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ARTICLE

Malaria and economic activity: Evidence from US agriculture

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Abstract

I conduct a disaggregated empirical analysis of the relationship between the reduction in malaria transmission and agricultural development in the United States. Exploiting exogenous geographic variations in malaria-suitable weather conditions and using historical county data together with a robust quasi-experimental approach, I show that the farm value per acre of arable land of more endemic counties increased by around eight percentage points after the eradication of the disease relative to less endemic counties. Using historical data on cropland distribution within the United States, I also find that arable land increased in high malaria-risk areas. Finally, I shed light on the increased productivity of farmers as a potential channel. Robustness checks from geographic variations in malaria prevalence within neighboring counties and placebo treatments reinforce the positive effect of eradicating malaria on agricultural development in the United States.

KEYWORDS

arable land, farm output, farm value, malaria, natural resources

JEL CLASSIFICATION

I15, N31, N32, O13, Q12

1 | INTRODUCTION

Improvements in general health conditions constitute an essential determinant in explaining comparative socio-economic development, with medical progress dramatically increasing life expectancy

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and labor productivity over the last century (Bleakley et al., 2014; Deaton, 2013). Nonetheless, when not matched by greater availability of natural resources, the associated increase in population might generate adverse effects on economic development and political stability (Acemoglu et al., 2020; Acemoglu & Johnson, 2007).

Particular importance has been given to malaria and associated vector-borne diseases, which are critical environmental and development economics concerns. Recent studies predict that future climatic conditions will likely be more favorable for spreading the disease (Caminade et al., 2014; Medlock & Leach, 2015). Therefore, understanding the historical socio-economic impacts of climate-related diseases on natural resources is critical to predicting how economies will be economically affected by climate change in the future.

This study provides evidence of the historical impact that the eradication of malaria had on farm value per acre of arable land in the United States and investigates the underlying mechanisms. Results reveal that, first, through exogenous variations in climatic conditions that are more or less suitable for the transmission of malaria, eradicating vector-borne diseases significantly increased the value of the land in more endemic counties compared to less endemic ones. Second, the boost in farm value per acre of arable land stemmed from the increase in farm output per farmer. This last result is in line with the literature investigating the eradication of malaria and better health of affected people (Barreca, 2010; Bleakley, 2003, 2010a).

The empirical analysis relies on a treatment/control strategy using a difference-in-difference (DID) estimation comparing farm value and output per acre of arable land between United States counties with climatic conditions more and less suitable for malaria transmission. This approach is permitted because sufficient time has passed to evaluate the long-term consequences of the eradication. Furthermore, the United States is well suited for this analysis for three reasons: First, the United States shows a remarkable degree of heterogeneity in weather variables, which in turn allows for sufficient variability in the malaria suitability values; second, reliable historical county-level data on agricultural output is available across the 1900s; and third, there is general scientific consensus on the first significant attempt to eradicate malaria in the United States, which took place in the early 1900s (Barreca, 2010; Gooch, 2017).

To guarantee the exogeneity of the identification of endemic counties, this study employs a spatial, time-invariant malaria stability index (MSI) created by Kiszewski et al. (2004). The MSI is based only upon climatic conditions that are more or less suitable for the reproduction of two particular species of mosquitoes, namely Plasmodium falciparum and Plasmodium vivax.

In addition to the MSI, I use a second measure of the spatial prevalence of malaria in the United States, namely the malaria risk index (MRI) developed by Hong (2007) and updated in Hong (2011). Similar to the MSI, the MRI utilizes ecological characteristics but weights them using reports of malaria from US army forts in the 19th century. Therefore, the MRI has the advantage of capturing the historical incidence of malaria in the United States, specifically before the onset of vector-control policies. The reasoning behind the inclusion of the second index of malaria incidence in the United States is that although the MSI has extensively been used in both scientific and economic studies, it provides a global measure of malaria prevalence, and it is not explicitly calibrated to finely measure its diffusion in the United States.

The exogenous variations in weather conditions that are more or less ideal for malaria transmission allow for a comparison between highly malaria-suitable counties and those showing a low malaria stability to determine the effects of the eradication campaigns on farm value per acre of arable land. The results obtained with the MSI are similar to those obtained with the MRI. County-specific demographic, farming, and crop suitability controls are included in the regressions in addition to the inclusion of year, county fixed effects, and state-specific linear trends. The county-specific suitability for cultivating four major cereal crops (i.e., soybean, maize, wheat, and rice) is included to account for possible effects on the farm value per acre of arable land caused by the different types of crops produced in each county.

Results reveal that eradication campaigns in the United States, which occurred between the 1900s and the 1920s (with the administration of quinine and the drainage of wetlands, as well as the development of new effective drugs and chemical components later), had significant positive effects on the farm value and output per acre of arable land. In particular, a standard deviation increase in the MSI is associated with a 8.8% point increase in total county farm value per acre, whereas a standard deviation increase in the MRI is associated with a 7.3% point increase in farm value per acre.

The first channel through which malaria transmission might impact agricultural development is linked to farmers' health, notably the most affected part of the population (Brown & Kramer, 2013; Robert et al., 2003; Tatem et al., 2008). The whole harvest will indeed be negatively affected if a farmer contracts malaria during the harvesting period. The adopted strategy aids in determining whether this is the case. The estimates provide suggestive evidence that the increased land value and output of counties with a higher incidence of malaria was primarily due to the increase in farmers' labor productivity resulting from better health after eradicating malaria.

Land-use conversion is another potential mechanism explaining the positive effects of the eradication of malaria disease on farm value per acre of arable land. In the United States, the drainage of swamps and wetlands was one of the oldest and most ordinary forms of land modification undertaken to improve health and lower the transmission of vector-borne diseases such as yellow fever and malaria. Surface water removal was thus a predominant public policy objective in the United States during the 20th century. This conversion of unused wetland into arable and more productive land might have increased the farm value and output per acre of arable land of endemic areas (Lanz et al., 2017). I specifically address this possibility and test this hypothesis. The results suggest that vector-borne control policies did increase the amount of arable land in counties with a high or very high risk of malaria transmission only, whereas no significant difference is found among areas with low-to-moderate risk of malaria.

One potential limitation of the present study is the possible endogeneity of the treatment. In other words, more endemic counties could have received the newly available treatments before the chosen cut-off date. Consequently, before taking 1900 as given, I adopt a series of strategies to examine whether there was an existing trend between the prevalence of malaria and farm value per acre of arable land before 1900 and whether the cut-off date is correct, with no other cut-off producing statistically significant results.

First, I implement a fully flexible estimating equation in which the treatment is interacted with a time dummy taking value equal to one for each decade.[1] Second, I implement placebo treatment tests to verify that 1900 is the only cut-off date and alternative dates yield not statistically significant results. Once again, the results show no different trends in farm values and output between more or less endemic counties before 1900.

Furthermore, to corroborate the validity of the estimates, I restrict the sample to neighboring counties showing a great degree of heterogeneity in the malaria indexes. This also alleviates concerns about including many potential endogenous factors affecting agricultural development (e.g., government policies and investments) that cannot be considered in this study because of the lack of such historical variables or plausible instruments. The evidence presented from the neighboring counties' analysis reinforces the positive effect of malaria eradication on farm value and output per acre of arable land.

This paper relates to several literatures. First, understanding the deep causes of divergent economic development has always been fascinating for economists and historians, and health conditions represent one documented cause of the socio-economic growth of different areas of the world. The effects of malaria and its eradication during the 20th century have been the object of several economic studies. Specifically, Bleakely (2003, 2009) and Cutler et al. (2010) have demonstrated how improved health (due to vaccination and disease prevention programs) affects gross domestic

[1]With flexible estimates, no relationship is expected between malaria prevalence and farm value and output per acre of arable land before the year 1900. That is, the estimates must be close to zero until the cut-off period.

product (GDP) indirectly through educational gains (better children's health translates into higher education levels and in turn into higher future income). These gains at the individual level will directly translate into GDP per capita gains unless the increase in population (also due to lower mortality) outweighs these productivity and educational gains.

To this regard, Gooch (2017) found a positive effect of the malaria eradication campaigns on population and population density during the 20th century. On the other hand, Acemoglu and Johnson (2007), Asharf et al. (2008), and more recently, Hansen and Lønstrup (2015) found that the decreased mortality rate due to scientific advancements has positively impacted population, whereas negligible or no effects were found on GDP per capita. Thus, although micro studies at the individual level have shown a positive impact of eradicating malaria, the aggregate effect on the economy is still debated. That being said, because malaria is generally more prevalent in rural areas than urban ones, with farmers being the most affected individuals (Robert et al., 2003; Tatem et al., 2008), eradicating the disease might generate an exogenous positive shock on farm value per acre of arable land. This study is the first to examine this relationship empirically.

Second, this paper relates to economic literature focusing on the relationship between agricultural shocks and economic growth. Adams (1989) first studied the relationship between global climate change and agriculture. Later, Wu and Gopinath (2008) and Gollin et al. (2014) examined world agricultural output rates using new disaggregated data and concluded that understanding agricultural development is at the heart of understanding world income inequality. Bustos et al. (2016), who studied the effects of adopting new agricultural technologies on structural transformation in Brazil, reached similar conclusions, finding that an exogenous positive agricultural shock caused by technological change led to industrial growth. Therefore, assessing the historical effects of malaria on agricultural development within the United States could also be crucial for understanding differences in the economic development of different United States areas during the 20th century.

2 | HISTORICAL BACKGROUND AND RELATED LITERATURE

There is general consensus on the role of malaria as a major factor explaining differential trajectories in the economic development. Until the early 1900s, the southeastern US and Europe were primarily affected by the disease. Figure A.1, in the online supplementary appendix, reports the global distribution of malaria since 1900 and is obtained from Lysenko and Semashko (1968).

The first significant discovery that reduced the diffusion of malaria was quinine in the late 17th century when it was initially imported into Spain as a curative plant. Nevertheless, people were reluctant to consider it as an accurate measure against malaria due to its bitter taste. Consequently, its beneficial effects were not fully understood for almost two centuries. It was not until the 20th century that medical innovations and modern chemical components made it possible to prevent malaria transmission.[2]

In the United States, quinine was made available at every state hospital in the early 1900s thanks to donations from the Rockefeller Foundation and the newly established United States Public Health Services (USPHS) with new methods such as the spraying of larvicides and wetland conversion. By 1912, each state's board of health followed the USPHS model.[3]

Thus, until the early 1900s, scientific advancements were not adequate to treat malaria. This caused more than 80% of the countries in the world to be affected by vector-borne diseases (Gallup &

[2]Only in 1898 Ronald Ross of the British Indian Medical Service discovered the association between malaria and the bite of a particular specie of mosquito (Ross, 1898). The second episode of malaria eradication in the United States took place between the 1930s and 1940s, with the availability of the DDT and lasted until malaria was declared eradicated in all United States states in 1952. The background section provides a detailed description of the attempts to eliminate malaria transmission and its associated vector-borne diseases in the United States.

