The Impact of Weather on U.S. Farm Productivity:
Historical Patterns and Relation to the Changing Disease Environment [*]

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Abstract

We consider the impact of weather on farm values through U.S. history. Using both cross-sectional and panel methods, we document economically and statistically significant differences in the response of farm productivity to weather over time. In recent decades, farm value has been (weakly) increasing in temperature and rainfall. On the other hand, high levels of temperature or rain depressed farm value in the nineteenth century. This suggests an important role for technological adaptation in reducing the impact on farm productivity of hotter and wetter weather (a possible outcome of climate change in some places). One particular adaptation—the eradication of malaria—accounts for a substantial fraction of this difference over time. These results also suggest that malaria reduced farm productivity by a factor of 2-3 in the most malarious parts of the South relative to the Plains in the late 1800s.

[*] This preliminary draft consists of an abstract, a brief outline, and some key tables and figures.
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This preliminary draft provides a brief outline of the article; a more complete draft will be available soon.

1. Significance and Aims

▪ This article has been motivated by recent studies of the forecasting of agricultural productivity change under global warming scenarios (Deschenes and Greenstone 2007; Schlenker and Roberts 2008). While previous studies have used modern (post-1950) weather records and agricultural data, this article extends the analysis to include data from as far back as the 1860s.

▪ Prior to 1950, agricultural technology and the ability to adapt to weather shocks was inferior to the modern period, which led to lower farm productivity. The advance of technological adaptation to weather shocks has reduced the impact of hotter, wetter weather on farm productivity.

▪ This article focuses on one particular adaptation: the eradication of malaria. Eradication efforts were made throughout the first half of the twentieth century, and malaria was eradicated from the United States in the 1950s.

▪ The key risk factor of malaria is climate, and its effect on mosquitoes. In nineteenth-century America, malaria ecology was frequently promoted by warm, wet weather and landforms such as swamps (Hong 2007). An increasing number of studies suggest that exposure to malarial environments deteriorated an individual's labor productivity, income, and health over the life cycle (Bleakley 2008; Hong 2007, 2008).

▪ The specific aims of this article are:

Aim 1. To document statistically significant economic differences in the response of farm productivity to weather in 1861–2000.
Aim 2. To measure the significance of malaria in explaining differential weather sensitivity.
Aim 3. To test the robustness of the role of malaria by considering other types of agricultural adaptations and alternative farm productivity measures.

2. Data

▪ <u>Analysis Unit and Period</u>: Counties in 1861–2000

▪ <u>Measure of Farm Productivity</u>: County average farm value per farmland acre, as found in the census of agriculture; this is the value of all land, housing, and outbuildings in the farm. This variable is consistently available over centuries. In the later part of this article, we will also use alternative measures of farm productivity.

▪ Weather Records: Decade (defined as the period 10 years prior to each census year) average of county annual mean temperature and annual accumulated precipitation. We constructed the weather variables using U.S. monthly weather data. The source of nineteenth century weather records is the *Nineteenth-Century US Climate Data Set Project* developed by National Climate Data Center. The source of the twentieth century weather records is the *Long-Term Daily and Monthly Climate Records from Stations across the Contiguous United States* provided by United States Historical Climatology Network. Not all the counties had weather stations. A "Kriging" interpolation method was used to estimate the climate variables for the entire country.

3. Fixed Effects Model

▪ To control for time trends, year-specific state factors, and time-invariant county factors, we will use several different fixed-effects models: (1) Year FE model, (2) State-by-Year FE Model, and (3) State-by-Year and County FE Model. In using the County FE model, we adjusted all variables to the 1870 boundary by using area-weight average to fix the problem of county boundary changes over time.

4. Differential Weather Sensitivity

▪ Figure 1: Historical Pattern

We present the historical patterns of the response of farm value to weather over time. In recent decades, farm value has been (weakly) increasing in temperature and precipitation. High levels of temperature or precipitation depressed farm value in the nineteenth century.

▪ Figure 2: These historical patterns are estimated by the following regression models. The coefficients of weather (β: the impact of weather on farm value by year) are plotted in Figure 2.

$$(1)\quad Y_{ijt} = \sum_{t=1870}^{2000} \beta_t \cdot W_{ijt} + \sum_{t=1870}^{2000} D(Year = t) \cdot X_{ijt} \cdot \Pi + \delta_t + \delta_{jt} + \delta_i + \varepsilon_{ijt}$$

, where i: county, j: state, t: year, W: weather variable, D(Year=t): dummy of year, X: standard regressors, δ: fixed FE

▪ Table 3: Differential Weather Sensitivity

In Table 3, we focus on the gap in farm productivity between two representative periods: the late nineteenth century (1870, 1880, and 1890) and the late twentieth century (1970, 1980, and 1990). Table 3 reports the coefficient β in the following regression model. The results suggest that the gap depended substantially on weather conditions. Hotter, wetter weather led to a larger gap in farm productivity. We also found that the impact of hot temperatures on farm productivity is compounded by more precipitation, and vice-versa.

$$(2) \quad Y_{ijt} = \alpha \cdot W_{ijt} + \beta \cdot W_{ijt} \cdot D_{19} + \delta_i + \delta_{jt} + X_{ijt} \cdot \Gamma + X_{ijt} \cdot D_{19} \cdot \Pi + \varepsilon_{ijt}$$

, where *i*: county, *j*: state, *t*: year, *W*: weather variable, D_{19}: dummy of 19th century, *X*: standard regressors, *δ*: fixed FE

5. Differential Weather Sensitivity and Malaria Ecology

▪ Figure 3: U.S. Malaria Ecology

We use malaria ecology as estimated in Hong (2007). The malaria risk index is estimated using U.S. climate data and geographical features at the county level.

