Climate and Agricultural Productivity

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Abstract: We use new data on climatic conditions and resources to test the determinants of agricultural input use and output level across countries. Our principal finding is that a previously undocumented climate trait -- the prevalence of seasonal frost -- is strongly associated with more investment in farm inputs and greater agricultural production, alongside soil quality and other variables. The model provides a natural explanation for faster factor accumulation in temperate regions than in the tropics, without geographic determinism: institutional changes affecting investment in public R&D could offset the climate effects.

Climate and Agricultural Productivity

Introduction

Why does agricultural productivity vary so widely around the world? In a statistical sense, most variation in agricultural output can be explained by variation in farmers' inputs and governments' policies, including public goods such as research (e.g. Craig, Pardey and Roseboom 1997, Fulginiti and Perrin 1997). But this begs the question of why some countries have consistently lower farm input use and less favorable government activity than others, and why those low-productivity countries are clustered together in tropical regions.

The patterns we see may be driven by the gradual diffusion of human institutions across space (Hall and Jones 1999), or contagion-type effects among neighbors (Easterly and Levine 1998), but these explanations offer little in the way of prescription--other than exhortation for farmers and governments in low-productivity regions to imitate those of more successful places.

This paper asks whether the low input use and unfavorable policies we observe are not historical accidents, but are in fact equilibrium responses to unobserved differences in the incentives offered by biophysical conditions. But even if biophysical conditions explain current productivity differences, they may not determine future productivity to the extent that deliberately targeted scientific innovation can overcome location-specific constraints. We consider both propositions: how closely historical productivity can be linked to specific agroclimatic conditions, and also how well productivity responds to modern scientific research.

Only recently do we have enough worldwide data on both geographic and economic variables to make quantitative tests of how biophysical factors might affect economic incentives and performance. Prominent recent work has drawn attention to the public-health consequences of tropical climate (Bloom and Sachs 1998). In this paper we focus specifically on agriculture, building on Gallup and Sachs (1999) and Wiebe et al. (2000), and extending McKinsey and Evenson (1999) to a cross-country framework. Our objective is to increase understanding of how climate matters for agricultural productivity, so as to help guide research towards the most fundamental kinds of constraints affecting regions with low productivity growth.

Agronomic conditions and productivity

The geographic tropics are defined in terms of latitude, as the area where the sun passes directly overhead (that is, between latitudes 23°27' north and south). This region covers a wide range of variation in temperature, rainfall, altitude, topography and the geologic origins of soils, and also variation in the genetic or behavioral adaptations of living organisms (Kellman and Tackaberry 1997).[1] Since tropical ecologies are so varied, broad generalizations about them have rarely been useful guides for technical change or policy choice (Lal and Sanchez 1992).

The variability of tropical ecosystems is an important observation, and could itself be a cause of low productivity if variability inhibits innovation and imitation. But economic productivity is consistently low across many very diverse tropical ecosystems (e.g. from tropical forest to savannah and semiarid regions), and consistently high across another wide variety of temperate ecosystems (again from forests to plains and semiarid regions).

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[1] Other major textbooks and conference volumes consulted for this review include Whitney (1925), Eden (1947), Mohr and van Baren (1954), Buringh (1968), National Research Council (1972), Young (1976), Stelly (1978), Lal and Greenland (1979), Dommergues and Diem (1982), Wrigley (1982), Norman, Pearson and Searle (1984), Scharpenseel et al. (1990), Lal and Sanchez (1992), Van Wambeke (1992), Mulongoy and Merckx (1993), Weischet and Caviedes (1993), Syers and Rimmer (1994), Woomer and Swift (1994), and Reddy (1995).

Despite their agronomic variability, tropical systems may have something of economic importance in common.

One factor that clearly distinguishes tropical from temperate ecologies is a faster breakdown of soil organic matter into its mineral components, given sufficient moisture for biotic activity of any kind (Greenland et al. 1992, pp. 28-29).[2] And partly because organic matter breaks down faster, most tropical soils are older and more highly weathered, with a much higher proportion of "variable charge" minerals whose cation exchange capacity (CEC) and hence ability to support plant growth depends on soil acidity (pH) (Sanchez and Logan 1992, pp. 40-41).

The economic relevance of more rapid breakdown of organic matter could be that it removes a natural source of support for high crop productivity over time. When a previously-fallow field is planted, crop yields tend to fall faster in the tropics than in temperate zones, unless and until farmers respond with soil amendments and other investments (Lal 2000). Tiessen et al. (1982) estimate that, in the Canadian prairies, slow mineralization of organic matter sustained yields for as long as 50 years before farmers began to apply inorganic fertilizer, whereas yields in tropical countries typically fall as quickly as the second year of cultivation, depending on the balance between nutrient withdrawals and soil formation (Michels et al. 1998, p. 1289). The greater difficulty of

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[2] Using ^{14}C labeling to measure the rate at which carbon in organic matter is mineralized and lost, Greenland et al. (1992) find that after one year the percent of labeled carbon remaining in the soil was 35% at Rothamsted in the UK, but under 20% at sites in Costa Rica and Nigeria. Based on calibrated soil models, Tiessen et al. (1998) estimate that when controlling for moisture regime, the carbon in organic matter cycles about five times faster in the tropics than in temperate zones. This cycling is directly related to biotic activity: the time period required for total turnover of microbial biomass has been estimated to be on the order of 6 months in tropical soils, and 1-2 years in temperate soils (Lavelle et al., 1992).

maintaining organic matter could help explain why the tropics contain virtually all of land area now thought to be affected by loss of nutrients (Syers 1997, p. 1013).[3]

To ask whether climate and associated soil processes have a significant economic role, we must first identify what measurable climatic variable might be responsible for the hypothesized "tropics effect". Latitude itself measures only the angle of solar radiation. Being closer to the sun generates warmer average temperatures and longer growing seasons, but those variables are not easily linked to productivity. A more plausible factor is seasonal frost: whether temperatures oscillate between a warm summer and a frozen winter. The presence of seasonal frost has a clear impact on all biotic activity, and the recent development of worldwide climate data allows us to test its effect on agriculture.

The most direct effect of seasonal frost is by killing exposed organisms, particularly microorganisms in the topsoil that break down organic matter and mineralize its nutrients (Scholes et al., 1994, p. 121). In addition, Van Wambeke (1992, p. 17) notes that frost helps break up otherwise compacted soils by the expansion of water on freezing, and also contributes to soil structure by preserving each year's plant residues in distinct layers. To these we may add another effect associated with moisture rather than soils: winter frosts preserve ground moisture after harvest, and help ensure that winter precipitation is preserved in ice and snow. Accumulated moisture is then released with the spring thaw, which helps make for more reliably moist conditions at planting time. These various effects suggest that ground frost frequency could be a useful variable, in distinguishing among the world's climates and testing the effect of climate on productivity.