[3]Williams (1952) presented a thorough history of the US Public Health Service. Humphreys (2001) and Saul (2002) summarized the history of malaria control efforts in the US. The Rockefeller Foundation's International Health Board (1919) annual report provides information about its anti-malaria demonstration projects. Much historical detail regarding the US is drawn from these sources.

Sachs, 1998). In the United States, before the implementation of vector-control policies, the problem was so severe that, for some southeastern counties, more than 10% of deaths from all causes were induced by malaria alone (Humphreys, 2001; Saul, 2002). In other words, 1 in 10 people died because of reasons linked to malaria. Figure A.2 in the online supplementary appendix details the proportion of deaths caused by malaria to the total number of deaths.[4]

In addition, throughout the 20th century, US agricultural production and prices have dramatically changed for reasons beyond the eradication of malaria and related vector-borne diseases. Figure A.3 in the online supplementary appendix shows the production (blue line) and prices (green line) of agricultural products in the United States between 1900 and the present day.[5] From this figure, it first emerges that real agricultural prices have trended downward since 1900. On the other hand, agricultural production increased in the same period. Second, agricultural prices dropped remarkably following three separate events from 1900 to 1950. The first shock occurred after WWI (1918–1920). The second shock happened during the great depression (1929–1932), and the third negative shock occurred with the onset of WWII (1939), followed by a slight increase after WWII terminated.

Bleakley (2010b) reports that during the first 20 years of early interventions against malaria, mortality rates from malaria declined by more than 70%. Similarly, Lucas (2013) found evidence of an increase in fertility rates after the eradication of malaria. Following the first positive results of the fight against malaria until the 1920s, a slight resurgence of the disease followed between the 1930s and 1940s, caused by the Great Depression and the Second World War. Finally, the use of Dichlorodiphenyltrichloroethane (DDT) and newly discovered chemical components further reduced the burden of malaria to negligible levels during the early 1940s.[6]

Economic literature has extensively studied the relationship between disease and economic growth loss, paying particular attention to malaria (Olmstead, 2020). Gallup and Sachs (2000) and Sachs and Malaney (2002) first highlighted the correlation between malaria transmission and economic growth, arguing that reversed causality would not pose a substantial problem.

Microeconomic papers have focused on the impact of different disease control policies on human capital, providing ample evidence of the positive impact of disease prevention campaigns on individual education levels, which are widely regarded as fundamentals of the persistent economic growth, according to Bleakley (2007, 2010a), Cutler et al. (2010), and Bleakley et al. (2014). Hong (2007), Barreca (2010), and Lucas (2005) find significant effects of either exposure to malaria or its eradication on schooling attainments, labor force participation, and individual wealth. Moreover, Brinkley (1995) examines the role that hookworm played in agricultural outputs, finding a negative relationship between hookworm infection and agricultural farm income per capita.

On the other hand, macroeconomic studies have generally emphasized the Malthusian view, arguing that the expansion in population in the short term due to the increase in life expectancy could not be matched by an increment in the availability of natural resources, thus leading to modest (if any) improvements to GDP per capita (Acemoglu & Johnson, 2007; Ashraf et al., 2008; Hansen & Lønstrup, 2015).

Acemoglu and Johnson (2007) and Hansen and Lønstrup (2015) argue that microeconomic studies likely overestimate the real impact of disease transmission reduction because they do not control for the general equilibrium effects of increased life expectancy due to reduced mortality. By instrumenting life expectancy with the predicted mortality rates of 15 major diseases of the 20th century, Acemoglu and Johnson (2007) found a negative relationship between the mortality rates and

[4]The map in Figure A.2 was created by Francis A. Walker using data from the Statistical Atlas from the Ninth Census of the United States in 1870.

[5]The agricultural price index is retrieved by the USDA Economic Research Service, using data from the Grilli–Yang agricultural commodity price index, the World Bank manufacture unit value (MUV) price index.

[6]Digitizing historical maps, Hay et al. (2004) quantified the anthropogenic impact on the distribution of malaria in the 20th century at six intervals between 1900 and 2002 (i.e., 1900, 1946, 1965, 1975, 1994, and 2002), with 1900 being the last year before the first adoption of eradication policies.

GDP per capita growth. Finally, using highly disaggregated data, Gooch (2017) revealed the positive effect of malaria eradication on world population and population density. That said, macroeconomic studies only consider mortality rates rather than data morbidity rates. Consequently, the economic burden of the infectious disease is likely to be underestimated because only a fraction of people affected by malaria effectively die. At the same time, most individuals find themselves physically debilitated and thus working inefficiently.

It is also essential to note that before any intervention against malaria, large portions of endemic countries' land were uncultivated or barely cultivated because of the prevalence of mosquitoes in those regions.[7] This means that the eradication of malaria could have allowed the cultivation of large portions of land that could not be used when malaria was prevalent. This greater availability of arable land could therefore have resulted in higher agricultural output, counterbalancing the increased population.

Nevertheless, none of those studies has yet attempted to evaluate the impact of malaria eradication on historical farm value and output per acre of arable land. Thus, establishing a clear relationship between malaria and farm value is crucial to understanding the causes of the historical economic development of different areas of the United States. Furthermore, it is essential to assess whether the impact of vector control on farm value was due to a mere increase in arable land (i.e., due to wetland conversion to cropland) or to an increase in the productivity of farmers who were no longer affected by malaria.

3 | DATA

This section describes the dataset used to construct the dependent variable, along with the treatment and the associated county-level weather, agricultural, and demographic controls.

To ensure a robust empirical investigation, I use two indexes measuring the spatial incidence of malaria in the United States, void of anthropogenic influences. The first index, developed by Kiszewski et al. (2004), considers climate variables only, making the survival of mosquito larvae more or less favorable. The second index, developed by Hong (2007, 2011) is specifically designed for the United States and considers the actual prevalence of malaria in the United States before any implementation of eradication policies. An interaction is triggered between the post-eradication indicator and the two measures of malaria prevalence in the United States.

To measure county farm value from 1870 to 1950, I use the natural logarithm of farm value and farm output per county acre of arable land. Finally, time-series gridded data on the total amount of historical cropland is also used to assess whether eradicating malaria increased the available cropland. The next section provides a detailed description of the data used.

3.1 | Measuring spatial prevalence of malaria

Malaria stability index

First, counties with climatic conditions ideal for the transmission of malaria and associated vector-borne diseases (i.e., warmer and more humid weather throughout the year) were identified using the MSI. The MSI was first developed by Kiszewski et al. (2004) and is a spatially disaggregated time-invariant global index representing malaria transmission stability. Biologically, the MSI measures the suitability of climatic conditions, which foster the reproduction of two particular species of

[7]For instance, as Brown (2017) reported in 1898, Fortunato and Franchaneti wrote a letter to their sponsor indicating the devastation caused by this disease in Italy: "Malaria disease leaves uncultivated 2 million hectares of land. It poisons every year about 2 million inhabitants and kills 15,000 of them. There is no other health problem so deeply linked to the prosperity of our country."

mosquitoes that are the natural vehicles of malaria. In their original paper, Kiszewski et al. (2004) indicated that regions such as Sub-Saharan Africa, Latin America, and Southeast Asia present the ideal climatic conditions for the reproduction of species of mosquitoes transmitting malaria to human beings.

Nevertheless, malaria was also prevalent in many other regions of the world. The eastern United States, southern Europe, and northern Australia are notable examples of endemic areas. The MSI is a continuous variable ranging from 0 to 39, where 0 represents a malaria-free grid, and 39 denotes weather conditions most suitable for the survival and reproduction of mosquito larvae.[8] A categorical version of the suitability index also exists. Grids with values from 0 to 0.05 are considered malaria free, whereas grids with values greater than 0.06 present climatic conditions suitable for a certain persistence of malaria transmission. Kiszewski et al. (2004) differentiated suitability levels into nine categories: $0-0.05$, $0.06-1$, $1.01-2$, $2.01-5$, $5.01-8$, $8.01-12$, $12.01-18$, $18.01-25$, and $25.01-39$.

The MSI has been used in several recent papers in development economics thanks to its advantage of being independent of any anthropogenic influence (Alsan, 2015; Giuliano & Nunn, 2013; Michalopoulos & Papaioannou, 2013; Easterly & Levine, 2016; Henderson et al., 2017). The use of a time-invariant index representing each county's suitability to the transmission of malaria and related vector-borne diseases is crucial to alleviate potential endogeneity issues. Another benefit of the MSI is that it is precise because it is based on information measured with contemporary geographical information system (GIS) software. This may explain why the suitability index captures moderate malaria prevalence more effectively.

The MSI is at a 0.5° latitude x 0.5° longitude, which corresponds approximately to 56 x 56 km at the equator.[9] To obtain the average MSI value for each US county, I intersect the spatial data on malaria with historical US county borders.[10] This procedure generates a time-invariant MSI for each county based on climatic conditions only.

Because the present study merges spatial data on historical county boundaries with 0.5° latitude x 0.5° longitude gridded data on malaria stability values, some historical counties had an area that was less than that of a grid. To fix this issue, the MSI is interpolated at a highly disaggregated geographic level (i.e., 0.2° latitude x 0.2° longitude) to yield at least one suitability value for each county.[11] Then, the mean of the index is calculated for each county.

The results from the intersection of the MSI and the historical US counties are presented in Panel A of Figure 1, which shows the spatial distribution of the MSI in the United States. It is worth noting that the MSI relative to the US territories ranges from 0 to ∼2. This means that malaria transmission was largely unstable, implying that climatic conditions suitable for mosquito larvae's survival and reproduction were mainly concentrated in one season (e.g., summer).

