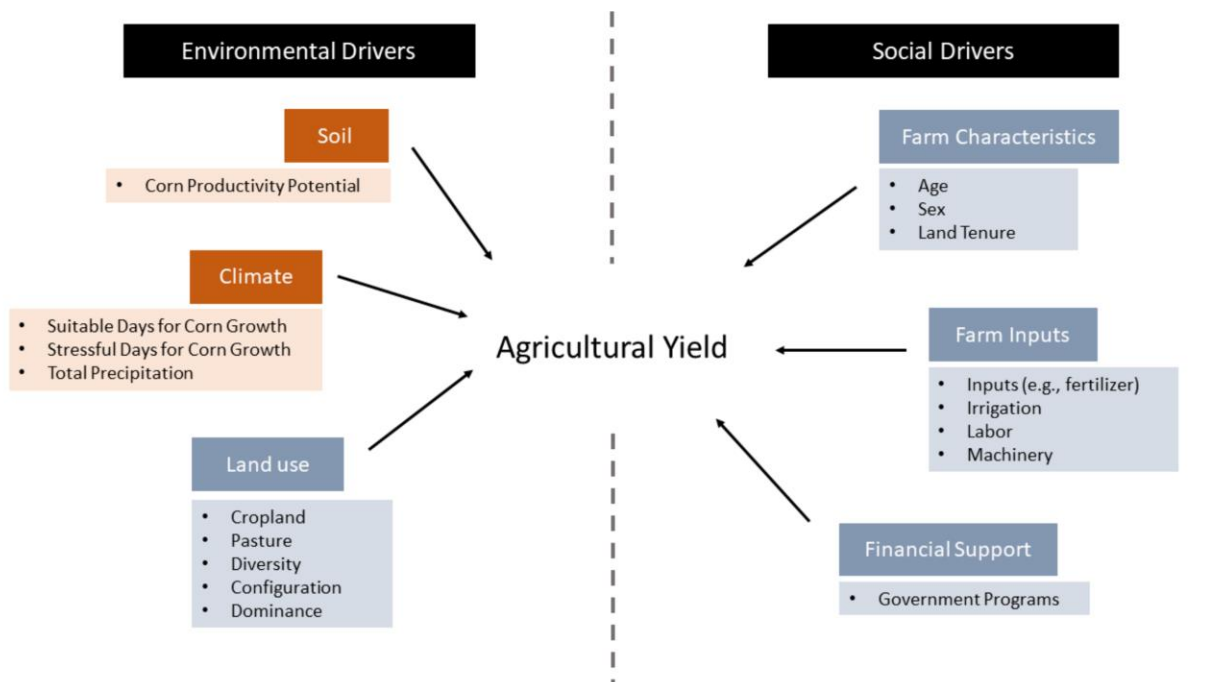
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179 **Figure 2:** Environmental and social correlates of agricultural production. Correlates deemed *nonactionable* are
180 shown in orange; *actionable* correlates are shown in blue.
181

182   To assess the contribution of these *actionable* factors to agricultural production, we
183 constructed a panel dataset describing the agricultural and land use characteristics of corn-producing
184 counties in the coterminous U.S. in recent USDA Census years (1997, 2002, 2007, 2012, 2017). The
185 USDA Agricultural Census is administered every five years to all farms and ranches selling at least
186 $1,000 of their products and is the only source of detailed county-level U.S. agricultural data that is
187 collected, tabulated, and published using a consistent methodology that covers the coterminous U.S.
188 Our analyses are limited to the actionable factors for which more than 80% of data was available for
189 the county-years of interest. This excluded interesting variables (e.g., crop insurance payments and
190 on-farm experience), but was necessary for modeling purposes. The final set of predictors we
191 compiled from the USDA Census included available data describing **farm and farmer**
192 **characteristics** (age, sex, and land tenure), **farm inputs** (fertilizer expense[1], labor expense, and
193 machinery costs), **financial support** (direct receipts from federal programs), and **land use** (percent
194 agricultural land in corn production, percent county land in pasture or cropland) (Figure 2). Given
195 the growing body of literature indicating that shifts in land use can affect agricultural productivity,
196 largely through the provisioning of ecosystem services, we also constructed additional indicators of
197 land use from the USDA Cropland Data Layer–a 30-meter annual land use dataset based on satellite
198 imagery and extensive ground truth data. In addition to the compositional indicators extracted from
199 the USDA Census, we constructed indicators of land use diversity (Richness, or the number of
200 distinct land use categories in a county) and dominance (Largest Patch Index, or the percent of the
201 total landscape covered by the largest patch in the county). We focus on these indicators of
202 composition to contribute to debates in the literature on the role of landscape specialization to
203 agricultural productivity (Abson, Fraser, & Benton, 2013; Davis, Hill, Chase, Johanns, & Liebman,
204 2012; Hass et al., 2018; Landis, 2017). Our previous research also indicates that high levels of land
205 use diversity are associated with high yields of corn, wheat, and soy (Burchfield et al., 2019), which
206 challenges the association between specialized and simplified landscapes and productivity (Key,
207 2019). In addition to these indicators of landscape *composition* (percent corn, percent cropland,
208 percent pasture, richness, and largest patch index), we also include two commonly used indicators of
209 landscape *configuration*: an indicator of the distribution of different land use categories across a
210 landscape (Interspersion and Juxtaposition Index) and an indicator of the patchiness of a landscape
211 (Edge Density). Managing for configurational complexity, where fine-grained agricultural landscapes
212 are well connected to surrounding habitats, has been shown to enhance natural enemies (Haan,
213 Zhang, & Landis, 2020) and increase yields in conventional systems (Martin, Seo, Park, Reineking, &
214 Steffan-Dewenter, 2016).
215   We used multinomial logistic regressions to estimate the effect of predictors on a county's
216 membership in the *bright* or *dark spot* categories as compared to the *average* category. This approach
217 allows the predictors to affect membership in each category differently. While this exploratory
218 approach does not imply that these correlates have a direct and causal effect on yield, it does provide
219 an indication of the characteristics typical of highly productive regions, allowing us to identify the
220 characteristics of places that defy expectations and to discuss whether and to what extent these
221 attributes can be managed for a sustainable future.
222   The analysis was performed in R using the `nnet` package (Venables & Ripley, 2002) to
223 compute the log-odds of a county in the *average* reference category changing membership to either a
224 *bright* or *dark* spot category as a function of farm characteristics, farm inputs, and land use. We