▪ Table 2: Climate, Malaria Ecology and Reported Malaria Mortality

The number of deaths from malaria had declined greatly throughout the early twentieth century. The result in this table suggests that the gap in reported county malaria deaths per 1,000 population between the nineteenth (1880 and 1890) and twentieth (1920 and 1940) centuries largely depended on weather condition and malaria ecology.

▪ Figures 4 and 5: Historical Pattern of the Impact of Malaria Ecology on Farm Productivity

We present the historical patterns of the response of farm value to malaria ecology over time in Figure 4. While farm value is irrelevant to malaria ecology in recent decades, high-malarial counties had much lower farm value in the nineteenth century. These historical patterns were estimated using fixed FE models. The key coefficients (the impact of malaria ecology on farm value by year) are plotted in Figure 5.

▪ Figure 6: Differential Weather Sensitivity by Malaria Ecology

We estimated differential weather sensitivity (*β* in Equation (2)) by the deciles of malaria ecology. The figures show that differential weather sensitivity depends on malaria ecology. Differential weather sensitivity is not found in low-malarial counties, but found significantly in high-malarial counties.

▪ Table 3: Differential Weather Sensitivity by Malaria Ecology

The findings in Figure 6 are estimated in Table 3. The negative coefficients of *weather***malaria***D*19 imply that differential weather sensitivity increased in malaria ecology. By controlling for malaria ecology, in addition, the size and significance of differential weather sensitivity (the coefficients of *weather***D*19) decreased greatly or disappeared.

6. Other Hypotheses

▪ Tables 4, 5 and 6: We have considered various agricultural factors as well as malaria in explaining differential weather sensitivity. We found that the role of malaria is still robust when we consider other types of technological adaptations.

▪ List of Hypotheses and Available Proxies Used in the Paper

(1) Land Use
- % of farmland used for crops
- % of improved farmland
- % of drained farmland c.1930
- % of irrigated farmland c.1890

(2) Crop Mix
- % of crop acres (cotton, tobacco, rice, wheat, corn, barley, oats, rye, hay, and potato)

(3) Industrial Organization
- Crop concentration measured by Herfindahl-Hirschman Index

$HHI = \dfrac{(H - 1/N)}{(1 - 1/N)}$, where $H = \sum_i CropAcres_i^2$ and N is the number of crops considered.

- % of share croppers and % of tenants

(4) Inputs
- log value of fertilizer cost per farmland acre

(5) Other Health Indexes
- Pellagra index

(6) Changes in those agricultural technologies over centuries

7. Alternative Measures of Farm Productivity

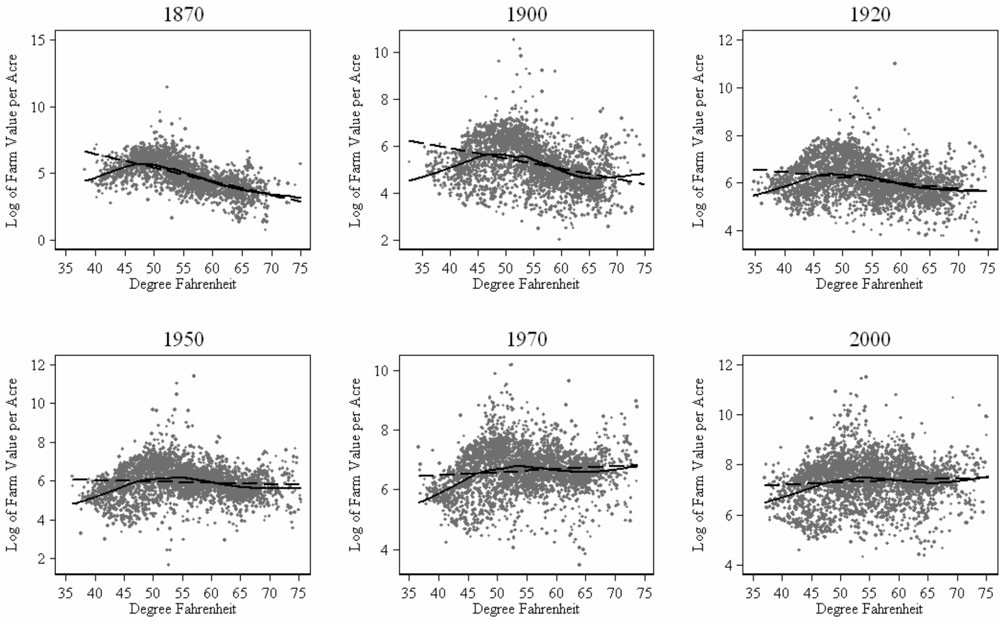
▪ Table 7: We use alternative measures of farm productivity: farm value per farmers, county population per acre, value of total farm output per farmland acre, value of crops per farmland acre, and cotton yields per acre (for cotton counties). We found that differential weather sensitivity is observed for these farm productivity measures. The role of malaria is also found, but relatively weaker than estimated for farm value as a measure of farm productivity.