Malaria risk index

The second measure of the historical incidence of malaria in the United States used in the analysis is the estimated malaria risk developed by Hong (2007, 2011). This index was constructed by using surgeons' reports on the annual incidence of malarial fevers among soldiers at 143 US forts during the mid-19th century. Hong (2007) first estimated the correlation between county-specific malaria incidence rates at forts and the climate variables of those forts, such as temperature, rainfall, and

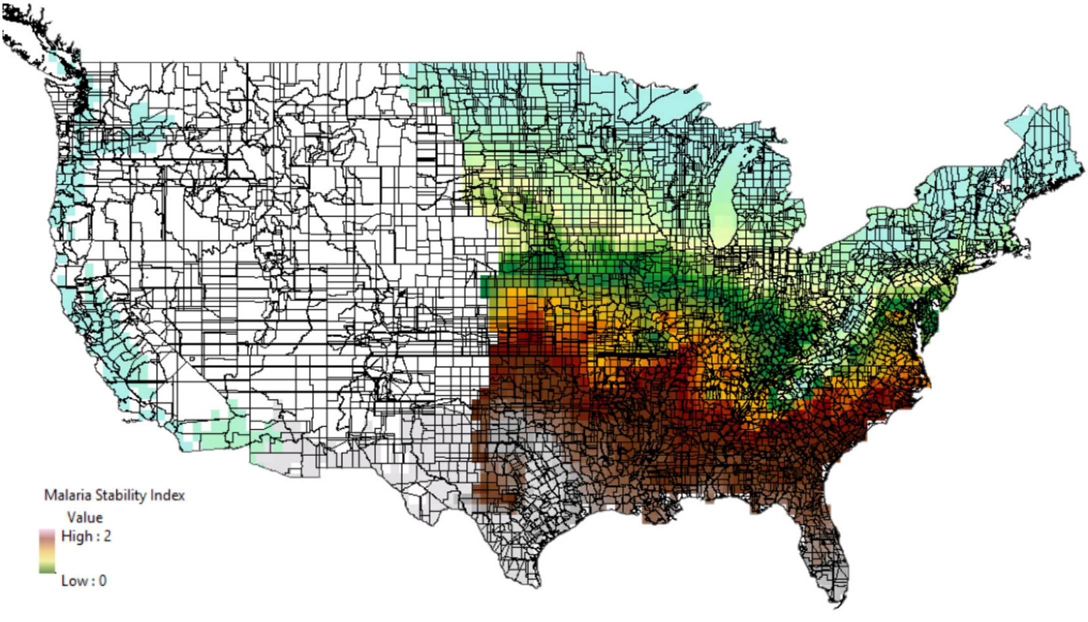
[8]Although the suitability index developed by Kiszewski et al. (2004) ranges from 0 for malaria-free areas to 39 for areas with weather conditions highly suitable to a persistent reproduction of the Plasmodium falciparum and Plasmodium vivax species, values in the United States range mainly from 0 to 2.

[9]Weather data used for constructing the MSI comprises monthly average, minimum and maximum temperature, humidity, and precipitations. The Climate Research Unit at the University of East Anglia provides climatic data.

[10]Spatial data on historical US county borders is retrieved from the Newberry of historical county borders of the Newberry Library. The historical US county borders contain publicly available spatial data on counties from 1629 to 2000.

[11]The natural neighbor interpolation method, automatically computed by the GIS software, is employed.

Panel A



Panel B

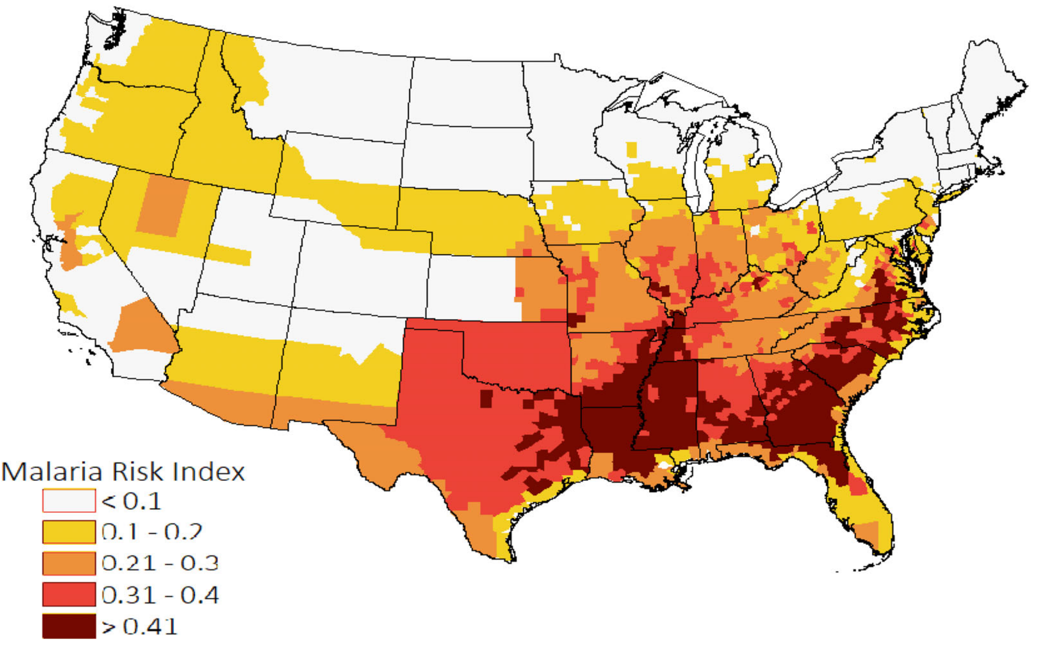


FIGURE 1 Graphical representation of the malaria stability index (MSI) (Panel A) and the estimated Malaria Risk Index (MRI) (Panel B) in the US. The MSI captures the potential stability of malaria transmission based on regionally dominant vector mosquitoes, temperature and precipitation data set (Kiszewski et al., 2004). This is intersected with US historical county borders (Ruggles et al., 2015). The MRI captures the estimated distribution of malaria risk in the US at the county level in the 1850s (Hong, 2007).

elevation. Then, using these correlates and county-level environmental factors, he estimated the malaria risk for US counties that did not have reliable statistics. The result is the MRI, a continuous variable capturing malaria distribution in the 1850s, before the onset of any malaria eradication policies.

MRI values range from 0 to 0.6, where values between 0 and 0.1 represent no risk of malaria. An MRI between 0.1 and 0.2 indicates a relatively low risk, whereas values between 0.2 and 0.3 represent a medium risk of malaria. Values between 0.3 and 0.4 represent a high risk of malaria, whereas values above 0.4 indicate the highest risk of malaria. Panel B of Figure 1 depicts the estimation results of the index developed by Hong (2007, 2011). Notably, risk rates were higher in the south-eastern regions of the United States.

The final dataset comprises 1703 US counties. Summary statistics are reported in Table A.1 in the online supplementary appendix and show that the average MSI and MRI were respectively 0.056 and 0.243. In particular, 249 counties showed no risk of malaria (i.e., MRI < 0.1); 442 counties showed low risk of malaria (i.e., 0.1 < MRI < 0.2); 439 counties showed moderate risk of malaria (i.e., 0.2 < MRI < 0.3); 319 counties showed high risk of malaria (i.e., 0.3 < MRI < 0.4); whereas 254 counties showed very high risk of malaria (i.e., MRI > 0.4).

3.2 | Farm value and output in the United States

Because malaria primarily affects farmers living in rural areas, we expect that eradicating the vector-borne disease resulted in significant increases in the land value and output per acre of arable land of the once-endemic areas. Historical, demographic, economic, and social data are as follows: The United States, 1790–2002 (Haines, 2005) provides two valid historical measures of agricultural development available for each US county. Those are the total farm value and farm output per county acre of arable land. By dividing the farm value (and farm output) per county acre of arable land, I consider the possibility of an increase in arable in more endemic counties. As a result, any increase in arable land is taken into account in the empirical procedure, which is described in the next section.

Farm value per county acre is defined as the value of all farmland, housing, and outbuildings at the time of census enumeration divided by the number of acres of arable land of a specific county. Farm value can be interpreted as land price because the value of the land on the farm accounts for a large portion of farm value (Bleakley & Hong, 2017).

Similarly, farm output is defined as the total value of all farm products, such as crop and livestock products, within the year before the enumeration day. Unfortunately, two separate issues are associated with farm output values. First, data between 1910 and 1930 is not available, and second, a double-counting issue exists because, as the US Bureau Census (1951, p. 26) reports, about half of corn production and the whole hay production returned in the census for the years until 1900 were consumed for the annual product of animal food. In other words, if the values of both the vegetable and the animal products are both counted, there will be a duplication of farm output. I address this possible concern in the next section.

Historical, demographic, economic, and social data are as follows: The United States, 1790–2002 provides data on farm value per county registered at each agricultural census starting from 1850 and undertaken every decade until 2000. Unfortunately, the quality of the farm census was acceptable only from 1870. This determined the choice to use farm value and farm output starting from 1870.

Another worthwhile consideration is the change in county boundaries during the period 1870–1950. These changes in county boundaries are important when county fixed effects are considered. As in Bleakley and Hong (2017), to partially fix the problem, farm value and all other variables are adjusted at the county level, which is controlled for the 1870 county boundary using the area-weighted average method.

Figure 2 shows the average annual farm value per county acre of arable land growth rates per US county for the period 1870 to 1900 (Panel A) and for the period 1900 to 1920 (Panel B). Counties where malaria was widespread experienced higher farm value per acre of arable land growth during the period 1900–1920 relative to less endemic counties.

Moreover, Figure A.4 in the online supplementary appendix depicts the correlation between the estimated risk of malaria and the average decadal growth of farm value per county acre before and after introducing vector-control policies. Panel A shows a negative correlation between the MRI and the farm value per county acre growth between 1870 and 1900. This relationship reversed after the eradication campaigns started in the United States as depicted in Panel B. Finally, this study uses the natural log of farm output value per farmer to assess the possible mechanism behind the increase in the value of once-endemic lands after eradicating malaria.

3.3 | Additional county-level controls

The empirical procedure also controls for county weather conditions, which might have affected farm value and output of more endemic areas. Data on historical county weather variables are retrieved from the US climate data set project developed by the National Climate Data Center. The advantage of this dataset is that it reports monthly mean temperature and monthly accumulated precipitation according to thousands of weather stations that have existed over the past two centuries and was previously used in economic studies (Bleakley & Hong, 2017). However, because temperature and rainfall are not available for all counties, I follow Bleakley and Hong (2017), and attribute the climatic value for a missing county as a weighted sum of the data values in surrounding counties.[12] Following this procedure, I obtain data for temperatures and precipitation by county for each decade for the period 1870–1950.