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[1] We initially included both an indicator of fertilizer and chemical use but found the two predictors to be collinear at
0.78, suggesting that farmers who apply fertilizer are also highly likely to apply chemicals (insecticides, herbicides,
fungicides, and other pesticides). We tested model sensitivity to inclusion of both predictors and found the effect size
and direction of the predictor to be similar across models, so we have only included fertilizer use in the final model.

225 standardized predictors (where applicable) to facilitate comparison across counties using "total
226 operated acres" which includes agricultural land used for crops, pasture, or grazing, as well as
227 woodlands, farm roads, and farm buildings (USDA NASS, 2019). All covariates included in the final
228 models had correlation coefficients less than 0.7 and variance inflation factor scores less than 5.
229
230 **Table 1:** Variable descriptions
231

Variable	Description and measurement
Hierarchical model predictors	
Soil suitability	National Commodity Crop Productivity Index (NCCPI) from the gSSURGO dataset (USDA NRCS Soil Survey Staff, 2019).
Growing degree days	Cumulative seasonal exposure to temperatures beneficial to corn production (between 10 and 30°C).
Stress degree days	Cumulative seasonal exposure to temperatures detrimental to corn production (above 30°C).
Total precipitation	Cumulative seasonal precipitation in millimeters.
Farm characteristics	
Age	Average age of primary producer; measured as average years across a county's primary producers.
% females	Percentage of agricultural acres operated by female primary producers; measured as the number of agricultural acres operated by female primary producers and standardized by the total number of agricultural acres operated, per county.
% owners	Percentage of agricultural acres operated by full owners (producers who operate *only* land they own); measured as the number of agricultural acres operated by full owners and standardized by the total number of agricultural acres operated, per county.
% tenants	Percentage of agricultural acres operated by tenants (producers who operate land they rent from others *and/or* land they worked on shares for others); measured as the number of agricultural acres operated by tenants and standardized by the total number of agricultural acres operated, per county. % partial owners not included in the model.
Farm inputs	
Fertilizer	Total expense of fertilizers, including lime and soil conditioners, rock phosphate and gypsum, and the cost of custom application, per agricultural acre; measured as total expense in USD $ and standardized by the total number of agricultural acres operated, per county.
Irrigation	Percentage of agricultural land in every county utilizing irrigation (includes all land irrigated by artificial/controlled means, including lagoon wastewater distributed by sprinkler or flood system); measured as the number of agricultural acres irrigated and standardized by the total number of agricultural acres operated, per county.
Labor	Total expense of all laborers, per agricultural acre; measured as the total expense of laborers (hired, contract, and migrant) in USD $ and standardized by the total number of agricultural acres operated, per county.
Machinery	Total asset value of agricultural machinery, per agricultural acre; measured as total machinery assets in USD $ and standardized by the total number of agricultural acres operated, per county.
Financial Support	
Gvt. Receipts	Total cash receipts of government programs, per agricultural acre; measured in USD $ and standardized by the total number of agricultural acres operated, per county.[2]

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[2] This category consists of direct payments from the government and includes: payments from Conservation Reserve Program, Wetlands Reserve Program, Farmable Wetlands Program, and Conservation Reserve Enhancement Program; loan deficiency payments; disaster payments; other conservation programs; and all other federal farm programs under which payments were made directly to farm operators. Commodity Credit Corporation (CCC) proceeds, local and state government agricultural program payments, and federal crop insurance payments are not tabulated in this category (USDA NASS, 2019, p. 759).

| Land use	
% corn	Percentage of total harvested acres in corn; measured as total harvested corn acres and standardized by total harvested cropland acres.
% cropland	Percentage of land in a county dedicated to cropland; measured as total acres cropland (includes crop failure, cultivated summer fallow, idle land, harvested cropland, and cropland used only for pasture) and standardized by the total number of acres in a county.
% pasture	Percentage of land in a county dedicated to pasture; measured as total acres pasture (excluding pastured cropland) and standardized by the total number of acres in a county.
Edge density	A measure of landscape *configuration*; measured as the sum of all edges (in meters per hectare) of a given class in relation to the landscape area. ED equals 0 if only one patch is present and increases, without limit, as the landscape becomes patchier (McGarigal, Cushman, & Ene, 2012).
Largest patch index	A measure of landscape *dominance*; measured as the percentage of the total landscape covered by the largest patch of the corresponding patch type. LPI approaches 0 when the largest patch is small and equals 100 when only one patch-class is present (McGarigal and Marks, 1995; McGarigal, Cushman, & Ene, 2012).
Interspersion & juxtaposition	A measure of landscape *aggregation* and *distribution*; measured as a percentage of the maximum possible. IJI ranges from 0 when a patch type is adjacent to only one other patch-class (patch types are poorly interspersed/there is a disproportionate distribution of patch type adjacencies) and 100 when a patch is adjacent to all patch-class types (patch types are well interspersed/equally adjacent to each other) (McGarigal and Marks, 1995; McGarigal, Cushman, & Ene, 2012).
Richness	A measure of landscape *diversity*; measured as the number of unique land use categories in a county. Richness approaches 1 when only one patch is present in a large landscape and increases, without limit, as the number of unique land uses increases, and the landscape area decreases (McGarigal, Cushman, & Ene, 2012).