8. Conclusion

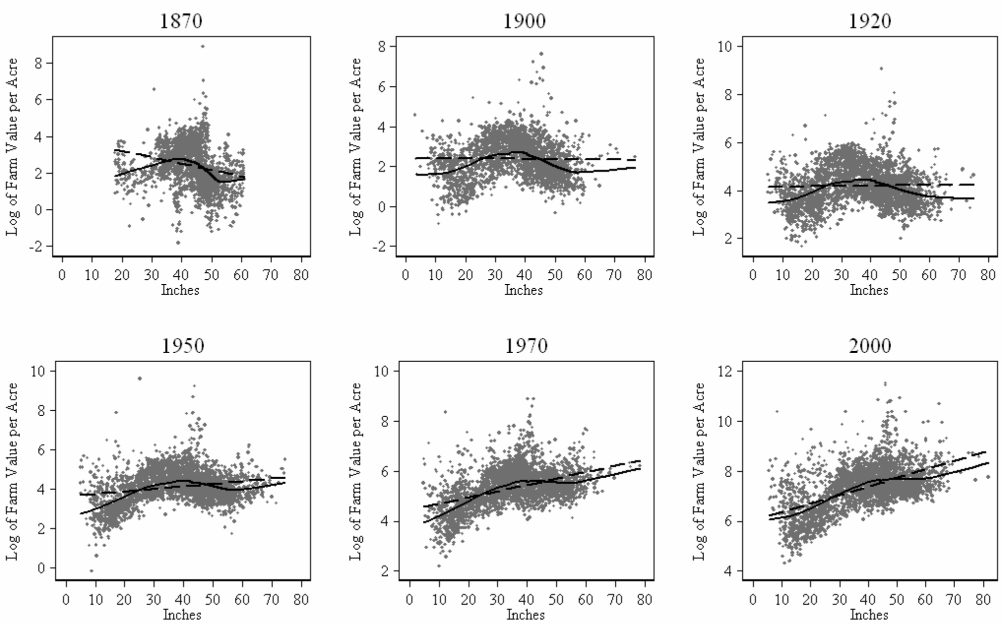
We consider the impact of weather on farm values throughout U.S. history. We document economically and statistically significant differences in the response of farm productivity to weather over time. In recent decades, farm value has been (weakly) increasing with temperature and rainfall. On the other hand, high temperatures or rain levels depressed farm value in the nineteenth century. This suggests an important role for technological adaptation in reducing the impact of hotter, wetter weather on farm productivity (a possible outcome of climate change in some places). One particular adaptation—the eradication of malaria—accounts for a substantial fraction of this difference over time.

Figure 1.
Scatter Plots: Log County Average Farm Value per Acre by Decade Climate
(Solid Curve: Lowess Fits, Dashed Lines: Linear Fits)

Decade Average of County Annual Mean Temperature



Decade Average of County Annual Accumulated Precipitation



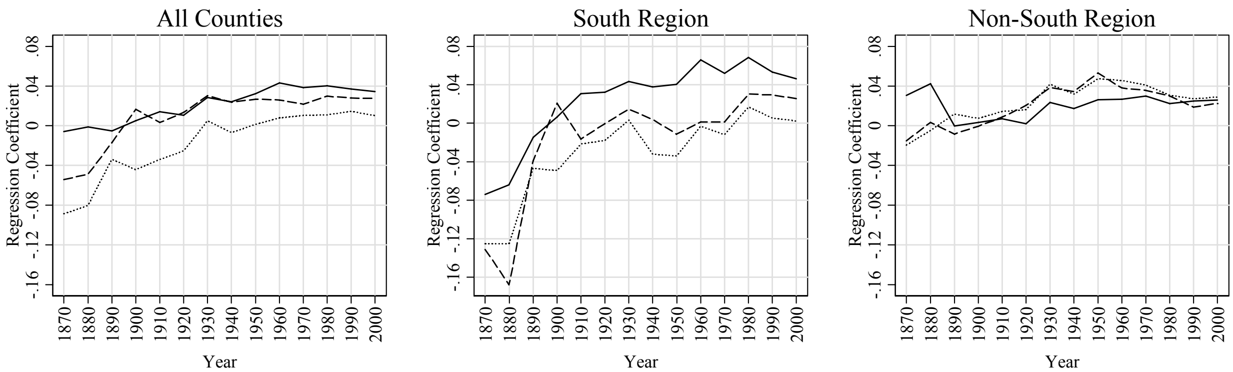
Note: Decade climate values are calculated by the 10-year average of annual weather records prior to each census year.

Figure 2.

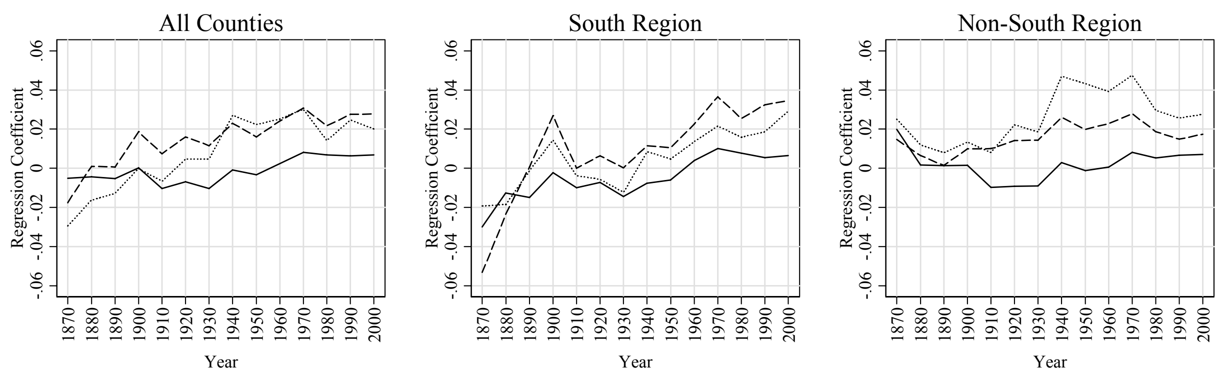
Long-Term Trends of Estimated Relationship between County Farm Value per Acre and Climate

(Dotted Line: Year FE, Dashed Line: State by Year FE, and Solid Line: State by Year & County FE)

(a) Temperature



(b) Precipitation



Notes: We ran the pooled regressions of log county farm value per acre on decade (10-year period prior to each census year) average of annual mean temperature and annul accumulated precipitation multiplied by census year dummies. Each panel is the graphical presentation of regression coefficients of those climate control variables. We used year fixed effects model, state by year fixed effects model, or state by year & county fixed effects model, respectively, for specified county groups (all, South, or non-South). Besides climate variables, we controlled for (1) the number of male farmers per farmland acre, (2) the ratio of white population out of county population, (3) the ratio of farmland out of total available county area, and (4) the interactions of (1)-(3) with census year dummies.