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[3] One estimate suggests that over the past 30 years cropped soils in Africa have lost 660 kg/ha of nitrogen (N), 450 kg/ha of potassium (K), and 75 kg/ha of phosphorus (P) (Smaling et al. 1997, p. 52). In contrast, commercially-farmed soils in temperate zones are estimated to have gained 2000 kg/ha N, 1000 kg/ha K, and 700 kg/ha P (Sanchez et al. 1997, p. 4). Further estimates of differences in soil degradation by region are given in Oldeman et al. (1991).

Our hypothesis is that the prevalence of seasonal frost helps sustain high output levels, by facilitating improved soil quality as a complement to farmers' input use. Purely organic accumulation of nutrients drove the agricultural revolution preceding industrial growth in northwestern Europe (the Netherlands, the Flanders region of Belgium, northwestern Germany and Denmark), where farmers were able to double their soil organic matter levels beginning in the 16th century (Sombroek 1994).[4] By facilitating the build-up of nutrient stocks in soil organic matter, seasonal frost could have helped raise crop productivity in the period before inorganic fertilizer was available.

The climate mechanisms that might have supported pre-industrial agriculture could also be important today, in maintaining organic matter levels as a complement to inorganic fertilizer use. Large-scale applications of fertilizer are necessary to sustain high and rising crop yields in both temperate and tropical environments, as shown by the diverse sets of long-term experiments reviewed by Greenland et al. (1992), Prasad and Power (1997, p. 63), and Dawe et al (2000). But the efficiency with which fertilizer nutrients are delivered to the plant still depends on the soil's ability to retain moisture and deliver the nutrients, which in turn depend largely on soil organic matter -- particularly in low-fertility settings.[5]

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[4] The resulting "Plaggen" soils are classed as Anthrosols in FAO soil maps to underscore their man-made quality, but all farming involves some transformation of the soil. Such transformations can either draw down soil capital or build it up, as demonstrated in long-run controlled experiments that date from 1843 at Rothamsted in the UK (Powlson and Johnson 1994), and from 1876 at the University of Illinois (Darmody and Peck 1997).

[5] A key aspect of nutrient delivery is the soil's effective cation exchange capacity. In many settings ECEC is determined mainly by the soil's clay-sized particles, rather than by its organic matter (Norman, Pearson and Searle 1995, p. 50). But when soil fertility is very low, organic matter may be a limiting factor (Zech et al. 1997, p. 153); in a large sample of African soils from across the continent, organic matter content was found to account for 56 to 95 percent of variance in ECEC, while geological factors such as clay and silt content were much less important (Asadu et al, 1997).

Farm technology can be adapted to different environmental conditions. Perhaps the most successful technique yet developed for tropical conditions is flooded rice, using irrigation water to help support plants and deliver nutrients. Clifford Geertz (1964) describes paddy rice fields as "an ingenious device for the agricultural exploitation of a habitat in which reliance on soil processes is impossible." Where flood irrigation is impossible, another widespread technique is the accumulation of crop residues above ground, and then burning them before planting to release nutrients and help reduce microbial activity in the soil (Araki 1993).[6]

Clearly it is possible for farmers in the tropics to overcome climatic constraints, through a variety of techniques.[7] The question is only whether doing so is systematically more difficult in the tropics than in temperate zones. Only recently have we begun to collect the data needed to resolve what is at bottom an empirical matter: do the differences in climate across regions, particularly differences in frost prevalence, affect productivity and incentives for farm investment? And if so, how large are these climate effects, relative to other factors such as national institutions?

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[6] The role of residue-burning is well explicated by Pedro Sanchez (1994, p. 455), who writes: "Burning releases to the soil about half of the nitrogen and phosphorus in the burning biomass and practically all of the other nutrients in the form of ash. Higher soil temperatures also accelerate mineralization of soil organic matter. The two factors provide high nutrient availability for one or two years of crop production… (then) nutrient deficiencies as well as increasing weed pressure impede further cropping and the fields are abandoned to a secondary forest fallow. The fallow period does not improve soil fertility per se; rather it accumulates nutrients in the plant biomass that can be tapped by future crops on slash and burn."

[7] A very large-scale effort to test how well temperate and tropical farmers actually manage their soils was recently completed by Peter Lindert (1996, 2000), who produced econometrically-estimated soil quality indexes from archive data on thousands of soil samples taken since 1923 in Indonesia and since 1932 in China. From these data he concludes that there was a substantial draw-down of soil nitrogen and organic matter in Indonesia up to 1970 and in China into the 1980s, followed by stabilization as farmers raised input use and management intensity.

Methodology

To test for climate effects on agricultural productivity we look first at people's choice of investment location within countries, and then look at the productivity of those investments at the country level. We examine the data using a variety of regression models, building evidence towards the most complete model in which climate effects on output and inputs are tested in a system of simultaneous equations.

The first test asks whether frost frequency affects the location of investment within countries, using data on peoples' choices of where to live and grow crops. The data represent about 12,500 individual 1°x1° cells covering almost all of the world's land surface. If productivity is higher where there is seasonal frost--defined here as the number of average number of frost-days per month in winter, after a frost-free summer--then we would expect population density and cultivation intensity to be higher in the cells with more seasonal frost, controlling for other factors including unobserved country characteristics. To test the hypothesis that some frost helps attracts people and investment in agriculture, we use the following estimating equations:

$$\text{(1a)} \quad pop.density_{ij} = constant + \beta_1 frost_{ij} + \beta_2 frost_{ij}^2 + \gamma(other\ factors_{ij}) + \delta_i + \varepsilon_{ij}$$

$$\text{(1b)} \quad cultiv.inten._{ij} = constant' + \beta'_1 frost_{ij} + \beta'_2 frost_{ij}^2 + \gamma'(other\ factors_{ij}) + \delta'_i + \varepsilon'_{ij}$$

The dependent variables are either population density (persons per square kilometer) or cultivation intensity (proportion of land under cultivation) at country i and cell j, which we hypothesize are higher where winter frost is more frequent (β_1 and β'_1 are positive), but perhaps not too much so (the quadratic terms, β_2 and β'_2, are negative), controlling for other factors that include average annual precipitation and temperature, elevation, latitude, and isolation in the sense of distance to a coast or navigable river, as well as country fixed effects or national average population density and cultivation intensity. We test these hypotheses first using OLS regression with White standard errors to account for heteroskedasticity in the error term (ε_{ij}), and also using standard errors computed following Conley (1999) to account for spatial autocorrelation in the error term across neighboring cells.