3. Results

Our model identifies 109 bright spots clustered in the heart of the Corn Belt, in southwestern Georgia, in the Texas Panhandle, and along the Lower Mississippi (Figure 3; SI Table 9). These are counties whose corn yields—as compared to regional expectations—are unexpectedly high (*bright spot*) or low (*dark spot*). Bright spots are clustered in the heart of the Corn Belt in western Illinois and parts of Iowa, as well as in southwestern Georgia, around the Oklahoma Panhandle, and along the Mississippi River in Arkansas and Louisiana. Dark spots are found along the periphery of the Corn Belt—in southeastern Kansas through northern Missouri, northern Michigan, and across the Dakotas. We also see a cluster of dark spots in northern Michigan and in central Virginia—areas where relatively little corn is grown (Figure 3; SI Table 10).

Table 2 presents the regression coefficients for fixed effects in the hierarchical model. These results indicate that the majority of U.S. corn yield variability is explained by differences in soil and climate (R^2 of 0.72; SI Tables 3 and 4). For example, a one standard deviation increase in soil suitability is associated with a corn yield increase 12.4 bushels per acre (Table 2). A one standard deviation increase in seasonal growing degree day exposure from average exposure rates (approximately 580 growing degree days) is associated with a yield increase of 25 bu/ac (Figure 4a), while increased exposure to seasonal temperature stress of 150 stress degree days is associated with a decrease in yields of 15 bu/ac (Figure 4b). Corn yields are less responsive to changes in total precipitation (Figure 4c), which reflects the importance of irrigation in mitigating the effects of precipitation variability on corn production (Cooper et al., 2020). These results correspond with existing research finding that seasonal weather variability explains up to 70% of yield variability (Liang et al., 2017; Ray, Gerber, MacDonald, & West, 2015; Ray, Ramankutty, Mueller, West, & Foley, 2012), that corn yields drop sharply when temperatures exceed 30°C (Schlenker & Roberts,

256 2009; Lobell et al., 2013; Messina et al., 2019; Schauberger et al., 2017), and that soil suitability is a
257 major determinant of productivity (Kravchenko & Bullock, 2000).
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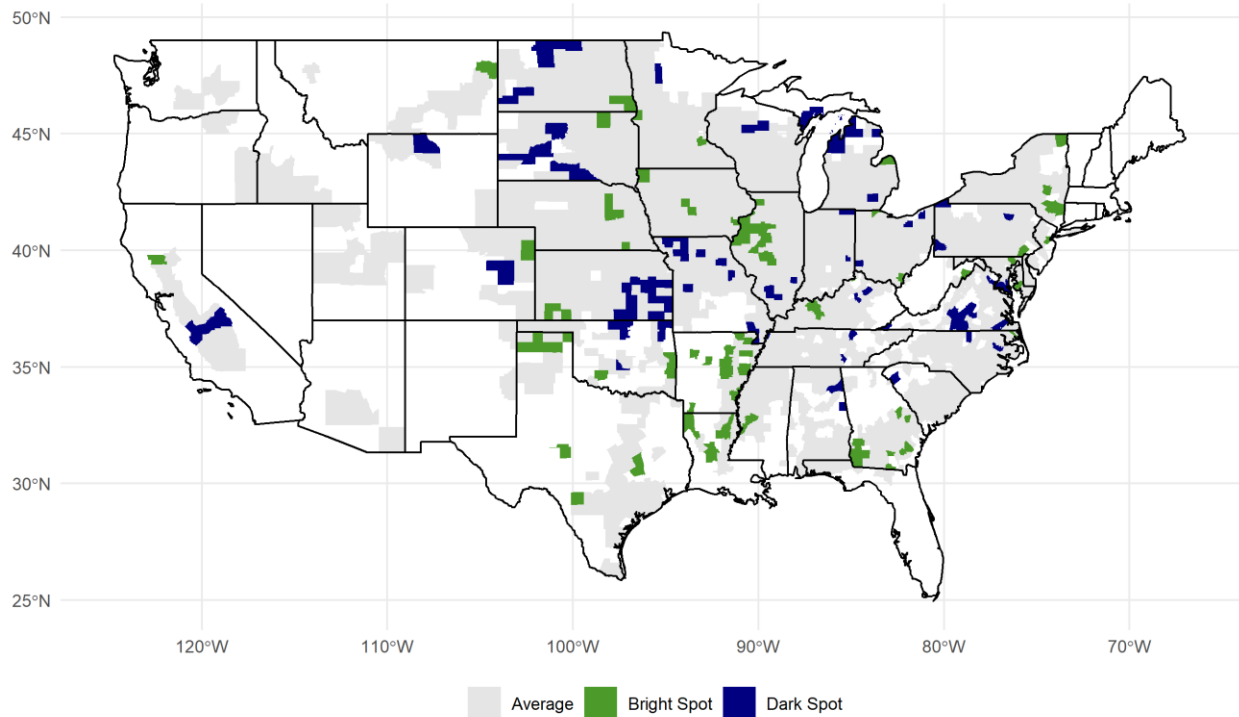
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260 **Figure 3:** Location of 109 bright spots (green) and 108 dark spots (blue) derived from the hierarchical model.
261

262 **Table 2:** Regression coefficients for fixed effects in the hierarchical model. Soil suitability was standardized
263 prior to analysis, so the effect reported below is based on a one standard deviation increase in soil suitability.
264 The baseline year in the model is 1997.
265

Variable	Mean	St. Dev.	0.025 quantile	0.975 quantile
Intercept	96.83	9.34	78.49	115.16
Soil suitability	12.37	0.76	10.88	13.86
Year 2002	6.35	0.70	4.97	7.72
Year 2007	22.31	0.71	20.92	23.70
Year 2012	21.42	0.75	19.95	22.90
Year 2017	43.65	0.68	42.33	44.98