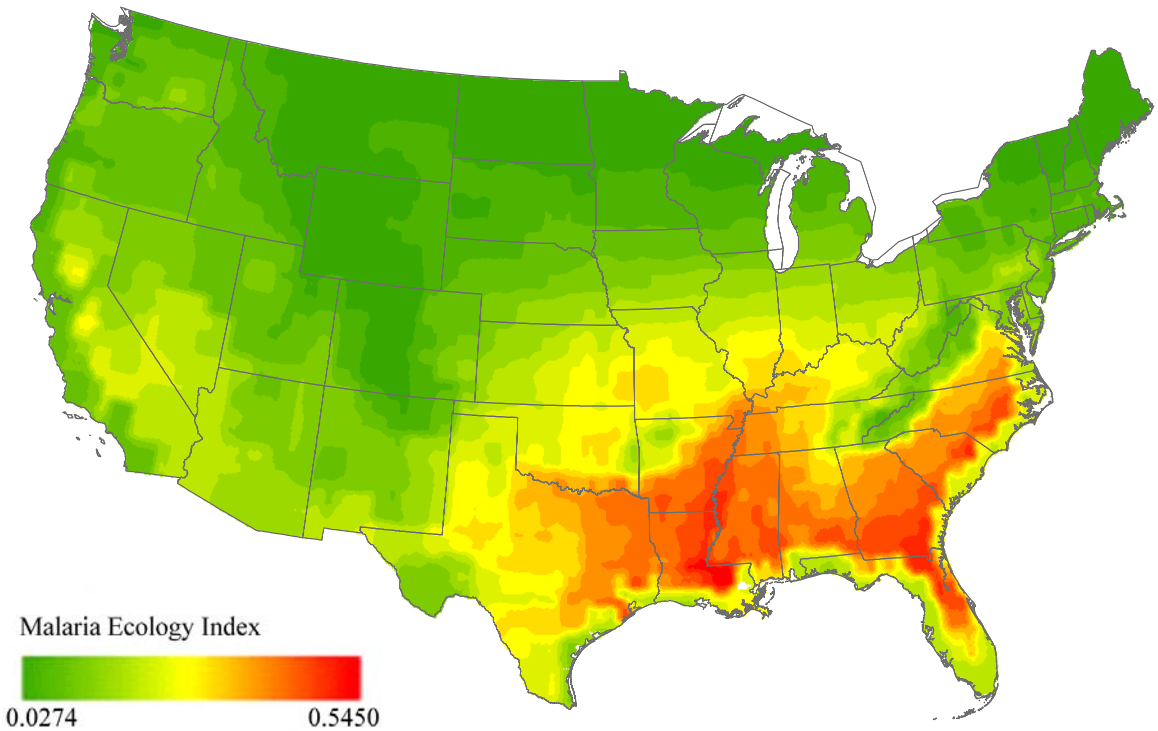
Table 1. Fixed-Effects Estimates of Differential Weather Sensitivity (Difference in Climatic Impacts on County Farm Value per Acre between the Late 19th and Late 20th Centuries)

Dependent variable: ln(county average farmland value per acre)

Key Control Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: All Counties								
Temperature (T) *D19	-0.0800***	-0.0607***	-0.0466***				-0.0512***	-0.0521***	-0.0520***
	(0.0021)	(0.0060)	(0.0063)				(0.0026)	(0.0058)	(0.0063)
Precipitation (P) *D19				-0.0374***	-0.0269***	-0.0164***	-0.0170***	-0.0210***	-0.0114***
				(0.0013)	(0.0024)	(0.0029)	(0.0016)	(0.0023)	(0.0029)
$(T-\mu_T)*(P-\mu_P)*D19$							-0.0024***	-0.0020***	-0.0020***
							(0.0002)	(0.0003)	(0.0003)
	Panel B: South Region								
Temperature (T) *D19	-0.0757***	-0.1052***	-0.0967***				-0.0824***	-0.0820***	-0.1049***
	(0.0050)	(0.0095)	(0.0102)				(0.0076)	(0.0114)	(0.0100)
Precipitation (P) *D19				-0.0228***	-0.0431***	-0.0283***	-0.0189***	-0.0189***	-0.0425***
				(0.0030)	(0.0035)	(0.0041)	(0.0051)	(0.0049)	(0.0059)
$(T-\mu_T)*(P-\mu_P)*D19$							0.0007	-0.0026***	0.0016***
							(0.0007)	(0.0007)	(0.0006)
	Panel C: Non-South Region								
Temperature (T) *D19	-0.0182***	-0.0431***	-0.0168**				0.0011	-0.0185**	-0.0183***
	(0.0045)	(0.0082)	(0.0073)				(0.0047)	(0.0088)	(0.0078)
Precipitation (P) *D19				-0.0069***	-0.0185***	-0.0090**	-0.0102***	-0.0157***	-0.0094***
				(0.0019)	(0.0031)	(0.0038)	(0.0030)	(0.0037)	(0.0045)
$(T-\mu_T)*(P-\mu_P)*D19$							-0.0005	0.0000	-0.0007***
							(0.0004)	(0.0005)	(0.0006)
Standard Regressors	NO	YES	YES	NO	YES	YES	NO	YES	YES
Year FE	YES	NO	NO	YES	NO	NO	YES	NO	NO
State by Year FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
County FE	NO	NO	YES	NO	NO	YES	NO	NO	YES

Notes: We compared the counties in the census years of 1870, 1880, and 1890 with those in the census years of 1970, 1980, and 1990 (reference group). For climate variables, we used the decade (10 years before each census year) average of annual mean temperature (T) and that of annual accumulated precipitation (P). μ_T and μ_P denote the mean value of temperature and precipitation across counties and years, respectively. D19 denotes the dummy variable indicating the census years in the 19th century (i.e. 1870, 1880 or 1890). In all the regression models, we also control for the climate variables without century dummy. The standard regressors include (1) the number of male farmers per farmland acre, (2) the ratio of white population out of county population, (3) the ratio of farmland out of total available county area, and (4) the interactions of (1)-(3) with D19. Standard errors, clustered on county, are reported in parentheses. Single asterisk denotes statistical significance at the 90% level of confidence, double 95%, triple 99%.