Finally, to account for possible effects on the farm value per acre of arable land caused by the different types of crops produced in each county, I consider the county-specific suitability for cultivating four major cereal crops (i.e., maize, wheat, and rice).[13]

3.4 | Cropland area

Finally, this study examines the effects of the eradication campaigns against malaria in the United States on the total amount of cropland using time-series gridded data from Klein Goldewijk et al. (2017). Cropland data considers both irrigated and rain-fed crops, whereas grazing land is excluded.[14]

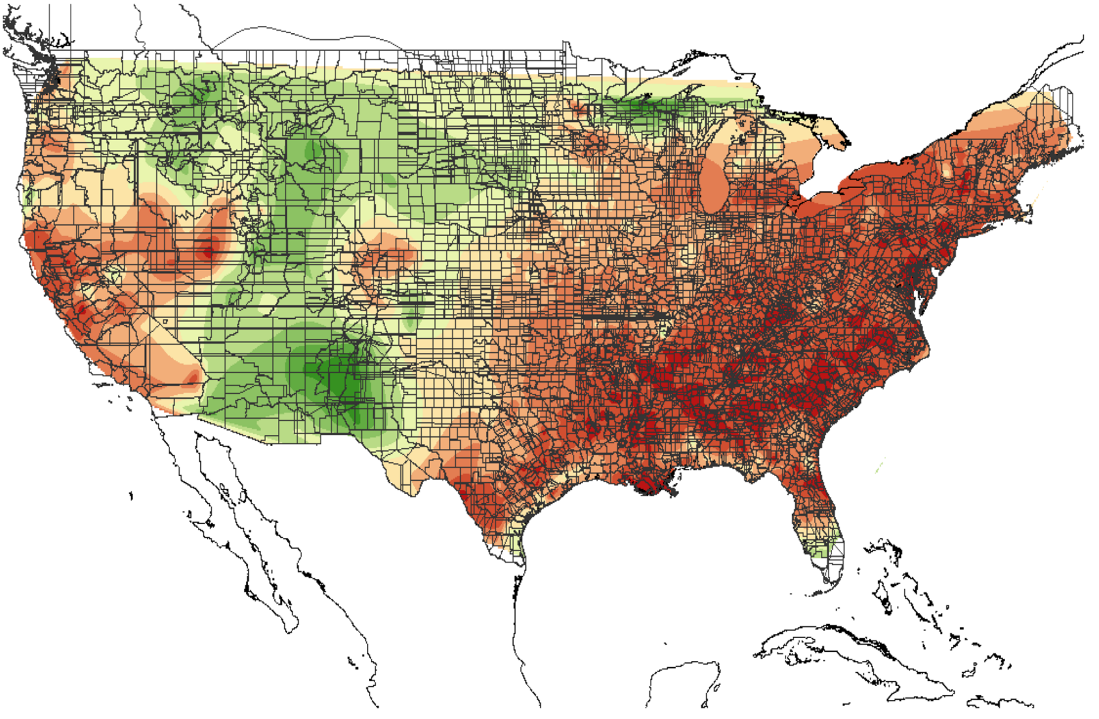
To compute the cropland areas, Klein Goldewijk et al. (2017) started with country totals for the FAO categories of "arable land and permanent crops" (Fritz et al., 2015). The FAO data reach back to 1960, and thus for the period 1960–2015, the FAO data were followed precisely, though complemented in some countries by subnational statistics. For the pre-1960 period, Klein Goldewijk et al. (2017) combined population estimates with per capita land use estimates from Mitchell (2003) for the 1890–1950 period. Further specific input statistics at the US county level were taken from US National Agricultural Statistics Service (NASS, 2008). Detailed information on the computation of cropland area is provided in the online supplementary appendix and in the Klein Goldewijk et al. (2017) documentation paper.

[12]This method is known as "Kriging" and is performed with a GIS software. For each target location Kriging assigns a decreasing weight to weather stations located at a greater distance (Oliver & Webster, 1990).

[13]Crop suitability data comes from the Food and Agricultural Organization (FAO) GAEZ database Fischer et al. (2012)

[14]The estimates for land used for grazing are much more uncertain (Klein Goldewijk et al., 2017).

Panel A



Panel B

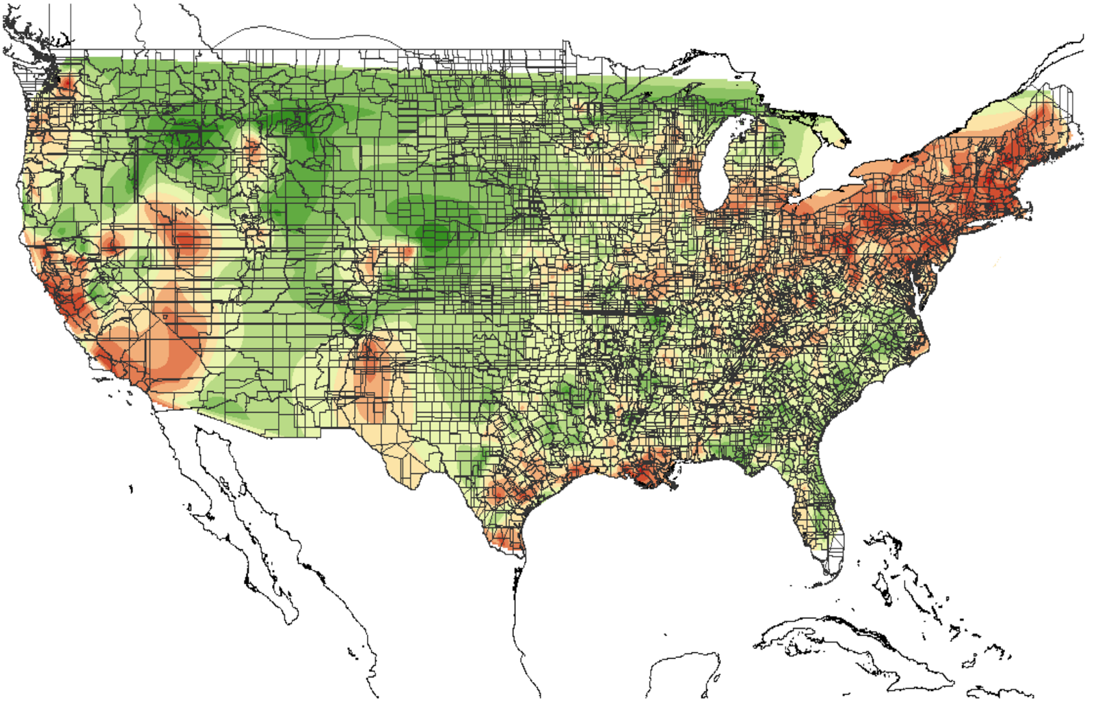


FIGURE 2 Average annual farm value per acre of arable land growth from 1870 to 1900 (Panel) and from 1900 to 1920 (Panel B). Source: Author's calculation using the geographical information system software ArcGis based on the "Historical, Demographic and Social Data. The United States, 1790–2002" (Haines, 2005).

4 | THE EFFECT OF MALARIA ERADICATION ON FARM VALUE AND OUTPUT

This section examines the causal effects of the eradication of malaria in the United States on farm value and output per acre of arable land. First, I describe the econometric strategy in which the treatment is defined as the interaction between the exogenous county variation in malaria prevalence and a post-eradication indicator variable. Then, the underlying mechanisms (i.e., better farmers' health and greater availability of arable land due to land conversion) are discussed using this identification strategy.

4.1 | Empirical framework

The estimation method presented below follows the same logic of a standard DID strategy. This allows for comparisons between farm value of highly endemic and less endemic counties before and after the eradication policies.

The difference between the empirical strategy presented in this study and the standard DID is that the treatment (which in this specific case is represented by the interaction between a post-treatment indicator variable and one of the two indices measuring malaria incidence) is not discrete.[15] It is a continuous measure (i.e., the study does not compare endemic counties with non-endemic ones rather more endemic with less endemic counties). The use of a continuous treatment allows for capturing more variation in malaria incidence. The regression presented below estimates the relationship between the county average MSI and MRI, and farm farm value per acre of arable land per county acre:

$$\begin{aligned} y_{i,s,t} = {} & \alpha \text{ Malaria}_i \cdot I_t^{Post} + \rho_1 T_{i,t} + \rho_2 P_{i,t} + \sum_{t=1870}^{1950} \Omega \mathbf{X}'_{i,s} I_t + \\ & + \sum_{t=1870}^{1950} \delta_t I_t + \sum_p \gamma_p I_t^p + \sum_{t=1870}^{1950} \sum_q \omega_q I_t^q + \varepsilon_{i,s,t} \end{aligned} \tag{1}$$

where index i represents each US county in state s, and t indexes time periods considered in the analysis (i.e., 1870, 1890, 1900, 1910, 1920, 1930, 1940, and 1950).

Based on historical evidence and related studies on the consequences of eradicating malaria, the years from 1870 to 1900 are part of the pre-eradication period. The post-treatment periods are considered after 1900, including 1910, 1920, 1930, 1940, and 1950 when the last round of the National Malaria Eradication Program (United States. Bureau of the Census) (1951) was undertaken (Interagency Working Group on Climate Change, Health (US), National Institute of Environmental Health Sciences, Centers for Disease Control, Prevention (US), United States. National Oceanic, & Atmospheric Administration, 2010).[16] This cut-off, however, is not taken for granted as I directly check for patterns in the data and the robustness of the estimates to alternative cut-offs.

The dependent variable is represented as $y_{i,s,t}$ which is the natural log of farm value and output per county-acre of arable land of county i, in state s, at time t.

The variable Malaria_i is one of the two indices representing the incidence of malaria, that is, the average time-invariant MSI of county i and the estimated MRI of county i. Variable I_t^{Post} is a post-treatment dummy variable that takes value 1 for years after 1900, and value 0 for years before the

[15]Table A.6 in the online supplementary appendix shows estimates of the relationship between malaria prevalence and farm value per acre of arable land using the binary version of the average county MSI following Callaway et al. (2021). Specifically, the MSI takes a value equal to zero for malaria-free counties and a value of one for counties with weather conditions suitable for malaria transmission.