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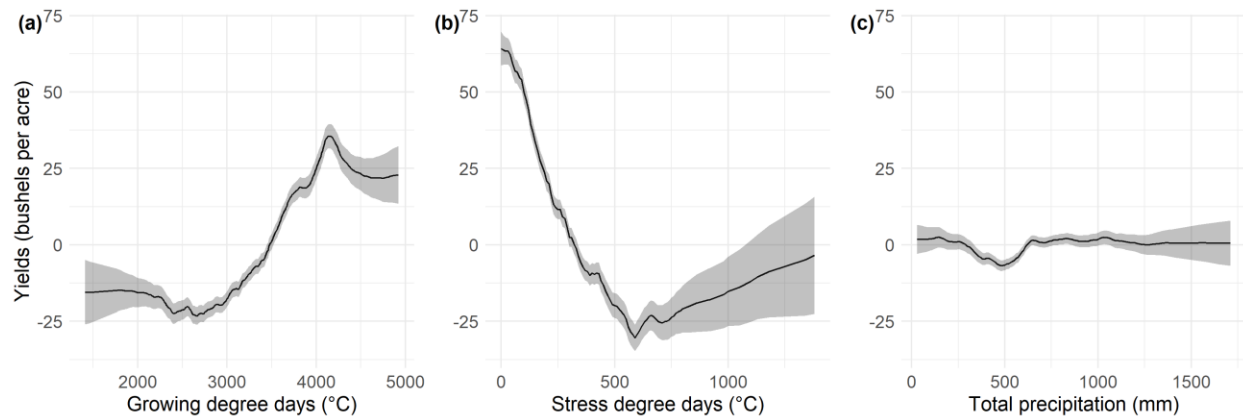
Figure 4: The non-linear response (first-order random walk) of corn yields (bushels per acre) to seasonal weather covariates in the hierarchical model. Solid lines show the median effect and shaded bands the 95% credibility limits.

We predict membership in one of three categories (*bright, average,* or *dark*) using the variables described in Table 1 with multinomial logistic regression analysis. Our model performs well on held-out data, correctly predicting 89% of the cases ($n = 8650$ county-years, McFadden's pseudo R^2 0.23). Results are robust to shifts in the threshold we used to define bright spots (SI Figures 4 and 5). Predictors were scaled prior to analysis, so the effects presented in Figure 5 and Table 3 are the relative risk ratios associated with a one standard deviation increase in each covariate. Keeping all other variables constant, variables with relative risk ratios less than one are more likely to shift towards the *average* category as the value of the variable increases; conversely, variables with relative risk ratios greater than one are more likely to shift to the *bright* (Figure 5a) or *dark* (Figure 5b) categories as the value of the variable increases. In what follows, we focus on the attributes with relative risk ratios greater than one, as these attributes are most likely to push a county out of the *average* category towards classification as a *bright* or *dark* spot.

The results of the multinomial logistic regression indicate that, after controlling for regional expectations, seasonal weather, and soil suitability, unexpectedly high yields are found in regions with higher levels of **farm inputs** (fertilizer, irrigation, labor) and **financial support** (government receipts) to production. For example, a one standard deviation increase in dollars spent on fertilizer ($26.34 per acre) is associated with an increase in the likelihood of a county being classified as bright by 35%. Increasing irrigated acreage by 13% increases the likelihood of a county being classified as bright by nearly 40%. A one standard deviation increase in dollars spent on labor ($73.01 per acre) or dollars received from government programs ($8.58 per acre) increases the likelihood of a county being classified as bright by 14% and 23% respectively. Surprisingly, as the asset value of machinery per acre increases, a county is more likely to be classified as *average* as compared to *bright*. Changes in **land use** have a mixed effect on the likelihood of a county being classified as bright. First, our findings suggest that surprisingly productive agricultural regions are also those with higher levels of land use specialization. *Bright* counties are associated with a higher percent of acres cultivated with corn (% corn) and lower levels of land use diversity (Richness), counter to findings by Burchfield et al. (2019) that high levels of diversity are associated with higher corn yields. A county is also less likely to be classified as dark if it is dominated by a single land use category (Largest Patch Index). While compositional diversity may not be associated with surprisingly productive regions, we find that as there is a greater *distribution* of land use categories in a landscape, i.e. a higher probability that different land use categories will be located close to one another (IJI), counties are more likely to be

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classified as *bright.* This may imply that it is not total land use *diversity* (Richness), but the *mixing* of
diverse land use categories across the landscape that is associated with higher yielding regions. This
is also supported by the finding that increased landscape patchiness (Edge Density) decreases the
likelihood of a county being classified as *dark.* Finally, **farmer characteristics** (age, sex) do not
have a clear effect on the likelihood of a county being classified as *bright,* suggesting that *what* a
farmer does matters more than *who* a farmer is.

Table 3: Multinomial logistic regression results presented as relative risk ratios. Our model performs well on
held-out data, correctly predicting 89% of the cases (n = 8650 county-years, McFadden's pseudo R^2 of 0.23).
Predictors were scaled prior to analysis, so the effects presented are the relative risk ratios associated with a
one standard deviation increase in each covariate (see SI Table 2 for descriptive statistics).