To examine aggregate productivity we must go to the country level, and aggregate the cell-level measure of frost frequency used in equations (1a) and (1b) to a national measure of frost prevalence. This national measure is defined as the proportion of a country's land surface that receives more than five frost-days per year, a threshold sufficient to kill microorganisms and significantly slow down mineralization of organic matter (Masters and McMillan 2000). If a greater prevalence of frost raises national productivity, then frost prevalence will be positively correlated with aggregate output when controlling for input use and other factors. And if frost also raises the productivity of input use, there will be positive interaction effects with those inputs, as the correlation between output level and input use is highest where frost is more prevalent. We test these hypotheses in a single-equation framework, and then test directly for an effect of frost prevalence on input use as well as output levels using simultaneous equations.

The initial test for frost effects on output uses the following estimating equation, computed first for total national output and input levels (including land as an input), and then also on a per-hectare basis.[8]

(2a) $(output_{\mathrm{it}}) = cons. + \alpha(inputs_{\mathrm{it}}) + \beta_1(fr.preval._{\mathrm{it}}) + \beta_2(inputs\mathrm{X}frost_{it}) + \varepsilon_{\mathrm{it}}$

(2b) $(outp./ha_{\mathrm{it}}) = cons.' + \alpha'(inputs'/ha_{\mathrm{it}}) + \beta'_1(fr.preval._{\mathrm{it}}) + \beta'_2(inputs/ha\mathrm{X}frost_{it}) + \varepsilon'_{\mathrm{it}}$

Our hypotheses here are that the coefficients on frost prevalence are positive (β_1 and β'_1), as are its interactions with input use (β'_2 and β'_2), where inputs are fertilizer application,

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[8] In both cases, to take account of heteroskedasticity due to differing country sizes we use a GLS procedure (in Stata, the "xtgls" command with the "panels(heteroscedastic)" option. Note that, unlike equation (1), we cannot introduce country dummy variables for a fixed-effects approach, because the long-run climate and soil variables are time-invariant constants for each country.

labor use, and agricultural research, plus annual rainfall, the extent of irrigation and the size of the national livestock herd, a national soil-quality index and the national degree of isolation (measured as the proportion of the country within 100 km of an ocean coast or navigable river, to measure the relative costs of trade).

If the interaction terms (β_2 and β'_2) matter, then we would expect that input levels might be chosen endogenously in response to climate. In that context, the estimated coefficients on inputs and frost (α, α' and β_1, β'_1) could be biased due to correlation between those regressors and the error term (ε_{it}, ε'_{it}). One remedy is an instrumental-variables approach, using instruments that are both exogenous to the model (that is, are uncorrelated with its error term) and also relevant (that is, would be significant determinants of input use in an auxiliary regression). To implement such an approach, we modify equation (2) to distinguish between the endogenous and exogenous variables and drop the interaction terms, since we now capture the interaction explicitly through the endogeneity of some inputs.

$$(2')\ (output_{it}) = constant + \alpha_1(endogenous\ inputs_{it}) + \alpha_2(exogenous\ inputs_{it}) + \beta(frost\ prevalence_{it}) + \varepsilon_{it}$$

The instruments we specify are factors thought to influence input use, but not be influenced by climate: here we use the exogenous inputs included in the regression, plus education and literacy levels and two different indexes that characterise national institutions. Following Greene (2000), we use the Hansen (1982) generalized method of moments (GMM) estimator as implemented by Baum (2000), which constructs optimally-weighted moment conditions to produce a more efficient estimate of β than could be achieved using two-stage least squares.

Once we have introduced the instrumental-variables approach, we can move beyond the single-equation framework to test more directly the effects of frost on input use, in separate equations estimated simultaneously with equation (2’). The first of these input equations is aimed at explaining fertilizer use, which is the main factor that might be chosen by farmers in direct response to climatic conditions:

$$(3a)\ (\mathit{fert./ha}_{it}) = \mathit{const.} + \gamma(\mathit{output/ha}_{it}, \mathit{rgdp/pers}_{it}, \mathit{agroclimatic\ factors}_{it}) + \mu_{it}$$

Equation (3a) posits that fertilizer applications depend on output per hectare[9] (to maintain nutrient supply for crop growth), plus farmers’ access to resources in general (measured by economywide real GDP per capita), plus the soil and climate characteristics that influence crops’ response to fertilizer (notably the extent of irrigation, a soil quality index, and frost prevalence, plus isolation to capture the relative costs of obtaining fertilizer). The coefficients on all of these variables are expected to the positive.

A second input-use equation is aimed at explaining labor intensity, in terms of farmers’ decisions to stay in agriculture or move to nonagriculture:

$$(3b)\ (\mathit{labor/ha}_{it}) = \mathit{const.} + \gamma'(\mathit{output/ha}_{it}, \mathit{rgdp/pers}_{it}, \mathit{off\text{-}farm\ prospects}_{it}) + \nu_{it}$$

Equation (3b) posits that farm labor intensity is a function of farmers’ potential earnings in agriculture (measured by output/ha) versus their off-farm prospects (measured by the economywide level of real GDP, plus the economywide level of literacy and stock of secondary education). As a result of mobility from farm to off-farm employment, we would expect to see a positive coefficient on output/ha, but negative coefficients on variables capturing off-farm prospects.

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[9] In fact fertilizer is applied before output is known with certainty; actual output is used here as the best available measure of farmers’ expectations at the time of fertilizer application.

Finally, a third input-use equation is aimed at explaining the country's level of spending on agricultural R&D:

(3c) $(R\&D/ha_{\mathrm{it}}) = const. + \gamma''(output/ha_{\mathrm{it}}, rgdp/pers_{\mathrm{it}}, govt.characteristics_{\mathrm{i}}) + e_{\mathrm{it}}$

Equation (3c) posits that the country's R&D expenditure depends on the responsiveness of agriculture to investment (measured by output/ha), the capacity of society to invest (measured by real income per capita), the responsiveness of government to the citizenry (measured by the ICRGE index of institutional quality), and the government's experience (measured by a categorical variable "state" representing the period since decolonization), and we expect all of these variables to have positive coefficients.