[16]By the end of the 1950s, malaria was eradicated in the US. The successful eradication was also due to newly discovered chemical components such as the DDT that were made available to farmers as an insecticide (Bleakley, 2010b; Acemoglu et al., 2020). In 1972 the US lifted a ban on its usage due to its adverse effects on the surrounding environment and human health.

interventions against malaria. This specification also includes county fixed effects $\sum_p \gamma_p I_t^p$, where p indicates the set of US counties, and time period fixed effects $\sum_{t=1870}^{1950} \delta_t I_t$.

To capture state-specific differences, which might have affected farm value per acre of arable land over time such as different agricultural prices during the 1900s, this study includes state fixed effects interacted with time fixed effects in the baseline specification presented in Equation (1). State-by-time fixed effects are represented as follows: $\sum_{t=1870}^{1950} \sum_q \omega_q I_t^q$, where q indicates the set of US states. With the state-year fixed effects, the coefficient of interest α is identified from within-state variation only; that is, the empirical strategy compares counties within the same state and is therefore subject to the same state policies.[17]

$\rho_1 T_{i,t}$ and $\rho_2 P_{i,t}$ represent respectively the county temperature and rainfall for each decade from 1870 to 1950.

$\mathbf{X}_{i,s}$ represents vectors of time-invariant county-specific agricultural and demographic controls included in the regression. As county-level controls, I use a set of relevant geographical and historical country-specific characteristics that might have affected farm value and output during the 20th century, as in Bleakley and Hong (2017). These are the following: county population density, the ratio of farmland to total available county area, the proportion of farmers reporting the use of fertilizers, the proportion of farmland that reported having received drainage, and the proportion of farmland with improved land and county average agriculture suitability index. Finally, I have also included the ratio of the white population out of the total number of the county population. The reason for the inclusion of this variable as a control is that historically white people owned the vast majority of farmland (Horst & Marion, 2019). Therefore, counties with a higher ratio of the white population might exhibit higher farm value and farm output.

As some of these control variables are endogenous to the eradication of malaria (e.g., demographics), I fix those variables at a base year before the intervention (i.e., 1900).[18]

Equation (1) also controls for the average county suitability for crop cultivation. The agricultural suitability index (ASI) is computed by the Center for Sustainability and Global Environment at the University of Wisconsin-Madison (Ramankutty et al., 2002). To calculate the climate suitability for agriculture, Ramankutty et al. (2002) relied on the weather and environmental conditions required for crop cultivation. Weather conditions were obtained from the global climatic database, compiled by the Climate Research Unit at the University of East Anglia.[19]

Based on historical evidence, the reduction in the burden of malaria resulted from critical scientific innovations overwhelmingly from outside the highly endemic counties and culminated in improved understanding of the origins of the disease and the discovery of new drugs and chemical components (Bleakley, 2007; Cutler et al., 2010; Gooch, 2017). Likewise, no evidence is found of campaigns to eradicate the malarial disease before 1900 (Bleakley, 2003; Gallup & Sachs, 1998).

Moreover, US counties had no decision power in terms of the availability and administration of quinine to people affected by malaria, the use of pesticides, and, later, the DDT and drainage of swamps and wetland (Humphreys, 2001; Williams, 1952). This attenuates possible concerns regarding the endogeneity of the treatment by areas of the US more affected by the vector-borne disease.[20]

[17]In this regard, it is important to emphasize that decisions to tackle malaria along with other vector-borne diseases (i.e., decisions regarding the supply of free quinine and the availability of newly discovered pesticides, among others) were made at the governmental level and implemented by each state. Counties had no power in deciding when and where to implement malaria eradication campaigns.

[18]A correlation matrix between the MSI and MRI on the one hand and these population and agricultural controls on the other is shown in Table A.2 in the online supplementary appendix.

[19]The database includes monthly data on weather conditions (e.g., precipitations, cloud cover, minimum and maximum temperature, and humidity) from 1900 until 2016.

[20]One spillover effect that could alter the interpretation of the results was if the diffusion of medical and technological innovation to US counties might have been hindered by having neighbors that were affected by malaria. To investigate violations of the Stable Unit Treatment Value Assumption, (SUTVA) (Bellemare & Nguyen, 2018), the specification above is modified to allow for specific cross-unit spatial interaction by creating spatial lags using a symmetric weighting matrix W: $y_{i,s,t} = \alpha \text{ Malaria}_i \cdot I_t^{Post} + \lambda \sum_j W_j \cdot \text{Malaria}_i + \sum_{t=1870}^{1950} \Omega \mathbf{X}'_{i,s} I_t + \varepsilon_{i,s,t}$. Here the λ represents the coefficient on the spatial lag of the indexes of malaria. Results reported in Table A.5 reveal that although the estimates of the relationship between the MSI and the MRI on one hand and the county farm value per acre of arable land on the other hand are largely unchanged, the estimates of the spatial lag of malaria are insignificant, suggesting that there is no evidence of spillover effects among nearby counties.

Finally, I test for alternative placebo cut-off dates. Results of placebo treatment periods are reported in Table A.7 in the online supplementary appendix and show that no other cut-off year produces statistically significant estimates.

4.2 | Existence of pretreatment trends

As with a standard DID, the empirical strategy adopted in this study relies on the assumption that no other event besides the availability of new drugs occurred in the early 1900s and affected agricultural development differently in each county. This is a crucial assumption that should not be taken for granted because the US has undergone numerous changes during the 20th century.

Hence, I adopt a number of precautions to examine whether the patterns in the data are consistent with this assumption. First, as described in the background section, the historical evidence suggests that in the US, early effective measures act to prevent the transmission of vector-borne diseases, which began with the establishment of the USPHS in the early 1910s. Given this evidence, the most reasonable cut-off date is 1900, with the year 1910 considered as the first post-eradication period. Second, to exclude the possibility that events other than the eradication of malaria occurred in the 1900s and affected farm value and output differently for each US county, I estimate a fully flexible estimating equation that takes the following form:

$$
\begin{aligned}
y_{i,s,t} = & \sum_{j=1870}^{1950} \alpha_j \text{ Malaria}_i \cdot I_t^j + \rho_1 T_{i,t} + \rho_2 P_{i,t} + \sum_{t=1870}^{1950} \Omega \mathbf{X}'_{i,s} I_t + \\
& + \sum_{t=1870}^{1950} \delta_t I_t + \sum_p \gamma_p I_t^p + \sum_{t=1870}^{1950} \sum_q \omega_q I_t^q + \varepsilon_{i,s,t}
\end{aligned}
\tag{2}
$$

The only difference from Equation (1) is that in Equation 2, rather than interacting Malaria_i with a post-adoption indicator variable, I interact the MSI and the MRI with each of the time-period fixed effects. The estimated vectors of α_j now reveal the relationship between the prevalence of malaria and farm value per acre of arable land in each period (e.g., we will have an estimate α_j for each decade from 1870 to 1950). If no other event occurred in the early 1900s, and the eradication of malaria had a positive effect on the agricultural development, then we would expect the estimated $\alpha_j s$ not to be statistically significant for the years until 1900, while becoming positive and significant after the eradication campaigns. Figure 3 shows the estimated $\alpha_j s$ compared to 1890 (i.e., the last year before the eradication of malaria in the United States started) along with the associated confidence intervals, which confirm our prediction. This robustness exercise also corroborates the robust zeroes for the pre-eradication period obtained with the modified version of the DID, following (De Chaisemartin & d'Haultfoeuille, 2020).

4.3 | Neighboring counties analysis

To further address the concern of the possible existence of differences between more or less endemic counties before the eradication policies, I restrict the sample by comparing neighboring counties that had a different prevalence of malaria. In particular, when considering the MSI, I compare each county showing weather conditions suitable for malaria transmission (i.e., $\text{MSI} \geq 0.06$) with its neighboring counties that presented weather conditions not suitable for malaria transmission (i.e., $\text{MSI} \approx 0$). Neighboring counties are defined as those counties having their centroids within a distance of 2° latitude x 2° longitude. Figure 4 shows the selected counties used for the neighboring counties exercise.

This restriction substantially reduces concerns of any difference between counties with more or less malaria prevalence.[21] The reasoning behind this restriction is that we would be sure to compare very similar counties (because they are very close in distance) and only differ in terms of malaria prevalence.[22]

A total of 549 counties were obtained following the restriction that belonged to a total of 219 - different neighborhoods. I, therefore, create an indicator variable I_n for each neighborhood n considered, which is added in equation (1) so to compare endemic counties with non-endemic counties belonging to the same neighborhood. The estimated regression, therefore, becomes the following:

$$y_{i,s,t} = \alpha_1 \text{ Malaria}_i \cdot I_n \cdot I_t^{Post} + \alpha_2 \; I_n \cdot I_t^{Post} + \rho_1 T_{i,t} + \rho_2 P_{i,t} + \\ + \sum_{t=1870}^{1950} \Omega \mathbf{X}'_{i,s} I_t + \sum_{t=1870}^{1950} \delta_t I_t + \sum_p \gamma_p I_t^p + \sum_{t=1870}^{1950} \sum_q \omega_q I_t^q + \varepsilon_{i,s,t} \quad (3)$$

where Malaria_i is again one of the two indexes measuring the prevalence of malaria interacted with a post indicator variable.

In Equation (3), the coefficient of interest α_1 is identified no more from within-state variations but within-neighborhood variation only. With this restriction, the econometric procedure compares counties very close in terms of distance.

The coefficient α_2, on the other hand, shows the estimate of the relationship between different neighborhoods of counties and the farm value and output after the malaria eradication policies began. Suppose counties with a higher incidence of malaria were effectively different from counties with a lower incidence of the disease. In that case, we should expect the parameter estimates of years before implementing vector control policies to be statistically significant. Figure 5 shows that this is not the case. Results obtained when considering the unrestricted sample of counties are thus confirmed by the restriction of neighboring counties.