	Dependent variable:	
	Bright	Dark
Farm characteristics		
Age	1.083	0.938
	(0.081)	(0.079)
% females	0.998	0.962
	(0.071)	(0.071)
% owners	1.019	**0.671***
	(0.104)	(0.073)
% tenants	**1.117***	**0.545***
	(0.073)	(0.066)
Farm inputs		
Fertilizer ($/acre)	**1.346***	0.820
	(0.133)	(0.124)
Irrigation (%)	**1.393***	**0.739***
	(0.075)	(0.114)
Labor ($/acre)	**1.139**	0.967
	(0.069)	(0.100)
Machinery ($/acre)	**0.536***	1.162
	(0.068)	(0.140)
Financial Support		
Gvt. programs ($/operation)	**1.235***	1.033
	(0.090)	(0.105)
Land use		
% corn	**1.310***	**0.408***
	(0.092)	(0.041)
% cropland	**0.652***	**0.732**
	(0.076)	(0.091)
% pasture	1.046	1.011
	(0.091)	(0.090)
Landscape		
Edge density	0.964	**0.780**
	(0.104)	(0.082)

11

Largest patch index	0.914	**0.730*****
	(0.086)	(0.064)
Interspersion & juxtaposition	**1.226*****	1.082
	(0.094)	(0.081)
Richness	**0.717*****	0.963
	(0.055)	(0.090)
Constant	**0.052*****	**0.035*****
	(0.004)	(0.003)

Note: *p<0.1,**p<0.05,***p<0.01

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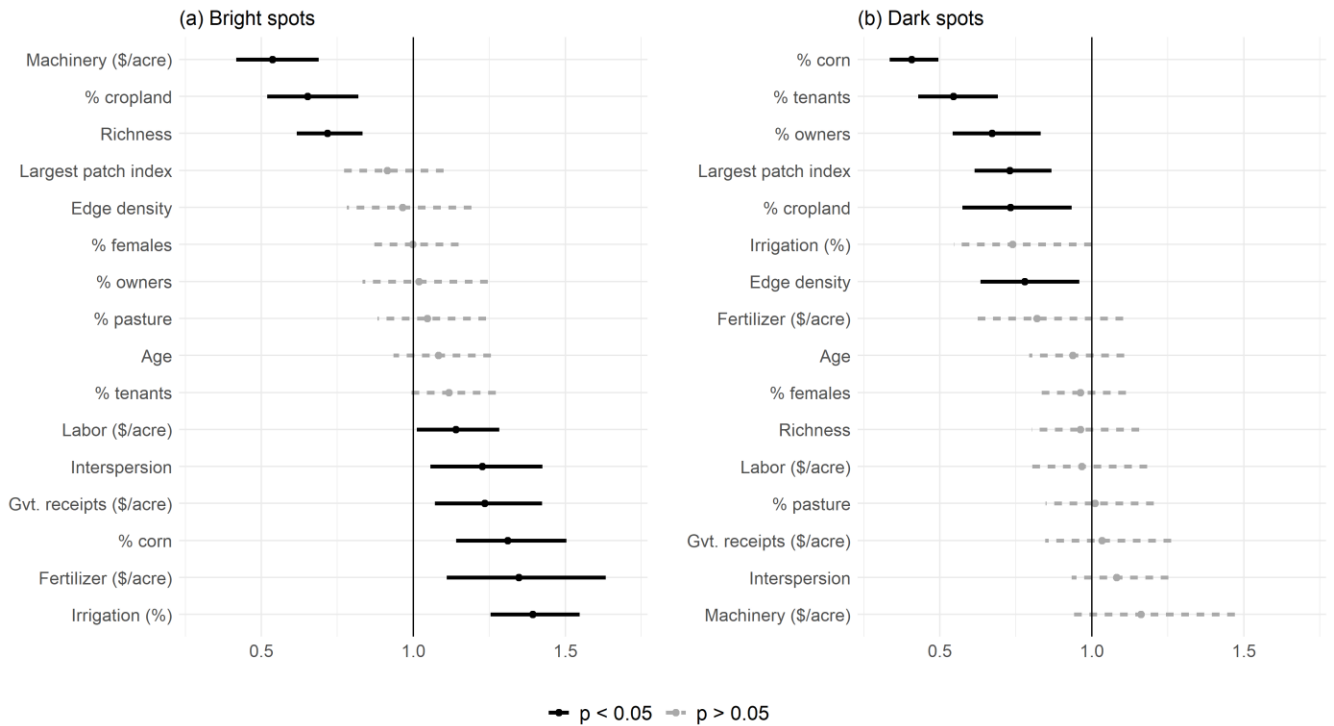
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319 **Figure 5:** Relative risk ratios associated with a county moving from (a) *average* to *bright* or from (b) *average* to
320 *dark*. Points are the risk ratios associated with membership in *bright* or *dark* spot categories as compared to the
321 baseline *average* category and lines represent the 95% confidence intervals for these estimates. Keeping all
322 other variables constant, variables with relative risk ratios greater than one are more likely to shift to the
323 bright (Figure 5a) or dark (Figure 5b) categories as the variable increases, while variables with relative risk
324 ratios less than one are more likely to shift towards the average category as the variable increases.

325
326 **4. Discussion**
327   While unsurprising (see for example, Liang et al., 2017, Ray et al., 2015, or Lobell & Gourdji,
328 2012), our finding that seasonal weather and soil explain much of the variability in U.S. corn
329 production highlights the role that *nonactionable factors* play in driving yield variability. Though
330 seasonal weather and soil did not show significant changes over our period of interest (SI Figure 1),
331 these *nonactionable* factors are likely to change in the future as climate change brings more frequent
332 extreme heat events, daily precipitation extremes, and more intense droughts over most of North
333 America (Romero-Lankao et al., 2014) and as agricultural mismanagement exacerbates soil quality