With these three specific equations for endogenous inputs, we then have a simultaneous system of four equations (2', 3a, 3b, and 3c), in which agroclimatic factors drive input use and farm output, which in turn influences labor allocations and R&D expenditure. To estimate this system, we use three-stage least squares as recommended by Greene (2000).

Data

The data used in this study derive from a variety of sources, and are presented here in the sequence with which they are used. The names of specific variables used in the models are given in italics. The cell-level database used for equation (1) includes time-invariant data on about 12,500 cells covering almost all of the world's land surface. These cells are average values for land areas that vary in size from about 12,000 square kilometers at the equator to nearly zero at the poles, so OLS regressions using these data are weighted by the land area in each cell. The country-level data for equations (2), (2'), (3a), (3b) and (3c) include annual observations for 1961-1997 on up to 110 countries.

Cell-level variables

The frost data we use are derived from values compiled by the Climatic Research Unit (CRU) of the University of East Anglia, and published by the International Panel on Climate Change (1999). The CRU data are reported as the average number of frost-days per month over the 1961-90 period, across 0.5-degree cells for all land mass except Antartica, interpolated from station observations. For stations not reporting frost observations, values are estimated from observed temperature level, temperature variation, and precipitation. Frost-days are defined as those where the estimated temperature of ground-level grasses falls below 0 degrees centigrade.

To obtain a measure of seasonal frost that is relevant for agriculture, we computed the average number of frost-days per month in winter, defined as December through February in the Northern hemisphere and June through August in the Southern hemisphere, for locations with no frost in the summer (June-August in the North, December-February in the South). To match the CRU data on frost frequency with other variables, we then drew on previous work by Gallup, Mellinger and Sachs (2000) by aggregating up from 0.5-degree to one-degree cells in ArcView GIS software (ESRI 1996). This yields the final database of about 12,500 cells.

The resulting *frost* variable as used in equation (1) is shown in Figure 1. It turns out that in most places winter frosts are either very rare (0-1 days per month) or very common (10-30 days/month), with a relatively narrow intermediate range. That transition line is closely but not perfectly correlated with latitude. Most of the geographic tropics are frost-free, but for a given latitude there is relatively frequent frost in Mexico, Chile and Southern Africa, and relatively little frost in South Asia and the Middle East.

The independent variables we seek to explain from the Gallup, Mellinger and Sachs database are *population density* in each cell (from Tobler et al. 1996) and the estimated *cultivation intensity* of each cell in terms of the percentage of the cell covered by crops (Matthews 1983).

Key determinants of population density and cultivation intensity, other than frost, are *precipitation* levels, *temperature*, *elevation* and *latitude* (from ESRI, 1995), *distance to a seacoast or navigable river* (computed originally by Gallup, Sachs and Mellinger 1999), and also the *Köppen-Geiger zones* used to classify ecosystems, as digitized from Strahler and Strahler (1992) following Geiger and Pohl (1954).

Country-level variables

To test for climate effects on productivity we aggregate the cell-level climate data up to countrywide averages, using a variety of procedures. First, the cell-level frost variable is transformed into a continuous measure defined as the proportion of the country's land receiving an average of five or more frost-days in winter, after a frost-free summer. This is the definition of *frost* used for equations (2), (2') and (3a). It ranges from zero to one, providing a simple scaling for the interaction terms between frost prevalence and other variables in equation (2). In addition to frost, the other cell-level data which we aggregate up to the country level is the degree to which the country is *coastal*, defined as the proportion of a country's land located within 100 kilometers of a seacoast or navigable river, as computed by Gallup, Sachs and Mellinger (1999).

Climate and location data are then matched with country-level estimates of total agricultural output, input use and resource quality assembled by Wiebe et al. (2000). *Output* is defined as the value of agricultural production in millions of international dollars. *Land* is land used in agriculture, which may be either arable land, permanent cropland or permanent pasture, in thousands of hectares. The variable denoted *arable* includes both arable land and permanent cropland, and includes all *irrigated* land. All of the above are drawn from FAO (1999), except values for *land* that were corrected by Wiebe et al. (2000) for Finland and Papua New Guinea, plus extrapolation (assuming permanent pasture fixed at 1994 levels) for 1995-97. *Labor* is the total economically active population in agriculture, in thousands. *Fertilizer* is a country's total inorganic fertilizer consumption, in metric tonnes. *Livestock* refers to live animal equivalent units, in thousands. These three variables are also drawn directly from FAO (1999), except for livestock units which are aggregated up from the FAO data on individual species using conversion ratios from Hayami and Ruttan (1985, p. 450).

Some of the resource-quality data assembled by Wiebe et al. (2000) are aggregated up from cell-level data. The basic land quality index (*LQI*) is the percentage of a country's cropland or cropland plus natural mosaic (classes 12 and 14 in the International Geosphere-Biosphere Programme classification, from one-kilometer grid data developed by USGS/UNL/JRC 1999), that is reported to be in the top three categories of suitability for agriculture of the World Soil Resources classification scheme (NRCS 1999). *Precipitation* measures average annual rainfall, in millimeters, on the country's cropland (here defined as IGBP class 12) from the half-degree precipitation data for 1961-96 published for the International Panel on Climate Change (1999).[10]

Additional resource-quality variables include the adult *literacy* rate, in percent, from World Bank (1999) plus linear inter/extrapolation for missing values, and the country's stock of *secondary education* as computed by Barro and Lee (1999). Measures of government performance are the ICGRE index of *institutional quality*, and a simple classification of the duration of *statehood* into countries that became independent prior to 1900 (given the value 0), between 1900 and 1950 (1), and after 1950 (2). All of these variables are drawn from the Gallup, Sachs and Mellinger (1999) database.

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[10] Precipitation data were originally supplied by the Climate Impacts LINK Project (U.K. Department of the Environment Contract EPG 1/1/16) on behalf of the Climate Research Unit, University of East Anglia; the same data have now been published on CD-ROM from IPCC (1999).

For real income levels we use Penn World Tables 5.6 (Summers and Heston 1991) data on real GDP per capita (chain indexed) in each year. And finally, a key variable is cumulative agricultural *R&D* expenditures, in dollars per country for individual years from 1961 through 1985, from Pardey et al. (1991).