Figure 3. U.S. Malaria Ecology Index in 1861-2000



Notes: This diagram shows the average of decade malaria ecology indexes in 1861-2000. More red (green) areas have a higher (lower) risk of contracting malarial fevers. Each decade's malaria ecology index is estimated by two main data sources: (1) the county-level environmental records on temperature, rainfall, and geographical features (standard deviation of elevation and dummy of ocean), and (2) the annual incidence of malarial fever found in the U.S. fort sickness reports between 1829 and 1874. We first estimated the correlation between forts' annual malaria incidence rates and those environmental factors around forts. Then, we imputed the risk index by plugging decade county-level environment variables into the above estimation result. More details of estimation procedure and its results are discussed in Hong, S.C. (2007), "The Burden of Early Exposure to Malaria in the United States, 1850-1860: Malnutrition and Immune Disorders." *The Journal of Economic History* 67(4): 1001-35.

Table 2. Explaining Differential Sensitivity in Reported Malaria Mortality: Climate and Malaria Ecology

Dependent variable: Malaria deaths per 1,000 population

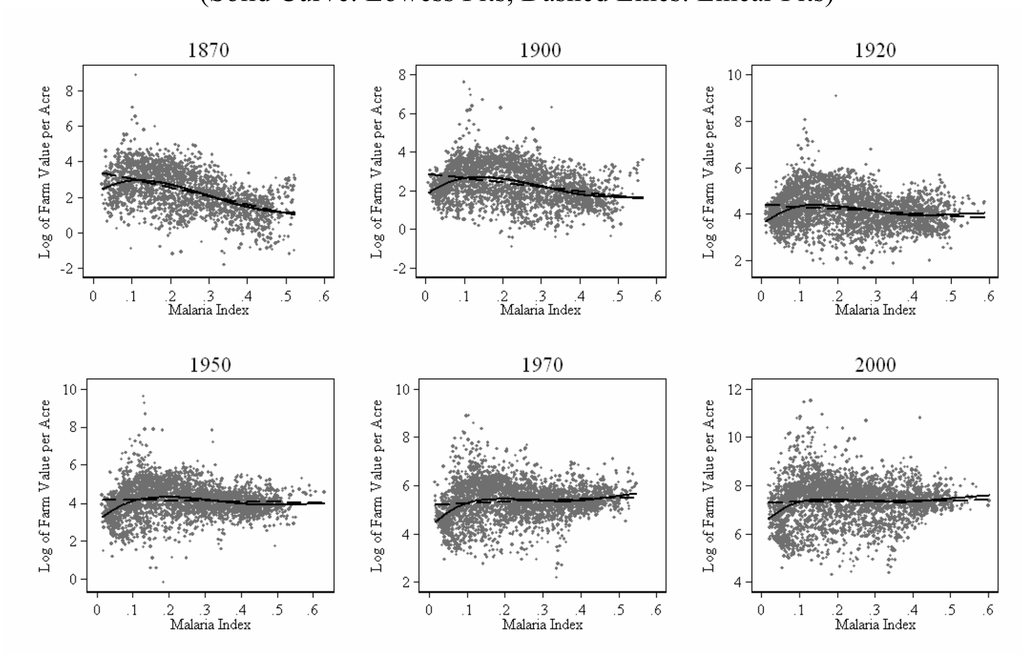
Key Control Variables	(1)	(2)	(3)	(4)
Temperature (T) **D* 19	0.0308*** (0.0058)		0.0348*** (0.0071)	
Precipitation (P) **D* 19		0.0115*** (0.0026)	0.0075*** (0.0020)	
$(T\text{-}\mu_T)*(P\text{-}\mu_P)*D19$			0.0011** (0.0004)	
*Malaria Ecology***D* 19				1.4357*** (0.2918)

Notes: The results in this table estimate how much the difference in reported county malaria deaths per 1,000 population between the 19th and 20th centuries depends on climate and malaria ecology. In particular, we compared the counties in the census years of 1880 and 1890 with those in the census years of 1920 and 1940 (reference group). For climate variables, we used the decade (10 years before each census year) average of annual mean temperature (T) and that of annual accumulated precipitation (P). μ_T and μ_P denote the mean value of temperature and precipitation across counties and years, respectively. Malaria Ecology is estimated as discussed in Figure 3. D19 denotes the dummy variable indicating the census years in the 19th century (i.e. 1880 or 1890).

We used state by year & county fixed effects models. The other control variables include (1)the climate variable without century dummy , (2) the number of male farmers per farmland acre, (3) the ratio of white population out of county population, (4) the ratio of farmland out of total available county area, and (5) the interactions of (2)-(4) with D19. Standard errors, clustered on county, are reported in parentheses. Single asterisk denotes statistical significance at the 90% level of confidence, double 95%, triple 99%.