334   declines already observed across many regions of the U.S. (Stavi & Lal, 2015). While many regions
335   stand to benefit from these changes, particularly the warming of the northern U.S. (Burchfield et al.,
336   2019; Lant, Stoebner, Schoof, & Crabb, 2016), these changes in soil and climate will alter where and
337   how we grow corn in the future, with profound implications for agricultural livelihoods (Lant et al.,
338   2016; Sleeter et al., 2012; Sohl et al., 2012). Given these probable changes in climate and soil, we
339   have conducted exploratory analyses to identify the attributes of U.S. counties that have shown
340   surprisingly high levels of productivity in recent years. While our analyses are correlative not causal,
341   they provide preliminary evidence for the management practices, farm characteristics, and land use
342   contexts associated with U.S. counties that have achieved surprisingly high yields—given local
343   climate and soil dynamics—allowing us to discuss the extent to which these correlates of
344   productivity can continue to be managed for a sustainable future.
345   One of the strongest predictors of whether a county is classified as *bright* is fertilizer use.
346   Over the years included in our analysis, farmers cultivating in bright counties spent an average of
347   $38.5 per acre on fertilizer as compared to $20.9 per acre in dark counties (Figure 6a). Chemical
348   application—though not included in our analysis due to its high collinearity with fertilizer use—is
349   also consistently higher in bright counties, with average spending of $26.2 per acre in bright counties
350   as compared to $13.1 in dark counties (Figure 6b). Farmers in *bright* counties also have greater
351   machinery assets (Figure 6g) and spend more on labor (Figure 6h). Mechanical technology
352   innovations have contributed widely to agricultural productivity in the U.S., significantly reducing
353   the need for on-farm labor (USDA ERSa). At the same time, the supply of farm labor has declined
354   and the cost of labor increased, encouraging farmers to grow less labor-intensive crops while
355   investing in labor-saving technologies and increasing labor productivity (Zahniser et al., 2018).
356   Given our findings that investing more in labor increases the likelihood of a county being classified
357   as *bright* and investing more in machinery makes a county more likely to be classified as *average* as
358   compared to *bright*, we suggest that more research investigating the nuanced links and feedbacks
359   between labor, machinery, and productivity is necessary in the future. Finally, many of the counties
360   with surprisingly high corn yields also have high rates of irrigation, with an average irrigation rate of
361   14.7% in bright counties as compared to only 2.6% in dark counties (Figure 6c).
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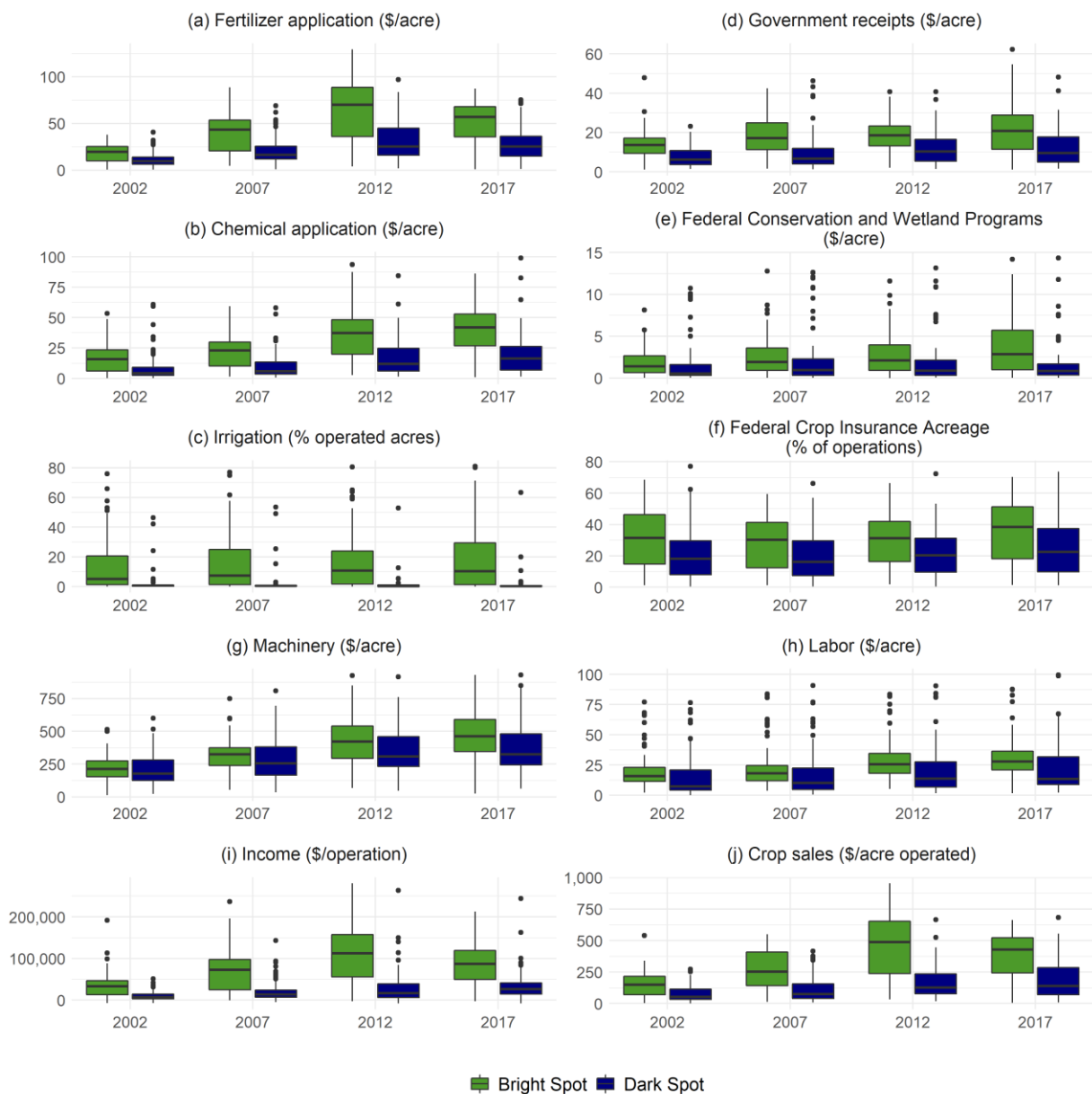
Figure 6. Box and whisker plot showing differences in physical and financial inputs across bright spots and dark spots. Bold horizontal lines represent the median. We include an indicator of chemical application (insecticides, herbicides, fungicides, pesticides, and the cost of application) not included in the formal analysis due to high collinearity with fertilizer use. We also include indicators of participation in specific government programs excluded from formal analysis due to limited data availability over our period of study. Due to data availability issues, 1997 was not included in these figures.