Results

Table 1 presents six tests of equation (1) using cell-level data. The first set of three columns test for climate effects on population density, and the second set of three columns test for climate effects on cultivation intensity. The first column of each set (columns 1 and 4) includes frost frequency, frost frequency squared, and controls only for biophysical factors unrelated to frost, namely total annual precipitation and distance from a coast or river. The second regression (columns 2 and 5) adds controls for factors that are correlated with frost, namely temperature, elevation, latitude and the interaction of elevation and latitude. The third (columns 3 and 6) replaces these with dummy variables for the twelve Köppen-Geiger climate subzones.

In the regressions, both frost-frequency terms enter as predicted, and they survive controls for other biophysical factors with little change in coefficients or standard errors. The magnitudes of the two frost terms are such that moving from zero to one day of frost per month in winter is associated with an increase of between two and three people per square kilometer, and an increase of between one-third and one percent of land area under cultivation. The other variables also enter as predicted, as the coefficients on precipitation and precipitation squared are significantly positive and negative (there are more people and more cultivated area) in locations with more rainfall, but not too much more, and the coefficient on distance to the coast or a navigable river is strongly negative.[11] The country fixed effects also matter: an F-test clearly rejects the hypothesis

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[11] Interestingly, isolation has a somewhat greater effect on population density than on cultivation intensity: moving 100 km away from the coast or navigable river is associated with a decrease of 1 person per square kilometer (an elasticity of 34.6 percent at the variable means), and a decrease of about 0.2 percent of land under cultivation (an

that all country fixed effects are jointly zero ($p<0.0000$). From this we conclude that frost frequency does have remarkable significance for economic behavior, independently of many other factors for which data are available.

Table 1 is estimated by weighted OLS regression with robust (White) standard errors, using dummies to capture omitted variables as fixed effects across countries. To take account of spatial correlation across cells, for example from omitted variables such as geological origin of soils or geographic proximity to cities, we re-estimate the basic regressions in Table 1b by OLS with spatial standard errors, following Conley (1999). In this case computing limitations prevent the use of weighted regression, so the results with White standard errors are repeated in unweighted form (from Table 1, columns 1 and 4) for comparison with the Conley standard errors.

In computing the results in Table 1b, the pattern of spatial autocorrelation is assumed to be circular, declining at a quadratic rate around each cell to a prespecified radius of 100 km (to capture one neighboring cell) and 500 km (to capture five neighboring cells). Only for the direct effect of frost on population density in column 3 does the standard error of the estimate rise enough to eliminate its statistical significance. Frost effects remain significant for cultivation intensity, despite this control for spatial autocorrelation.

Table 2 tests equation (2) using country-level data, over an estimation sample of 93 countries and 25 years, for a total sample of 2325 observations (not all countries are observed in all years). The first column regresses total output on total inputs including land, and the second column regresses output per hectare on inputs per hectare. Since the countries differ in variance, we use GLS and take account of heteroskedasticity over the panel.

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elasticity of 25.0 percent). This is consistent with an “agricultural hinterlands” effect in which more remote areas attract less non-farm investment, and so have a comparative

In the first column of Table 2, land itself is not significant (recall this is FAO's measure of all agricultural land, including low-productivity grazing areas), nor is the land quality index except when interacted with frost. All other variables are significant, and most are of the expected sign. The only exception is irrigation, whose coefficient is significantly negative. This variable, which measures the proportion of cropland classed by the FAO as irrigated, may paradoxically be highest in the lowest-potential areas, where very little land can be cultivated without irrigation. The measure in Egypt, for example, is 100 percent.

In the second column of Table 2, again the land quality index is not significant and again irrigation is paradoxically negative, but all other variables are significant and of the expected sign. In both columns, the interaction terms are of particular interest. In several cases the coefficients on a variable and on its interaction with frost are of opposite signs, indicating that the variable is correlated differently with output at one end of the frost spectrum than at the other. For example, a one-percent increase in labor use is associated with 0.3-percent higher output in the no-frost (tropical) countries, but the interaction term is of opposite sign (-0.24 in column 1, and -0.21 in column 2), so where the country is entirely exposed to winter frost the net effect of one-percent more labor is only 0.1-percent more output. For irrigation, the positive interaction term is of a larger magnitude than the negative direct effect, so the negative correlation holds only at low levels of frost. The coefficients on R&D expenditure indicate that where frost is zero, a one-percent increase in R&D stocks is associated with a 0.12-0.13 percent increase in output, and about half of this effect applies where the country is fully exposed to frost.

The significance of the interaction effects in Table 2 suggests that input response varies systematically with frost prevalence, and hence input use is likely to be endogenous to climatic conditions. To take account of such endogeneity, we would need to identify instrumental variables which are uncorrelated with climate but which have some

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advantage in agriculture (more cultivated land per person).

influence on the endogenous labor and fertilizer variables. For this we use the measures specified above as variables in equations (3a, 3b and 3c), and then test their relevance explicitly in a simultaneous-equations framework later.

Table 3 tests equation (2’) using standard 2SLS instrumental variables regression, and then using GMM to obtain optimal weighting of moment conditions given the instruments provided. Results are broadly similar using the two methods, and the magnitude of the estimated coefficients is larger: an elasticity of 0.6 on R&D and 0.12 on frost prevalence, for example. The negative coefficient on fertilizer, however, is unexpected. To clarify the relationship, we test the determinants of input use directly using simultaneous equations.

Table 4 provides the simultaneous-equations regression results for the same variables as in Table 3, using 3SLS to estimate the distinct effects of each exogenous variable that was used as an instrument in Table 3. Two sets of results are presented. Model 1 (columns 1-4) uses agroclimatic information only, while model 2 (columns 5-8) controls for unobserved continent characteristics using dummy variables.

The determinants of R&D, from equation (3c) shown here in columns (1) and (5), include the level of farm output and economywide income as hypothesized. Institutional quality and statehood status are also significant. Perhaps surprisingly, the statehood variable enters positively: countries that decolonized more recently undertake slightly more R&D, although not nearly enough more to equalize R&D levels.[12] Note also that when regional dummy variables are included in the system (model 2), the magnitude of the institutional-quality variable falls and it remains significant only at the 10 percent level.

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[12] This is likely to be an effect of foreign aid, which pays for much of the agricultural R&D done in low-income countries (Pardey, Roseboom and Anderson 1991, p. 204).

The determinants of labor use, from equation (3b) shown here in columns (2) and (6), again include both farm output and off-farm employment prospects as hypothesized. All coefficients are significant and of the expected sign, and they are not much affected by inclusion of continent dummy variables.