Figure 4. Scatter Plots: Log County Average Farmland Value per Acre by Decade Malaria Risk Index

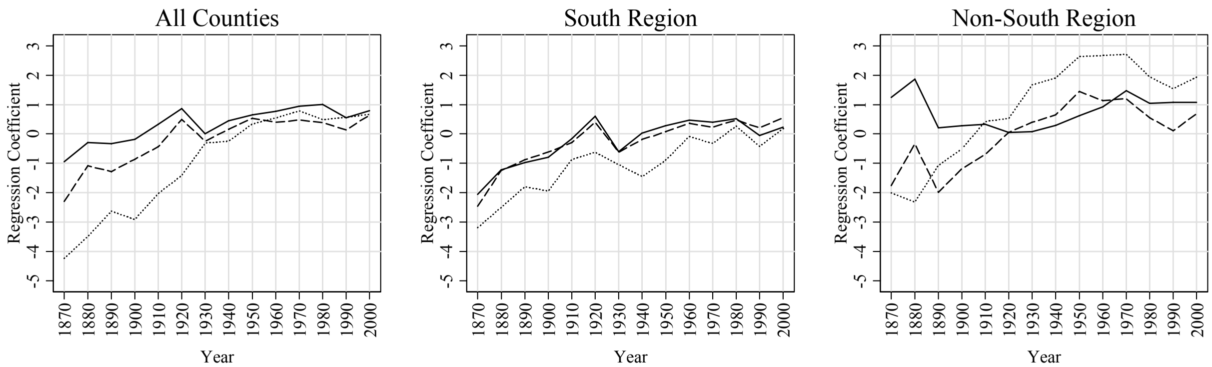
(Solid Curve: Lowess Fits, Dashed Lines: Linear Fits)



Note: For the estimation of decade malaria risk index, see the note of Figure 3.

Figure 5. Long-Term Trends of Estimated Relationship between County Farm Value per Acre and County Malaria Ecology

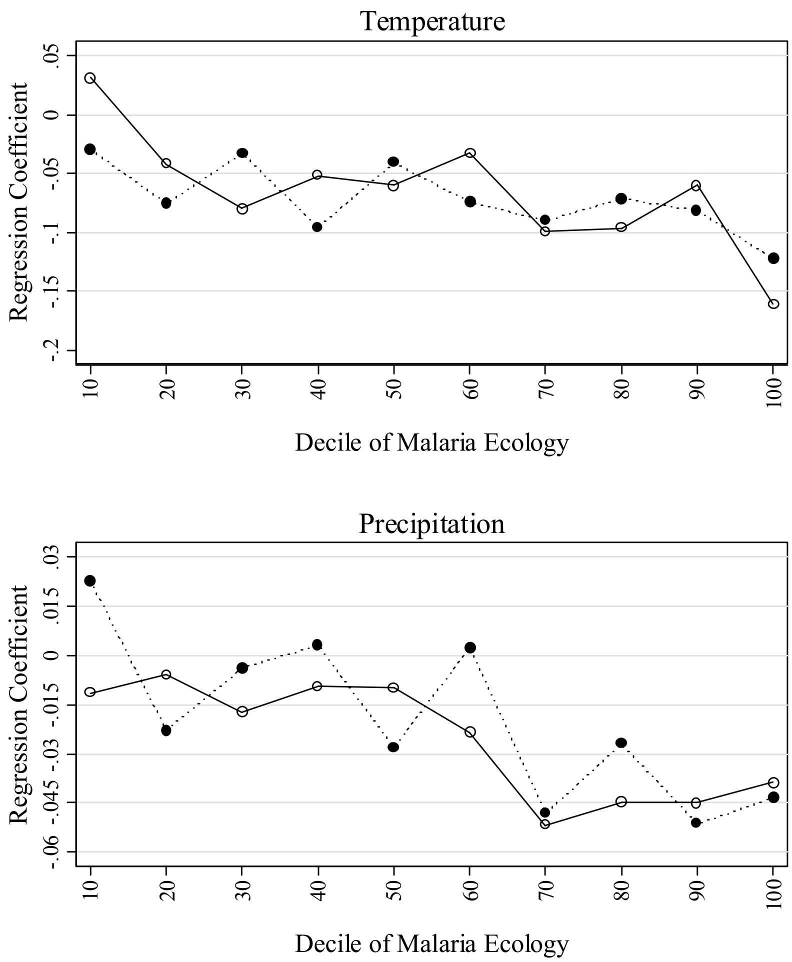
(Dotted Line: Year FE, Dashed Line: State by Year FE, and Solid Line: State by Year & County FE)



Notes: We ran the pooled regressions of log county farm value per acre on the estimated malaria ecology index multiplied by census year dummies. Each panel is the graphical presentation of regression coefficients of those malaria ecology control variables. We used year fixed effects model, state by year fixed effects model, or state by year & county fixed effects model, respectively, for specified county groups (all, South, or non-South). Besides malaria ecology variables, we controlled for (1) the number of male farmers per farmland acre, (2) the ratio of white population out of county population, (3) the ratio of farmland out of total available county area, and (4) the interactions of (1)-(3) with census year dummies.

Figure 6. Difference in Climatic Impact on Farm Value between the Late 19th and Late 20th Centuries by Average Malaria Ecology Deciles

(Solid Line: State by Year FE, Dotted Line: State by Year & County FE)



Notes: In regression models (2), (3), (5), and (6) of Table 1, we estimated the difference of climate impacts on farm value between the late 19th and late 20th centuries by census regions (all, South, or non-South), using state by year FE or county FE models. Here we conducted the same regressions for the 10 county groups divided by average malaria ecology deciles. The above graphs show the difference of climatic impacts between the 19th and 20th centuries by malaria ecology (the regression coefficients of *Climate***D*19 in Table 1, where D19 is the dummy of years in the 19th century).