5 | RESULTS

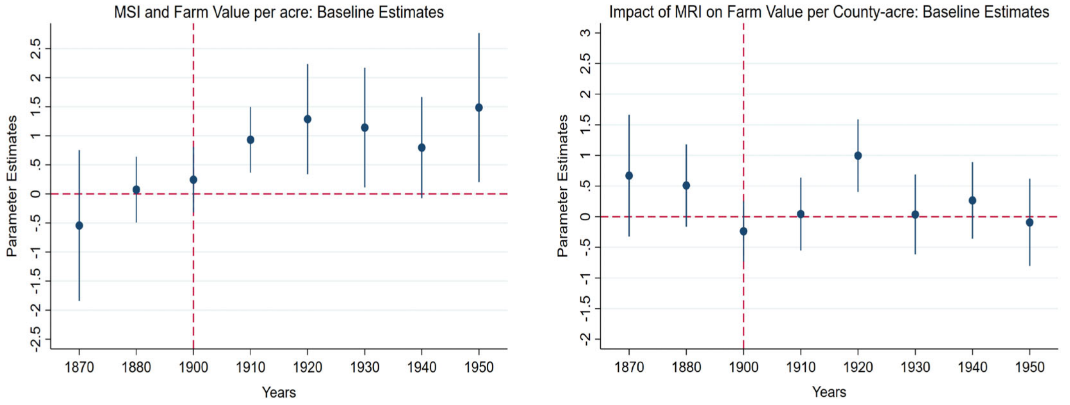
Table 1 reports different specifications of Equation (1), where the variable of interest is the suitability of malaria (Panel A) or the estimated risk of malaria (Panel B). Therefore, the results reported in Table 1 demonstrate the effects of the eradication of malaria after 1900 on the farm value per county acre of counties with initially high weather suitability for the transmission of malaria compared to those with initially less suitability for malaria. Column (1) of Panel A includes only state-specific linear trends and time and county fixed effects. One standard deviation increase in the MSI was associated with an 8.8% point increase in county farm value and output per acre of arable land after 1900.

Moving across columns, additional controls are added, including controls on population density, the proportion of white people out of the total county population, the use of fertilizers, drainage of the land, the use of improved land, and the average agricultural suitability of county i. Nevertheless, the coefficients indicating the relationship between the MSI and farm value per acre do not appear to change considerably in magnitude and statistical significance, thus reducing the concern for selection on unobservables (Altonji et al., 2005).

[21]The restriction to neighborhoods allows to select only those containing at least one endemic and a non-endemic county. The same reasoning was applied to neighborhoods with no county with a high incidence of malaria. In this way, we do not compare a malarious county in Alabama with a malaria-free county in Montana.

[22]When considering the MRI as a variable representing the risk of malaria, I compare each county showing higher risk (i.e., MRI ≥ 0.1) with its neighboring counties that showed no risk of malaria (i.e., MRI < 0.1).

Panel A



Panel B

FIGURE 3 Flexible coefficients of the relationship between the two indexes of malaria incidence and the natural log of farm value per county-acre (Panel A) and the natural log of farm output per county-acre (Panel B). The periods span between 1870 and 1950, and are observed every other decade. In this specification, the malaria stability index (MSI) and the malaria risk index (MRI) are interacted with an indicator for each sample period. All regressions include year and county fixed effects, state linear trends, the county agricultural suitability index, and the decadal temperature and rainfall interacted with the full set of time-period fixed effects, and the full list of county-specific control variables fixed at 1900. Coefficients are reported with confidence intervals based on standard errors, clustered at the county level.

The preferred specification is reported in Column (4) of Table 1. It includes all population and agricultural controls other than state-specific linear trends as well as time and county fixed effects. This specification also includes a dummy variable indicating whether county i belongs to a state situated in the south of the United States. Results in Column (4) show that after implementing malaria eradication policies, a standard deviation increase in the MSI was associated with an 9.4% increase in farm value per acre after 1900 of more endemic counties compared to less endemic ones. The estimates reported in Column (4) in Panel B suggest that a standard deviation in the MRI accounted for approximately 8.8% points in farm value per county acre of arable land in the United States.

Finally, as noted in the data section there could be a measurement error problem due to double counting in farm output value (although there is no such concern for farm value data). Regarding this issue, the US Bureau Census (1951, p.26) reports that about 46.6% of corn production and the

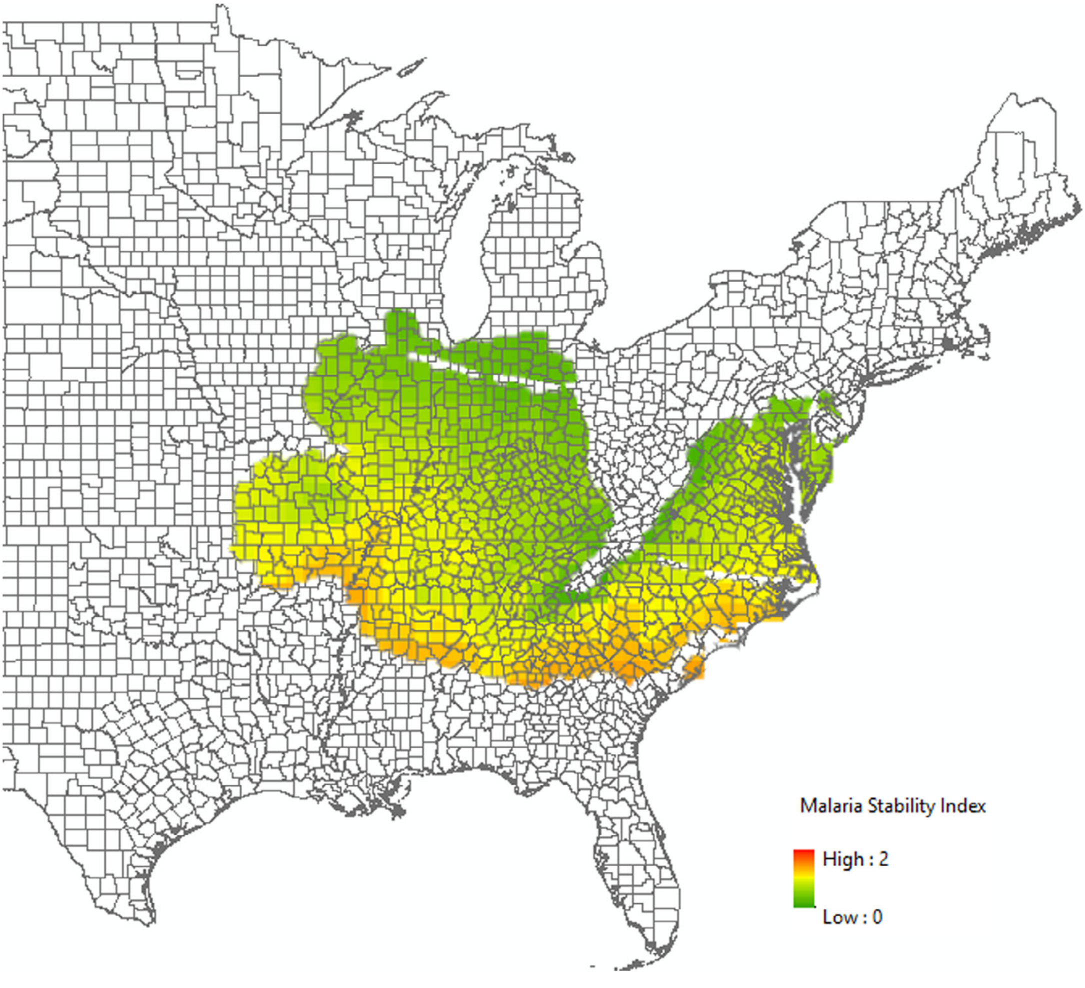


FIGURE 4 Neighboring counties with different prevalence of malaria (malaria stability index [MSI]). The sample is restricted to counties showing weather conditions suitable for malaria transmission (i.e., MSI ≥ 0.06) and neighboring counties (i.e., whose centroid lies within 2°latitude x 2°longitude) that presented weather conditions not suitable for malaria transmission (i.e., MSI ≈ 0).

whole hay production was estimated as the proportion of double counting; the ratio declined to 14.2% in the 1982 agricultural census for corn, whereas hay production persisted in being double counted.[23]

This does not seem to constitute a major concern in the estimation strategy presented in Equation (1) because the analysis is limited to 1950 (with farm output data missing between 1910 and 1930). Nevertheless, based on this information, to partially alleviate this possible issue, I employ a similar strategy as in Bleakley and Hong (2017) and Olmstead and Rhode (2008). Specifically, I recalculate county farm output values by excluding 50% of corn production and all hay production

[23]Following, I report the extract on the double-counting issue from the US Bureau Census (1951, p.26): "*A large part of the corn, and a still greater portion of the hay, returned in the census are consumed for the purpose of the annual product of animal food. If the values of both the vegetable and the animal products are counted, there will be duplication to this extent. An investigation of the distribution and consumption of the corn crop of 1882, undertaken by the statistician of the department of agriculture, made the consumption for free of cattle and swine, for flesh-making or fattening purposes, 46.6% of the total crop*."

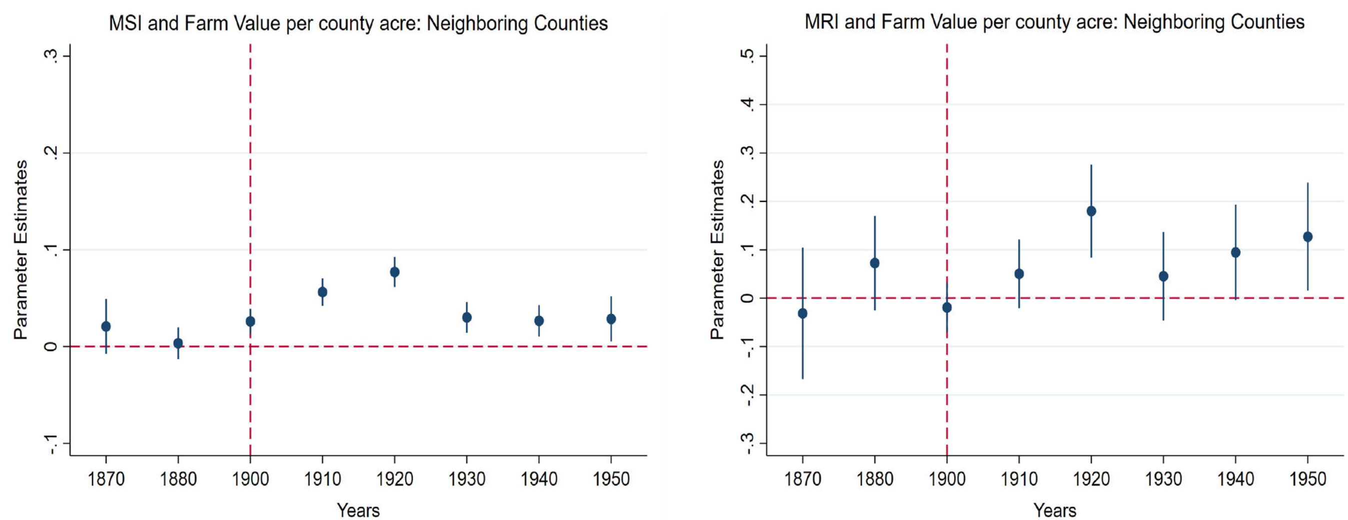


FIGURE 5 Flexible coefficients of the relationship between the natural log of farm value per county-acre and malaria stability index (MSI) (left) and malaria risk index (MRI) (right): Neighboring counties. The periods span between 1870 and 1950, and are observed every other decade. In this specification, the MSI and the MRI are interacted with an indicator for each sample period. All regressions include year and county fixed effects, state linear trends, the county agricultural suitability index, and the decadal temperature and rainfall interacted with the full set of time-period fixed effects, and the full list of county-specific control variables fixed at 1900. Coefficients are reported with confidence intervals based on standard errors, clustered at the county-neighborhood level (within 2 latitude and 2 longitude).