The determinants of fertilizer use, from equation 3(a) shown here in columns (3) and (7), include quite strong effects for both seasonal frost and soil quality, but no effect at all for irrigation, and the significance of coastal location is lost when controlling for continent dummy variables. Equation (2') in this context is shown in columns (4) and (8). In model 1, all variables are significant and of the expected sign. In model 2, using continent dummies eliminates the direct effect of frost, and reduces the significance of fertilizer, but strong R&D effects remain. The estimated coefficients on the continent variables are themselves of interest. Controlling for all the other factors in the model, Sub-Saharan Africa and South Asia have the lowest output levels, and somewhat surprisingly the Eastern Europe and Central Asia region has a slightly higher output level than do the high income countries (which is the omitted region captured by the constant).[13] This may arise because that region has relatively high agroclimatic productivity for its level of income.[14]

The estimated coefficients in Table 4 can be used to compute the net effect of each exogenous variable on each endogenous one, by substituting equations (3a), (3b) and (3c) into equation (2') to obtain output as a function of the exogenous variables, and then substituting back to obtain each input as a function of the exogenous variables. The resulting expressions are evaluated here using the coefficient estimates from model (2), to

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[13] High income countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, U.K. and USA.

[14] Note that the only Central Asian country in this particular dataset is Turkey, so the region is represented primarily by Eastern European countries with exceptionally favorable agroclimatic conditions.

net out any unobserved continent characteristics and thus limit the variation we might attribute to climate.

Table 5 presents the reduced-form response of each endogenous variable to variation in each exogenous factor. To judge the relative importance of each factor, however, it is necessary to consider the magnitude of its variation as well. Table 6 puts variation and response together, summarizing the extent to which the model presented in Table 4 can explain observed production differences in terms of climate differences as opposed to other factors.

The first four rows of Table 6 present the differences to be explained: the mean values of all variables used in the model, for the whole sample and then for the low- and middle-income countries only, for Sub-Saharan Africa, and for the high-income countries. The differences in these mean values are very large: output per hectare is twelve times larger in the high-income countries ($642/ha) than in Africa ($53/ha), R&D investment is 17 times larger, and fertilizer use is 200 times larger, while labor use is less than one-half as much. The model explains these differences in terms of the exogenous variables presented in the last eleven rows of Table 6, where the first four columns present the mean values of each exogenous variable in each subsample, and the last three columns present their effects, in the sense of the percentage change in output that would result from eliminating any difference relative to the high-income countries.

One key result shown in Table 6 is that eliminating the effect of frost prevalence, which averages 0.2 percent in Africa and 0.7 percent in all low- and middle-income countries, but over 87 percent in high-income countries, would raise average output by 8.5 percent in Africa and 6.5 percent for all low- and middle-income countries. A somewhat smaller effect is attributable to land quality: increasing the percentage of land in the highest quality classes to its level in the high-income countries would increase output by 5.1 percent in Africa and 2.7 percent in all low- and middle-income countries. Institutional quality is found to have an independent effect, through investment in agricultural research: raising the institutional-quality index to its level in the high-income countries would raise output by about 14 percent in Africa and in all low- and middle-income countries. Irrigation and coastal-location effects are relatively small, and the rainfall effect is negative since there is less total precipitation in the high-income countries. Finally, there is a very large effect from higher economywide income, literacy and secondary education, which enter the model by pulling resources out of agriculture and reducing output.

Conclusions

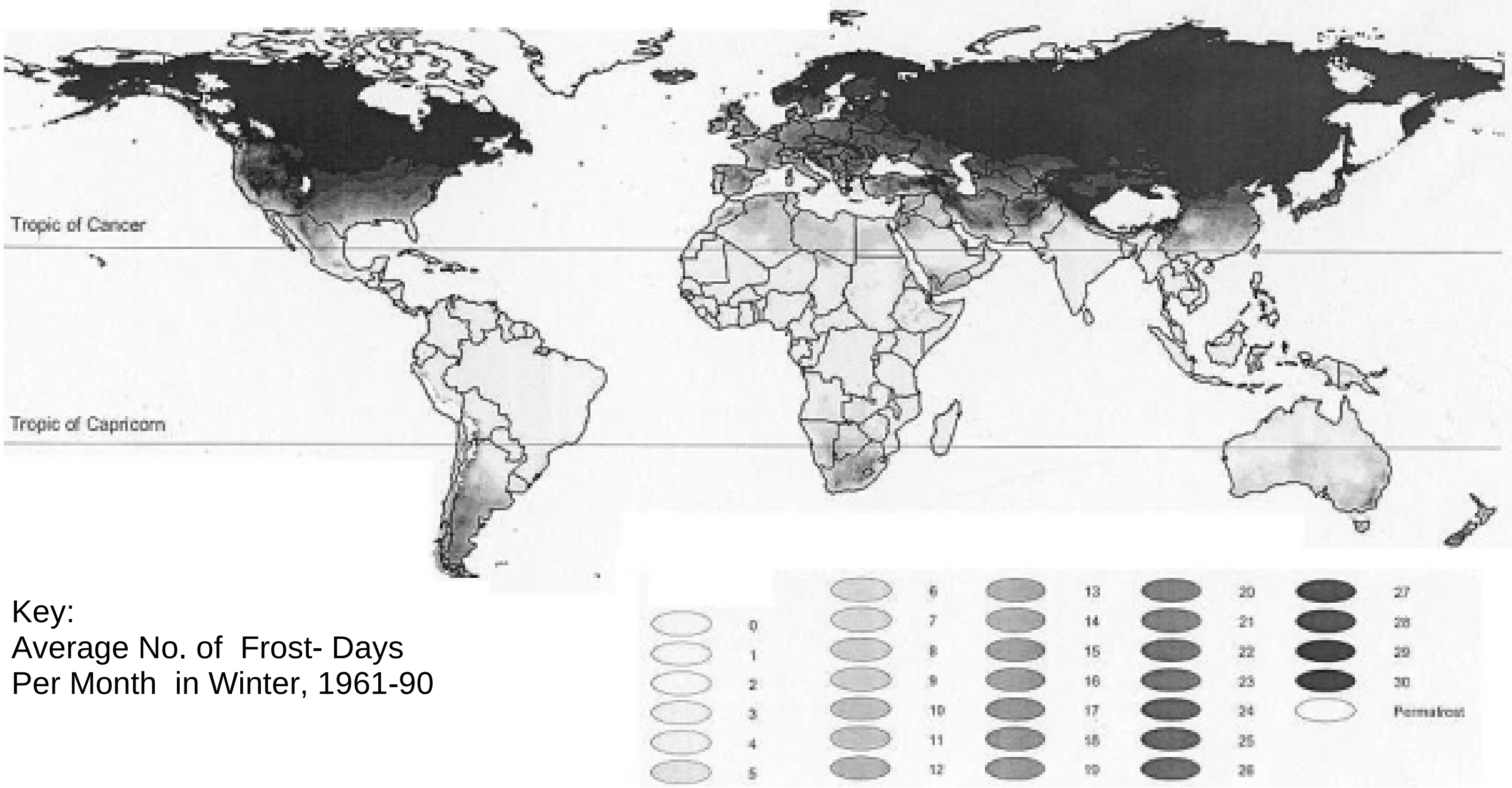
This study asks to what extent input use and output levels can be attributed to climate differences across countries, among other factors. We introduce a new measure of climate -- the prevalence of seasonal frost -- which we hypothesize is an important complement to key inputs. Using a range of models we find consistent evidence that fertilizer use is higher where there is both frost and relatively high land quality, that output levels are higher where frost combines with both higher land quality and more fertilizer use, and that agricultural R&D can be seen as part of a virtuous circle of productivity growth whose location is associated with agroclimatic advantages but is also reinforced by the quality of governmental institutions and other socioeconomic variables.