Table 3. Explaining Differential Weather Sensitivity: Malaria Ecology

Dependent variable: ln(county average farmland value per acre)

	Base	Malaria
Key Control Variables	(1)	(2)
Temperature (*T*)**D* 19	-0.0520***	-0.0286***
	(0.0063)	(0.0093)
Precipitation (*P*)**D* 19	-0.0114***	0.0016
	(0.0029)	(0.0064)
$(T-\mu_T)*(P-\mu_P)*D19$	-0.0020***	-0.0008*
	(0.0003)	(0.0005)
*T*Malaria*D* 19		-0.1596***
		(0.0382)
*P*Malaria*D* 19		-0.0785***
		(0.0281)

Notes: This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to that of Table 1. 'Base' regression is adopted from the model (9) of Table 1. 'Malaria' denotes the estimated county malaria ecology index, which is discussed in Figure 3. We use time-invariant county malaria ecology index. In model (2), we also controlled for (1) the interactions between climate and malaria ecology without century dummy and malaria and (2) the malaria ecology with century dummy. The malaria ecology variable itself was dropped by county fixed effects model.

Table 4. Explaining Differential Weather Sensitivity: Pre-Existing Agricultural Factors

Dependent variable: ln(county average farmland value per acre)

Key Control Variables	Base (1)	Malaria (2)	% Cropland (3)	% Improved Farmland (4)	% Drained Areas c. 1930 (5)	% Irrigated Areas c. 1890 (6)	Crop HHI (7)	% Share-croppers (8)	% Tenants (9)	ln(Fertilizer Cost per Acre) (10)	Pellagra Index (11)
Temperature (T)*D19	-0.0520***	-0.0286***	-0.0141	-0.0273***	-0.0273***	-0.0285***	-0.0222**	-0.0182*	-0.0258***	-0.0299***	-0.0213**
	(0.0063)	(0.0093)	(0.0090)	(0.0089)	(0.0089)	(0.0091)	(0.0091)	(0.0098)	(0.0099)	(0.0100)	(0.0101)
Precipitation (P)*D19	-0.0114***	0.0016	0.0054	0.0069	0.0065	0.0035	0.0073	0.0007	0.0072	-0.0049	-0.0045
	(0.0029)	(0.0064)	(0.0059)	(0.0063)	(0.0064)	(0.0063)	(0.0063)	(0.0066)	(0.0068)	(0.0071)	(0.0067)
$(T-\mu_T)*(P-\mu_P)*D$19	-0.0020***	-0.0008*	-0.0003	-0.0001	-0.0005	-0.0004	-0.0002	-0.0008*	-0.0005	-0.0013**	-0.0006
	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)
T*Malaria*D19		-0.1596***	-0.0697**	-0.0688**	-0.1700***	-0.1671***	-0.1254***	-0.1785***	-0.1376***	-0.1347***	-0.1943***
		(0.0382)	(0.0345)	(0.0350)	(0.0375)	(0.0375)	(0.0365)	(0.0404)	(0.0402)	(0.0371)	(0.0409)
P*Malaria*D19		-0.0785***	-0.0896***	-0.0707***	-0.0816***	-0.0807***	-0.0922***	-0.0745***	-0.1031***	-0.0541*	-0.0489*
		(0.0281)	(0.0243)	(0.0268)	(0.0268)	(0.0273)	(0.0268)	(0.0280)	(0.0286)	(0.0297)	(0.0285)
$T*(Factor-\mu_F)*D$19			0.0885***	-0.0028	-0.0059	0.1315***	0.1752**	0.0695***	0.0062	0.0029*	0.0128
			(0.0165)	(0.0123)	(0.0124)	(0.0486)	(0.0749)	(0.0242)	(0.0202)	(0.0017)	(0.0234)
$P*(Factor-\mu_F)*D$19			0.0462***	0.0603***	0.0410***	0.0233	0.2205***	-0.0136	0.0119	-0.0024**	-0.0382***
			(0.0113)	(0.0075)	(0.0089)	(0.0448)	(0.0486)	(0.0144)	(0.0120)	(0.0010)	(0.0140)

Notes : This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to those of Tables 1 and 3. 'Base' and 'Malaria' regressions are adopted from Table 3. 'Factor' means the value of agricultural factors denoted in the head of each column. μ_F is its average value. The detailed information of each agricultural factor is reported in page 5 of this draft. In models (3)-(11), we also controlled for (1) the interactions between climate and factor without century dummy and malaria, (2) factor with century dummy, and (3) factor without century dummy.

Table 5. Explaining Differential Weather Sensitivity: Crop Selection

Dependent variable: ln(county average farmland value per acre)

	Basis	Malaria	Cotton	Tobacco	Rice	Wheat	Corn	Barley	Oats	Rye
Key Control Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature (*T*)*D19	-0.0520***	-0.0286***	-0.0072	-0.0345***	-0.0348***	-0.0332***	-0.0155	-0.0296***	-0.0240***	-0.0252***
	(0.0063)	(0.0093)	(0.0104)	(0.0092)	(0.0090)	(0.0092)	(0.0108)	(0.0092)	(0.0093)	(0.0092)
Precipitation (*P*)*D19	-0.0114***	0.0016	0.0020	0.0034	-0.0004	0.0050	-0.0020	0.0048	0.0019	0.0020
	(0.0029)	(0.0064)	(0.0069)	(0.0063)	(0.0063)	(0.0064)	(0.0078)	(0.0063)	(0.0064)	(0.0063)
$(T-\mu_T)*(P-\mu_P)*D19$	-0.0020***	-0.0008*	-0.0005	-0.0007	-0.0010**	-0.0005	-0.0009**	-0.0007	-0.0008*	-0.0008*
	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)
$T*Malaria*D19$		-0.1596***	-0.2045***	-0.1677***	-0.1534***	-0.1107***	-0.1297***	-0.1598***	-0.1520***	-0.1564***
		(0.0382)	(0.0428)	(0.0376)	(0.0375)	(0.0374)	(0.0399)	(0.0374)	(0.0371)	(0.0376)
$P*Malaria*D19$		-0.0785***	-0.0841***	-0.0811***	-0.0618**	-0.0765***	-0.0729**	-0.0858***	-0.0753***	-0.0822***
		(0.0281)	(0.0294)	(0.0274)	(0.0273)	(0.0270)	(0.0289)	(0.0271)	(0.0274)	(0.0272)
$T*(Crop-\mu_C)*D19$			0.2159*	-5.4906***	1.5995	0.0836**	0.2122***	0.2060	0.3000**	2.0222***
			(0.1127)	(1.3061)	(2.3045)	(0.0384)	(0.0622)	(0.2860)	(0.1310)	(0.6301)
$P*(Crop-\mu_C)*D19$			-0.0449	0.7215*	-0.1793	0.1647***	0.0096	0.3113***	-0.0020	-0.6937**
			(0.0442)	(0.4104)	(0.3382)	(0.0247)	(0.0391)	(0.1176)	(0.0662)	(0.2956)