Whether these high rates of input use can mitigate projected changes in climate and soil is unclear. On the one hand, these are important means of replicating ideal cultivation conditions in regions that are not particularly well-suited to the cultivation of a specific crop. On the other hand, there are significant environmental implications of this reliance on external inputs, particularly their negative influence on the *nonactionable* factors—soil suitability and climate—that drive much of yield variability in the U.S. For example, though fertilizer application is an important means of boosting

379 agricultural productivity, its overuse is associated with a number of social and environmental
380 externalities including eutrophication and hypoxia (Van Meter, Van Cappellen, & Basu, 2018),
381 biodiversity loss (Mozumder & Berrens, 2007), soil chemical and biological degradation (Stavi & Lal,
382 2015; Mulvaney et al., 2009), and human infections and diseases (Horrigan, Lawrence, & Walker,
383 2002). Of particular concern is the contribution of increased fertilizer use to global emissions of
384 nitrous oxide (N_2O), a greenhouse gas whose global warming potential is nearly 300 times that of
385 CO_2 (Davidson, 2009; Fu, Lee, Griffis, Dlugokenchy, & Andrews, 2017; Park et al., 2012). These
386 emissions exacerbate global climate change, further deteriorating the climatic conditions on which
387 successful corn cultivation depends (Pinder et al., 2012). Similarly, irrigation allows agricultural
388 systems to achieve higher yields than could be supported by the natural environment alone;
389 however, in many regions, irrigation rates are rapidly exceeding sustainable limits, raising questions
390 about their capacity to continue to support high levels of productivity into the future. For example,
391 the bright counties in the Texas Panhandle withdraw groundwater from the Ogallala Aquifer, in
392 which up to 24% of irrigated area may be lost this century (Deines et al., 2019). The cluster of bright
393 counties in eastern Arkansas—a region that has seen a remarkable expansion of irrigated area in
394 recent decades—withdraws from an aquifer currently classified as "critical" due to significant
395 groundwater declines and water quality degradation (Vories & Evett, 2014). In the Lower Mississippi
396 River Valley—where we find a large concentration of bright spots—aquifer levels have declined by
397 an average of 370 million cubic meters per year over the last 25 years (Kebede, Fisher, Sui, & Reddy,
398 2014). Both the Southeast and the Midsouth are expected to see an increase in the prevalence and
399 severity of drought in the future, exacerbating water stress in these regions (Mearns, Giorgi,
400 McDaniel, & Shields, 2003; Strzepek, Yohe, Neumann, & Boehlert, 2010).
401   In addition to the environmental implications of high input use, increased use of inputs may
402 also have implications for agricultural livelihoods. Per farm average expenditures reached over
403 $176,000 in 2017; labor, machinery, fertilizer, and chemicals together comprise over 30% of these
404 expenses (USDA NASS, 2018). Over the period covered in this study, farmer debt also increased by
405 60% from $241 billion (inflation adjusted USD$) in 1997 to $390 billion in 2017—levels not seen
406 since the 1980s farm crisis (USDA ERSc). Over the same period, median farm income has declined,
407 with 2019 net farm income nearly 36% below its peak of $136.5 billion in 2013 (USDA ERSb).
408 While our data shows that farmers in *bright* counties earn more in terms of income and crop sales
409 than those cultivating in *dark* counties (Figure 6i and 6j), we do not have data describing differences
410 in farmer *debt* across these two groups. In addition, more farmers cultivated as tenants in *bright*
411 counties than in *dark*. Given that *bright* spots are defined by high corn yields, the higher rates of
412 tenancy emphasize the need to understand landowner-tenant relationships and on-farm decision-
413 making (Perry-Hill & Prokopy, 2014; Ranjan et al., 2019; Ulrich-Schad, Babin, Ma, & Prokopy,
414 2016). If, for example, land renters are more concerned about short-term profitability than long-
415 term land value, and are tasked almost exclusively with management decision-making, renters may
416 prioritize high yields at the expense of the long-term sustainability of the lands they lease (Rogers,
417 1991; Soule et al., 2000).
418   Based on these results and the literature on the potential environmental and livelihood
419 impacts of *mis*management of these inputs, we argue that one of the most important areas for
420 sustainable change in U.S. corn production is to increase the *efficiency* with which current inputs,
421 particularly fertilizer and irrigation water, are applied. Though agricultural total factor productivity
422 (TFP) growth has been significant over the last decades, gains have been biased by technologies that
423 are land- and labor-saving, but input-intensive (Coomes, Barham, MacDonald, Ramunkutty, &
424 Chavas, 2019; USDA ERSd). Though results from this study cannot speak to input-use efficiency
425 directly, it remains that agricultural inputs are often not applied efficiently. For instance, an
426 estimated 65% of farming operations do not follow best management practices for fertilizer