Our final model is a set of simultaneous equations designed to estimate the net effect of the exogenous variables on output, both directly and through higher input use. The reduced-form parameters derived from the coefficient estimates suggest that eliminating the differences between high-income and other countries in frost prevalence would raise other countries’ output by 6.5 percent, and eliminating their differences in soil quality would raise other countries’ output by 2.7 percent. Other variables are also important -- most notably, eliminating the differences in the ICRG institutional quality index would raise the other countries’ output by 14.2 percent, through its effect on increased agricultural R&D.

The climate effects help explain why output, productivity and research are concentrated in certain geographic regions, but our results do not imply geographic determinism about the future. The basic mechanism is a self-reinforcing growth process whereby output is reinvested in both inputs and R&D. Individual techniques may be location-specific, but R&D can be valuable anywhere: available evidence suggests that the economic returns to R&D are consistently above the cost of capital, and do not vary by region (Alston et al. 2000). Thus, we conclude that although R&D levels are now much higher in the climatically-favored regions, public R&D could be deployed elsewhere to create new opportunities for investment and growth. In the absence of such deliberate technical change, however, the climate-induced productivity gap identified in this paper can be expected to persist.

Figure 1.

Frequency of Seasonal Frost



Key:
Average No. of Frost- Days
Per Month in Winter, 1961-90

Source: Mapped from data in International Panel on Climate Change*, Data Distribution Centre CD-ROM* (Norwich, UK: Climatic Research Unit, Univ. of East Anglia), April 1999.

Note: for higher resolution use FrostMap.pdf (9.5 MB)

Table 1. Climate effects on population density and cultivation intensity at the cell level

Dependent variable:	population density (pers. per sq. km.)			cultivation intensity (% of land area cultivated)		
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)
frost days/mo. in winter	2.308***	3.319***	2.996***	0.520***	1.378***	0.396**
	(0.767)	(0.825)	(0.808)	(0.198)	(0.202)	(0.199)
frost-days squared	-0.239***	-0.253***	-0.266***	-0.034***	-0.028***	-0.028***
	(0.023)	(0.023)	(0.025)	(0.006)	(0.006)	(0.006)
precipitation (mm)	0.874***	0.806***	0.582***	0.262***	0.204***	0.115***
	(0.097)	(0.099)	(0.100)	(0.025)	(0.024)	(0.023)
precipitation squared	-0.003***	-0.003***	-0.002***	-0.001***	-0.001***	0.000***
	0.000	0.000	0.000	0.000	0.000	0.000
dist. to coast/river (km)	-0.012***	-0.014***	-0.013***	-0.003***	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)	0.000	0.000	0.000
temperature avg ann (c)		-1.272***			0.058	
		(0.177)			(0.063)	
elevation in meters		-0.010*			-0.001	
		(0.005)			(0.001)	
absolute latitude		0.562***			-0.378***	
		(0.170)			(0.055)	
abs.lat. x elevation		0.000***			0.000***	
		0.000			0.000	
k-g subzones			X			X
Country effects	X	X	X	X	X	X
Observations	12442	12440	12302	12408	12406	12290
Adj. R-squared	0.42	0.44	0.44	0.27	0.31	0.3

Notes: Parameter estimates are computed by OLS regression, with White standard errors in parentheses. Asterisks indicate significance at 10% (*); 5% (**) and 1% (***). All observations are weighted by land area in each cell, and all specifications control for country fixed effects. Columns (3) and (6) also include dummy variables for the 12 Koppen-Geiger subzones. F-tests find country fixed effects to be jointly significantly different from zero at p<0.000.

Table 1b. Climate effects at the cell level -- correcting for spatial correlation

Dependent variable:	population density (pers. per sq. km.)			cultivation intensity (% of land area cultivated)		
standard error:	White	Conley 100 km	Conley 500 km	White	Conley 100 km	Conley 500 km
Independent variables:	(1)	(2)	(3)	(4)	(5)	(6)
Frost days/mo. in winter	2.073	2.073	2.073	0.722	0.722	0.722
	(0.8170)	(0.7929)	(1.6766)	(0.2003)	(0.1960)	(0.3799)
Frost-days squared	-0.241	-0.241	-0.241	-0.042	-0.042	-0.042
	(0.0240)	(0.0233)	(0.0526)	(0.0063)	(0.0063)	(0.0126)
Precipitation (mm)	0.935	0.935	0.935	0.264	0.264	0.264
	(0.0910)	(0.0911)	(0.1438)	(0.0230)	(0.0228)	(0.0379)
Precipitation squared	-0.003	-0.003	-0.003	-0.001	-0.001	-0.001
	(0.0000)	(0.0004)	(0.0006)	(0.0001)	(0.0001)	(0.0002)
Dist. to coast/river (km)	-0.009	-0.009	-0.009	-0.002	-0.002	-0.002
	(0.0008)	(0.0009)	(0.0020)	(0.0003)	(0.0003)	(0.0006)
Country effects	X	X	X	X	X	X
Observations	12442	12442	12442	12408	12408	12408
Adj. R-squared	0.400	0.400	0.400	0.270	0.270	0.270

Notes: Parameter estimates are computed by OLS regression. Standard errors (in parentheses) are computed with the White heteroskedasticity-consistent estimator, and again following Conley (1999) to correct for spatial autocorrelation around a radius of 100 km and 500 km from each cell. Autocorrelation is assumed to follow a quadratic path, declining at (1-distance/radius)^2 All specifications control for country fixed effects.