Notes: This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to those of Tables 1, 3 and 4. 'Crop" means the percentage of crop (as denoted in the head of each column) out of total available crop land. μ_C is its average value.

Table 6. Explaining Differential Weather Sensitivity: Change in Agricultural Factors

Dependent variable: ln(county average farmland value per acre)

Key Control Variables	Basis (1)	Malaria (2)	Δ % Cropland (3)	Δ % Improved Farmland (4)	Δ Crop HHI (7)	Δ % Cotton Acres (8)	Δ % Tenants (9)	Δ Fertilizer Cost (10)
Temperature (*T*)**D* 19	-0.0520***	-0.0286***	-0.0348***	-0.0275***	-0.0279***	-0.0164*	-0.0249***	-0.0275***
	(0.0063)	(0.0093)	(0.0082)	(0.0088)	(0.0088)	(0.0097)	(0.0091)	(0.0092)
Precipitation (*P*)**D* 19	-0.0114***	0.0016	0.0085*	0.0071	0.0026	-0.0021	0.0037	0.0022
	(0.0029)	(0.0064)	(0.0049)	(0.0065)	(0.0060)	(0.0066)	(0.0066)	(0.0065)
$(T-\mu_T)*(P-\mu_P)*D$ 19	-0.0020***	-0.0008*	-0.0002	-0.0002	-0.0006	-0.0010**	-0.0005	-0.0007
	(0.0003)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
*T*Malaria*D* 19		-0.1596***	-0.1162***	-0.1350***	-0.1489***	-0.1922***	-0.1813***	-0.1625***
		(0.0382)	(0.0334)	(0.0350)	(0.0360)	(0.0398)	(0.0383)	(0.0380)
*P*Malaria*D* 19		-0.0785***	-0.0867***	-0.0753***	-0.0779***	-0.0642**	-0.0831***	-0.0783***
		(0.0281)	(0.0223)	(0.0272)	(0.0261)	(0.0278)	(0.0278)	(0.0277)
$T*(\Delta Factor-\mu_{\Delta F})*D$ 19			-0.0077	0.0320**	-0.1795***	-0.0460	0.0007**	0.0241***
			(0.0131)	(0.0126)	(0.0395)	(0.0909)	(0.0003)	(0.0093)
$P*(\Delta Factor-\mu_{\Delta F})*D$ 19			0.0242***	-0.0288***	-0.0391**	0.0709***	0.0005**	-0.0146
			(0.0076)	(0.0078)	(0.0197)	(0.0271)	(0.0002)	(0.0099)

Notes : This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to those of Tables 1, 3, 4 and 5. 'ΔFactor' means the change of agricultural factors denoted in the head of each column. $\mu_{\Delta F}$ is its average value. The detailed information of each agricultural factor is reported in page 5 of this draft.

Table 7. Differential Weather Sensitivity and Malaria, using Alternative Farm Productivity Measures

	ln(Farm Value per Farmer)		ln(County Population per Acre)		ln(Value of Total Farm Output per Acre)		ln(Value of Crops per Acre)		Cotton Yields per Acre (only Cotton Counties)	
Key Control Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature (*T*)**D* 19	-0.0580*** (0.0093)	-0.0279*** (0.0106)	-0.0520*** (0.0063)	-0.0694*** (0.0161)	-0.0631*** (0.0125)	-0.0255* (0.0149)	-0.1132*** (0.0149)	-0.1108*** (0.0149)	-0.0499*** (0.0094)	0.0501 (0.0354)
Precipitation (*P*)**D* 19	-0.0336*** (0.0045)	0.0149* (0.0076)	-0.0114*** (0.0029)	0.0418*** (0.0096)	-0.0441*** (0.0066)	0.0475*** (0.0092)	-0.0027 (0.0073)	0.0102 (0.0102)	-0.0084 (0.0059)	-0.0029 (0.0172)
$(T-\mu_T)*(P-\mu_P)*D$ 19	0.0012* (0.0007)	-0.0008 (0.0006)	-0.0020*** (0.0003)	0.0006 (0.0006)	0.0005 (0.0009)	0.0017** (0.0007)	-0.0014 (0.0010)	-0.0009 (0.0007)	0.0006 (0.0007)	0.0009 (0.0009)
*T*Malaria*D* 19		0.0627 (0.0383)		0.0881 (0.0599)		-0.0046 (0.0564)		-0.0209 (0.0605)		-0.2898*** (0.0987)
*P*Malaria*D* 19		-0.0574* (0.0344)		-0.1374*** (0.0411)		-0.2209*** (0.0405)		-0.0063 (0.0470)		-0.0209 (0.0455)

Notes : This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to those of Tables 1 and 3.