TABLE 1 The impact of malaria eradication on US county farm value per acre of arable land

	Dep. variable: ln(farm value per acre)			
	(1)	**(2)**	**(3)**	**(4)**
Panel A: MSI				
MSI x Post 1900	1.279***	1.310**	0.971**	1.159***
	(0.491)	(0.515)	(0.439)	(0.437)
Adjusted R^2	0.880	0.926	0.945	0.948
Panel B: MRI				
MRI x Post 1900	0.687***	0.555***	0.886***	0.732***
	(0.216)	(0.145)	(0.113)	(0.120)
Adjusted R^2	0.826	0.916	0.938	0.941
County Fixed Effects	Yes	Yes	Yes	Yes
State *X* Year	No	Yes	Yes	Yes
Demographic controls	No	Yes	Yes	Yes
Agricultural controls	No	No	Yes	Yes
Weather controls	No	No	Yes	Yes
Crops suitability	No	No	No	Yes
Mean of dep. variable	5.21	5.21	5.21	5.21
Observations	13,598	13,598	13,598	13,598

Note: The periods range from 1870 to 1950, and are observed every other decade. The dependent variable is the natural log of the county average farm value per county acre of arable land. In Panel A the variable of interest is the average county Malaria Stability Index. In Panel B the variable of interest is the average county malaria risk index. The post indicator variable equals zero for the periods 1870–1900 and one for the periods 1910–1950. The inclusion of a control variable interacted with the full set of time-period fixed effects is indicated by a yes; no indicates that the control is not included in the specification. Coefficients are reported with standard errors, clustered at county level, in parentheses. *** and ** indicate significance at the 1 and 5% levels, respectively.
Abbreviations: MRI, malaria risk index; MSI, malaria stability index.

for the 19th century censuses (i.e., 1870, 1880, and 1890) and 15% of corn production and all hay production for 20th century censuses (i.e., 1900, 1940, and 1950).

Results of this restriction are presented in Column (5) of Table 2 and are not significantly different from the baseline estimates. Thus, reinforcing the relationship between malaria eradication and farm value and output in the United States.

Furthermore, I consider the possibility that not all US states began the eradication campaigns in the same period. If this is the case, the baseline estimates might be partly driven by the counties that have eradicated malaria first. To address this potential bias, I estimate the DID model using its modified version (De Chaisemartin & d'Haultfoeuille, 2020). Here, I consider a hypothetical scenario in which counties with a high or very high risk of malaria (i.e., MRI > 0.3) began eradicating malaria in 1900. Counties with a moderate risk of malaria began eradicating the vector-borne disease in 1910, whereas counties with no or low risk of malaria began eradicating the disease in 1920.[24] Dynamic treatment effects from the modified DID estimator applied to the differences from 1900 are reported in Figure A.5. I find robust zeros for the pre-eradication period, indicating no significant differences in the pretreatment for the sample used to identify the effects of the eradication of malaria. This corroborated the positive role of the eradication of malaria on farm value and output in the US.

[24]A total of 691 counties showed no or low malaria risk, 439 showed a moderate risk of malaria, and 573 exhibited a high or very high malaria risk.

TABLE 2 The impact of malaria eradication on US county farm output per acre of arable land

	Dep. variable: ln(farm output per acre)				
	(1)	(2)	(3)	(4)	(5) Discounting the prod. of corn and hay
Panel A: MSI					
MSI x Post 1900	1.323***	1.153**	0.614**	0.666***	0.768***
	(0.386)	(0.510)	(0.215)	(0.226)	(0.233)
Adjusted R^2	0.705	0.878	0.920	0.920	0.847
Panel B: MRI					
MRI x Post 1900	2.142***	0.415***	0.589***	0.635***	0.739***
	(0.082)	(0.072)	(0.065)	(0.070)	(0.085)
Adjusted R^2	0.729	0.878	0.922	0.922	0.851
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
State *X* Year	Yes	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	Yes	Yes	Yes
Agricultural controls	No	No	Yes	Yes	Yes
Weather controls	No	No	Yes	Yes	Yes
Crops suitability	No	No	No	Yes	Yes
Mean of dep. variable	3.69	3.69	3.69	3.69	3.69
Observations	8958	8958	8958	8958	8958

Note: The periods range from 1870 to 1950, and are observed every other decade. The dependent variable is the natural log of the county average farm output per county acre of arable land. In Panel A the variable of interest is the average county malaria stability index. In Panel B the variable of interest is the average county malaria risk index. The post indicator variable equals zero for the periods 1870–1900 and one for the periods 1910–1950. Data for farm output for the years 1910, 1920, and 1930 is missing. The inclusion of a control variable interacted with the full set of time-period fixed effects is indicated by a yes; no indicates that the control is not included in the specification. Coefficients are reported with standard errors, clustered at county level, in parentheses. *** and ** indicate significance at the 1 and 5% levels, respectively. Abbreviations: MRI, malaria risk index; MSI, malaria stability index.

5.1 | Results with flexible estimates

Figure 3, Panel A illustrates the relationship between the MSI (on the left) and the MRI (on the right) and the natural log of farm value per county acre. Panel B of Figure 3 uses the natural log of farm output per county acre.

Taken together, Panel A and B of Figure 3 display a clear pattern; that is, until 1900 (i.e., the last year before the onset of the eradication policies), the relationship between malaria incidence and agricultural development for each US county is not statistically significantly different from zero. A spike between 1910 and 1920 emerges, followed by a slight resurgence during the 1930 s and a steady decrease in magnitude from 1940. The coefficients shown in Figure 3 are also crucial to exclude any other event except eradicating malaria during the periods immediately before the implementation of vector-control policies. These results demonstrate that after 1900, the farm value and output per acre of arable land of counties with a higher incidence of malaria began to increase relative to counties that were less endemic and less suitable for the transmission of vector-borne diseases.

5.2 | Results of neighboring counties analysis

Figure 5 presents the estimates of the relationship between the two indexes of malaria and farm value per county-acre of arable land relative to a baseline time period, which this study considers to be

1890. Therefore, the absolute level reveals the difference in the relationship relative to an arbitrarily chosen baseline. One would then expect the parameter estimates of 1870, 1880, and 1900 (i.e., years before the discovery of anti-malaria methods) not to be statistically significantly different from the baseline year while being positive from 1910 onward. An observation in this study is that before the eradication of malaria, the relationship between malaria diffusion and farm value per acre of arable land was not statistically different from zero. After 1900, however, this relationship became positive until the 1920s. Thereafter, the 1930s and 1940s saw a resurgence of malaria transmission followed by a stable decrease in the number of infected people, translating into higher growth rates of farm value per acre of arable land.

Estimates of Equation (3) are reported in Table 3. Here the dependent variable is represented by the natural logarithm of county average farm value per county acre and the treatment of either the MSI (Panel A) or the MRI (Panel B). Column (1) includes only state-specific linear trends as well as time and county fixed effects. The results show that one standard deviation increase in the MSI resulted in more than six percentage-point increase in farm value per acre.

As before, concerns regarding selection on unobservables are also mitigated by the fact that across columns, coefficients indicating the relationship between the MSI and farm value per acre do not appear to change in magnitude and are statistically significant. The preferred specification is reported in Column (4) and includes controls on county population density; the ratio of the white population to the total county population; the ratio of farmland to total available county area; the proportion of farmers reporting the use of fertilizers; the proportion of farmers who had their farm drained; the proportion of farms with improved land fixed at the year 1900; and the time-invariant county average agriculture suitability index, other than that including state-specific linear trends as well as time and county fixed effects. The results in Column (4) indicate that one standard deviation increase in the MSI resulted in an increase of approximately seven percentage points in farm value per county-acre of arable land.

6 | MECHANISMS

This section addresses the possible mechanisms behind the increase in farm value and output in more endemic US counties. One possible mechanism behind the agricultural development is linked to the greater availability of cropland due to wetland conversion. Evidence is provided that the increase in farm value and output was not due to the drainage of swamps and conversion from wetland to arable land. Furthermore, the eradication of malaria is shown to have increased farmers' agricultural output in more endemic areas.

6.1 | Increased arable land

There is evidence that one of the principal measures against the diffusion of malaria was the drainage of swamps and wetlands, and the relative conversion of the latter into cropland (Majori, 2012; Snowden, 2008). Suppose the agricultural output results were merely driven by the increase in cropland in counties with a higher initial incidence of malaria. If this is the case, one should find a significant relationship between malaria-endemic weather conditions and the total amount of cropland for each US county.