427 application (Ribaudo et al., 2011), with fertilizer often applied in excess of crop requirements
428 (Ladha, Pathak, Krupnik, Six, & van Kessel, 2005). This decreases soil productivity over time,
429 increasing farmer reliance on synthetic fertilizers (Mulvaney et al., 2009). Similarly, in many of the
430 water-stressed aquifers that supply irrigation water to bright spots, water is applied inefficiently,
431 further depleting water supplies and raising energy costs for producers (Kebede et al., 2014).
432 Significant efficiency gains can be made by promoting *information*-intensive—rather than *input*-
433 intensive—innovations in U.S. agriculture (Burchfield et al., 2019; Fuglie, 2018). Advances in
434 precision agriculture including the use of Global Positioning Systems, weather prediction, satellite
435 imagery, and drones to target inputs like fertilizer, pesticides, and irrigation water can significantly
436 increase resource use efficiency (Bongiovanni & Lowenberg-Deboer, 2004). Genetic innovations
437 designed to mitigate climate, soil, and pest variability have already generated significant efficiency
438 gains (Khatodia, Bhatotia, Passricha, Khurana, & Tuteja, 2016; Tester & Langridge, 2010; Cooper et
439 al., 2014; Messina et al., 2020; Mueller, Messina, & Vyn, 2019). These innovations in technology,
440 coupled with ecosystem-based approaches (e.g., crop rotation, integrated crop-livestock systems) to
441 TFP growth, have the potential to enhance agricultural sustainability (Coomes et al., 2019).
442   In addition to higher rates of input use, we also find that farmers cultivating in bright
443 counties receive nearly double the **government receipts** as those cultivating in dark counties ($15.5
444 per acre versus $8.9 per acre respectively). This variable includes payments for farmer participation
445 in conservation programs, loan deficiency payments, disaster payments and "all other federal farm
446 programs under which payments were made directly to farm operators" (USDA NASS, 2019, p.
447 759). Due to high rates of missing data, we were unable to formally assess the interactions between
448 farmer participation in *specific* programs and corn productivity; however, we compare available data
449 across *bright* and *dark* counties in Figure 6d-f. Participation in federal crop insurance programs has
450 increased consistently through time, reflecting national trends (Annan & Schlenker, 2015)—with
451 higher participation rates in *bright* counties than *dark* counties. Federal programs are an important
452 source of income stabilization for U.S. farmers; however, participation in these programs is
453 governed by policies that often promote specialization, influencing what, where, and how food is
454 produced (Reganold et al., 2011) with implications for farm-level adaptive capacity and resource use.
455 For example, an increased participation in federal crop insurance programs is associated with a
456 decrease in adoption of adaptive practices meant to mitigate the negative yield impacts of changing
457 climate (Annan & Schlenker, 2015), reduced on-farm diversification (Di Falco & Perrings, 2005;
458 O'Donoghue, Roberts, & Key, 2009), the cultivation of more water-intensive crops (Deryugina &
459 Konar, 2017), and the expansion of corn production into regions poorly suited to its cultivation
460 (McGranahan, Brown, Schulte, & Tyndall, 2013; Olson, 2001). Though participation in federal
461 conservation and wetland programs is low, the higher rates of participation in bright counties merit
462 further exploration. In addition to preserving important ecosystems, participation in these programs
463 has been shown to boost ecosystem services for agriculture while supplementing farmer income
464 (Gleason, Laubhan & Euliss, 2008; Morefield, Leduc, Clark & Iovanna, 2016).
465   Changes in **land use** have a mixed effect on the likelihood of a county being classified as
466 bright. Our results indicate that surprisingly productive regions are those with higher levels of land
467 use specialization (lower Richness, higher percent cultivated in corn, lower Largest Patch Index). At
468 the same time, however, we find that counties with more complex configurations (higher edge
469 density, higher Interspersion and Juxtaposition) are more likely to be bright or average as compared
470 to dark. The different ways in which landscape composition and configuration interact with yield
471 suggest that there may be ways in which agricultural stakeholders can manage entire landscapes to
472 support agricultural production. This aligns with published research suggesting that managing
473 agricultural lands to support the provisioning of ecosystem services essential to agricultural
474 production can increase both ecosystem health and yields (Duarte, Santos, Cornelissen, Ribeiro, &

475 Paglia, 2018; Shackelford et al., 2013); however, more research is needed to assess the specific ways
476 in which shifting land use affects production and input use (Burchfield et al., 2019). We note,
477 additionally, that there are many well-established agricultural practices farmers can employ to *manage*
478 *for* ecosystem services that we were unable to include in our analysis due to limited data availability.
479 For example, setting aside even a small portion of agricultural land to natural cover has been found
480 to boost ecosystem services essential to agricultural production (e.g., increased pollinator abundance)
481 while maintaining yields (Schulte et al., 2017). Agricultural practices like this, that *both* maintain yields
482 and promote environmental outcomes, must be included in future analyses (once data is available at
483 U.S. scales) to further understand sustainability as it relates to management practices and agricultural
484 outcomes (e.g., yields) in the U.S.
485
486 5. Conclusion
487   For our food production systems to thrive in the future, they must meet human demand
488 while also sustaining the environmental resource base and providing economically viable options for
489 farmers (NRC, 2010). We have identified surprisingly productive regions of the U.S., identified the
490 shared attributes of these regions, and questioned the overall sustainability of these attributes. Rather
491 than identifying the highest or lowest yielding places in the U.S., we identify places *that defy*
492 *expectations* to uncover potential actionable levers to boost agricultural sustainability. This exploratory
493 hypothesis-generating expedition both highlights the extent to which *nonactionable* climatic and
494 edaphic factors explain yield variability and identifies the major correlates of productivity: high levels
495 of input use, land use specialization, and government support. These correlates, in turn, affect the
496 environmental conditions that ultimately define agricultural productivity.
497   We conclude by emphasizing the importance of future work exploring agricultural bright
498 spots to generate novel insights and new hypotheses about sustainable solutions to the complex
499 problems facing U.S. agriculture (Bennet et al., 2016). We propose future research in bright counties
500 where relatively few inputs are used. Bright areas reporting low rates of fertilizer use—located
501 primarily in Texas and Oklahoma (SI Figure 6)—and low irrigation rates—located in western
502 Illinois, parts of the Great Plains, and throughout Texas (SI Figure 7)—are areas that achieve
503 surprisingly high yields without heavy use of fertilizer and irrigation water. Future research in these
504 areas can merge the "big data" presented in this analysis with "deep data" describing the intersecting
505 social and ecological dynamics that allow farmers to achieve high yields in surprising contexts.