In addition, using time-series gridded data on cropland from 1870 until 1950, I examine whether malaria eradication campaigns increased the portion of arable land in counties with an initial higher incidence of malaria. Figure 6 shows that only counties with a very high risk of malaria (i.e., MRI > 0.4) experienced a significant increase in cropland after the eradication policies compared to counties with no risk of malaria (i.e., MRI < 0.1). Specifically, I find that the proportion of cropland out of the total county area in counties with a very high risk of malaria increased by 1.2% relative to

TABLE 3 The impact of malaria eradication on US county farm value per acre of arable land. Neighboring counties analysis

	Dep. variable: ln(farm value per acre)			
	(1)	(2)	(3)	(4)
Panel A: MSI				
MSI x Post 1900	0.322**	0.489***	0.319***	0.320***
	(0.126)	(0.097)	(0.093)	(0.086)
Neighborhood x Post 1900	−0.004***	−0.001	−0.002*	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.913	0.940	0.949	0.952
Panel B: MRI				
MRI x Post 1900	0.117***	0.151***	0.106***	0.104***
	(0.034)	(0.026)	(0.024)	(0.022)
Neighborhood x Post 1900	−0.004***	−0.002	−0.002*	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.918	0.945	0.950	0.953
County Fixed Effects	Yes	Yes	Yes	Yes
State *X* Year	No	Yes	Yes	Yes
Demographic controls	No	Yes	Yes	Yes
Agricultural controls	No	No	Yes	Yes
Weather controls	No	No	Yes	Yes
Crops suitability	No	No	No	Yes
Mean of dep. variable	5.42	5.42	5.42	5.42
Observations	4921	4921	4921	4921

Note: The periods range from 1870 to 1950, and are observed every other decade. The dependent variable is the natural log of the county average farm value per county acre of arable land. In Panel A the variable of interest is the average county malaria stability index. In Panel B the variable of interest is the average county malaria risk index. The Post Indicator variable equals zero for the periods 1870 to 1900 and one for the periods 1910 to 1950. The inclusion of a control variable interacted with the full set of time-period fixed effects is indicated by a yes. Coefficients are reported with standard errors, clustered at the neighborhood level (i.e., 2°latitude x 2°longitude), in parentheses. ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively.
Abbreviations: MRI, malaria risk index; MSI, malaria stability index.

malaria-free counties. On the other hand, I find no significant increase in the amount of cropland in areas with low and moderate malaria risk compared to malaria-free ones after 1900.

Figure A.7 in the online supplementary appendix complements those results showing only a modest relationship between malaria prevalence and the available cropland per county. The conversion from wetland to arable land, therefore, does not appear to have remarkably increased arable land in more endemic counties relative to less endemic ones after the eradication of the vector-borne disease. This result is in line with Gooch (2017), which found no strong evidence for the positive impact of the worldwide eradication campaigns during the 20th century on cropland.

Taken together, the estimates in Figures 6 and A.7 show that counties with a very high risk of malaria experienced a slight increase in cropland compared to malaria-free areas.

6.2 | Farmer productivity

This section investigates whether farmers, who were highly affected by vector-borne diseases (because they were living and working in rural areas), became more productive due to the reduced

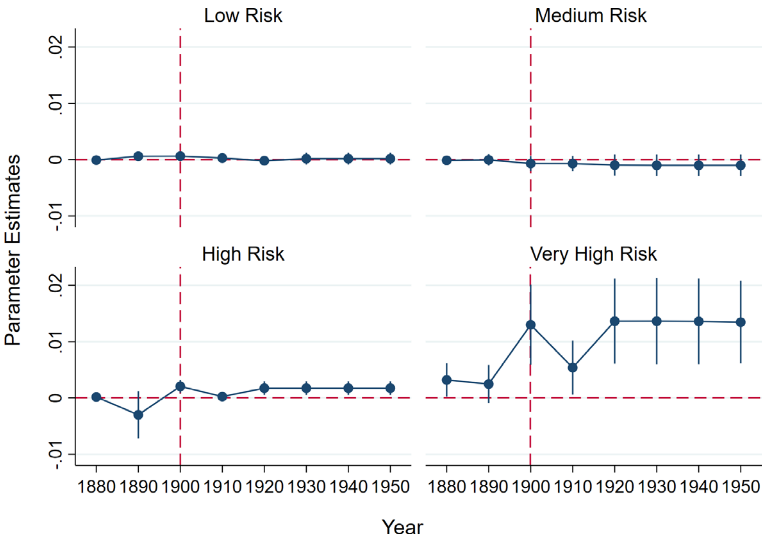


FIGURE 6 Flexible coefficients of the relationship between proportion of cropland out of total county area and malaria risk index (MRI) per class of malaria risk. Counties belonging to each malaria-risk class are compared to the reference class of no risk of malaria (MRI ≤ 0.1). Low malaria-risk is represented by (0.1 < MRI ≤ 0.2), followed by moderate risk (i.e., 0.2 < MRI ≤ 0.3), high risk (i.e., 0.3 < MRI ≤ 0.4), and very high risk (i.e., MRI > 0.4).

diffusion of malaria. Nevertheless, the lack of historical data on farmers' health (such as hospitalization or death rates due to malaria) does not allow us to test this hypothesis directly.

This is a clear limitation of the paper. However, as a workaround, I investigate the effects of eradicating malaria in the US on each county's agricultural output per farmer. The empirical strategy described below mimics that described in Equation (1), except that the dependent variable now consists of farm output per farmer instead of farm value/output. The treatment is again defined as the interaction between the exogenous county variation in weather conditions that are more or less suitable for spreading malaria and a post-eradication indicator variable.

$$\begin{aligned} y_{i,s,t} = \alpha \ \text{Malaria}_i \cdot I_t^{Post} + \rho_1 T_{i,t} + \rho_2 P_{i,t} + \sum_{t=1870}^{1950} \Omega \mathbf{X}'_{i,s} I_t + \\ + \sum_{t=1870}^{1950} \delta_t I_t + \sum_p \gamma_p I_t^p + \sum_{t=1870}^{1950} \sum_q \omega_q I_t^q + \varepsilon_{i,s,t} \end{aligned} \tag{4}$$

This time the dependent variable $y_{i,s,t}$ is the natural log of the total farm output per farmer as defined in the data section, in year t, county i, and state s.

Similarly to Equation (1), the variable Malaria$_i$ represents the historical incidence of malaria in county i before its eradication. $\mathbf{X}_{i,s}$ represents vectors of time-invariant county-specific agricultural controls included in the regression. I include the same controls as in Equation (1), that is, county population density, the ratio of the white population to county population, the ratio of farmland to total available county area, the proportion of farmers reporting the use of fertilizers, the proportion of farmland that reported having received drainage, the proportion of farmland with improved land, and county average agriculture suitability. State fixed effects are represented as follows: $\sum_q \omega_q$. Where q indicates the set of US states.

The coefficient of interest α indicates if counties with a higher prevalence of malaria had greater agricultural output per farmer after 1900. The inclusion of state by time fixed effects, the coefficient

TABLE 4 The impact of malaria eradication on US county farmer productivity

	Dep. variable: ln(farm value per farmer)			
	(1)	**(2)**	**(3)**	**(4)**
Panel A: MSI				
MSI x Post 1900	0.142***	0.131***	0.118***	0.135***
	(0.047)	(0.047)	(0.023)	(0.021)
Adjusted R^2	0.701	0.715	0.846	0.852
Panel B: MRI				
MRI x Post 1900	0.013	0.756***	0.798***	0.730***
	(0.218)	(0.178)	(0.201)	(0.195)
Adjusted R^2	0.757	0.810	0.829	0.833
County Fixed Effects	Yes	Yes	Yes	Yes
State *X* Year	No	Yes	Yes	Yes
Demographic controls	No	Yes	Yes	Yes
Agricultural controls	No	No	Yes	Yes
Weather controls	No	No	Yes	Yes
Crops suitability	No	No	No	Yes
Mean of dep. variable	0.41	0.41	0.41	0.41
Observations	15,271	15,271	13,581	13,552

Note: The periods range from 1870 to 1950, and are observed every other decade. The dependent variable is the natural log of the county average farm value per farmer. In Panel A the variable of interest is the average county Malaria Stability Index. In Panel B the variable of interest is the average county malaria risk index. The Post Indicator variable equals zero for the periods 1870–1900 and one for the periods 1910–1950. All regressions include time periods fixed effects, county fixed effects, and state linear trends. The inclusion of a control variable interacted with the full set of time-period fixed effects is indicated by a yes; no indicates that the control is not included in the specification. Full details of each control variable are provided in the text and the online supplementary appendix. Coefficients are reported with standard errors, clustered at county level, in parentheses. *** indicates significance at the 1% level.
Abbreviations: MRI, malaria risk index; MSI, malaria stability index.

of interest α is identified from within-state variation only; that is, the empirical strategy compares counties within the same state.

Table 4 lists the results of the relationship between either the MSI or the MRI on farm output per farmer. Given the limitation on the available data, the results indicate the farm output per farmer in more endemic counties increased after the malaria eradication campaigns began in 1900 compared to less endemic counties. This last result provides useful insights on the mechanism behind the increase in the value of the land due to the eradication of vector-borne diseases in the United States.

7 | CONCLUDING REMARKS

There is a consensus on the positive relationship between improved health conditions and economic activity, with differences in disease prevalence partly explaining different economic performances within countries today. A valid example is given by the medical innovations that led to the successful eradication of malaria in the US between the early 1900s and 1950s.

In this study, I investigate the effects of the health campaigns that helped eradicate malaria on the farm value and output per acre of arable land in the United States. Evaluating malaria-control policies has considerable advantages. First, their timing is well defined. In fact, before 1898, medical science had not yet discovered the origins of malaria, and affected areas continued to suffer from uncontrolled malaria incidence. Second, exploiting exogenous geographical differences in weather suitability for the reproduction of mosquito larvae allows for a treatment/control design.

I provide novel evidence that the prevention strategies supported the agricultural development of counties with climatic conditions ideal for the transmission of vector-borne diseases. I also find that the increased output value of land in more endemic counties was primarily due to better farmers' health. In contrast, wetland conversion did not play a significant role.

Results are robust to controlling for a variety of alternative hypotheses, including differential timing of adoption for US counties, differential trends across states, changing weather conditions during the 19th and 20th centuries, and different indexes measuring the incidence of malaria in the United States.

Caution is necessary when interpreting these results. First, although I use a robust empirical approach, this study focuses on the historical farm value and output in the United States. Therefore, the results may not directly apply to today's poorer parts of the world. Second, although malaria notably affects individuals living in rural areas (e.g., farmers) and directly impacts their labor productivity, the same cannot be said for other diseases that spread in densely populated areas (e.g., bacteria and viruses).

Overall, this paper provides novel insights into understanding the economic effects of medical innovations on socio-economic development by demonstrating that eradicating a climate-related disease can increase population and improve labor productivity, thus leading to economic growth. This motivates the example of the eradication of malaria in the United States, resulting in positive farm value and output growth.

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Additional supporting information can be found online in the Supporting Information section at the end of this article.

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