Table 2. Climate effects on output and parameter coefficients

	(1)	(2)
Dependent variable:	lout	ln(output/ha)
Independent variables:		
ag.land [ln(land)]	0.0064	
	(0.0054)	
ag.labor [ln(labor)]	0.2999***	
	(0.0056)	
labor * frost	-0.2350***	
	(0.0084)	
livestock [ln(lvstk)]	0.4931***	
	(0.0065)	
fert. [ln(fert)]	0.0234***	
	(0.0029)	
fert. * frost	0.2680***	
	(0.0066)	
precip. (mm)	0.0002***	0.0002***
	(0.0000)	(0.0000)
precip * frost	-0.0004***	-0.0004***
	(0.0000)	(0.0000)
irrig. [ln(irrig.pct.)]	-0.0244***	-0.0406***
	(0.0034)	(0.0032)
irrig. * frost	0.0890***	0.0958***
	(0.0042)	(0.0040)
LQI [ln(lqiigbp2)]	0.0009	0.0041
	(0.0033)	(0.0036)
LQI * frost	0.0242***	0.0063
	(0.0073)	(0.0076)
coastal [ln(lt100cr)]	0.0375***	0.0421***
	(0.0019)	(0.0019)
R&D [ln(randd)]	0.1157***	
	(0.0053)	
R&D * frost	-0.0596***	
	(0.0075)	
frost [ln(plfst5)]	-0.0212***	-0.0423***
	(0.0042)	(0.0046)
ag.lab./ha [ln(laborph)]		0.3055***
		(0.0063)
labor/ha * frost		-0.2068***
		(0.0097)
livestock/ha [ln(lvstkph)]		0.5215***
		(0.0065)
fert./ha [ln(fertph)]		0.0148***
		(0.0027)
fert/ha * frost		0.2659***
		(0.0064)
R&D/ha [ln(randdph)]		0.1267***
		(0.0050)
R&D/ha * frost		-0.0615***
		(0.0062)
Constant	-3.8917***	-4.6749***
	(0.0703)	(0.0558)
Observations	2325	2325
Number of countries	93	93

Notes: Parameter estimates are from FGLS regression accounting for heteroskedasticity across countries. Standard errors in parentheses. Asterisks indicate significance at 10% (*); 5% (**) and 1% (***).

Table 3. Climate effects on output with endogenous inputs

	(1)	(2)
Dependent variable:	ln(output/ha)	ln(output/ha)
Independent variables:		
R&D/ha [ln(randdph)]	0.6310***	0.5768***
	(0.1466)	(0.1485)
ag.lab./ha [ln(laborph)]	0.0913***	0.0800***
	(0.0240)	(0.0197)
fert./ha [ln(fertph)]	-0.2748**	-0.2470**
	(0.1144)	(0.1121)
livestock/ha [ln(lvstkph)]	0.6148***	0.6450***
	(0.0364)	(0.0344)
irrig. [ln(irrig.pct.)]	-0.0273**	-0.0274**
	(0.0132)	(0.0132)
LQI [ln(lqiigbp2)]	0.1055***	0.0983***
	(0.0239)	(0.0212)
coastal [ln(lt100cr)]	0.0530***	0.0537***
	(0.0071)	(0.0092)
frost [ln(plfst5)]	0.1215***	0.1176***
	(0.0193)	(0.0175)
precip (mm)	0.0002***	0.0002***
	(0.0001)	(0.0000)
Constant	-1.8903**	-2.3938***
	(0.8462)	(0.8995)
Observations	1725	1725
No. of countries	69	69
R-squared	0.73	
Hansen’s J		8.5288
P-value [chi-sq(1)]		0.00350

Notes: Estimates and standard errors (in parentheses) are computed by 2SLS for col. 1, and GMM for col. 2. Asterisks indicate significance at 10% (*); 5% (**) and 1% (***). Instrumented variables are the first three regressors (R&D, labor and fertilizer use). Instruments are the other regressors, plus the determinants of labor and fertilizer used in equations (3a) and (3b) and shown in Table 4.

Table 4. Climate effects on inputs and output in a simultaneous system

	Model 1				**Model 2**			
Dep. var. (in logs):	(1) R&D/ha	(2) labor/ha	(3) fert./ha	(4) output/ha	(5) R&D/ha	(6) labor/ha	(7) fert./ha	(8) output/ha
Indep. vars.:								
ln(output/ha)	0.9780***	0.9593***	1.2996***		1.0050***	0.9474***	1.2822***	
	(0.0266)	(0.0153)	(0.0445)		(0.0248)	(0.0142)	(0.0424)	
income [ln(rgdpch)]	0.2884***	-1.075***	0.5063***		0.3568***	-1.057***	0.5490***	
	(0.0475)	(0.0238)	(0.0556)		(0.0482)	(0.0230)	(0.0565)	
inst.qual. [icrge80]	0.0596***				0.0293*			
	(0.0166)				(0.0168)			
statehood [years]	0.2053***				0.2434***			
	(0.0347)				(0.0351)			
literacy [ln(pct)]		-0.152***				-0.165***		
		(0.0345)				(0.0341)		
sec.ed. [ln(years)]		-0.174***				-0.169***		
		(0.0219)				(0.0213)		
irrig. [ln(irrig.pct.)]			-0.0171				0.0130	
			(0.0153)				(0.0173)	
LQI [ln(lqiigbp2)]			0.1715***				0.2065***	
			(0.0195)				(0.0208)	
coastal [ln(lt100cr)]			0.0365***				0.0144	
			(0.0117)				(0.0133)	
frost [ln(plfst5)]			0.0713***	0.0263***			0.0657***	0.0014
			(0.0165)	(0.0063)			(0.0166)	(0.0044)
ag.lab./ha [ln(laborph)]				0.1316***				0.3096***
				(0.0145)				(0.0132)
lvstk/ha [ln(lvstk/ha)]				0.3424***				0.2656***
				(0.0195)				(0.0190)
fert./ha [ln(fertph)]				0.1869***				0.0433*
				(0.0265)				(0.0251)
R&D/ha [ln(randdph)]				0.2936***				0.3227***
				(0.0366)				(0.0327)
precip (mm)				0.0001***				0.0001***
				(0.0000)				(0.0000)
Sub-Sah.Af								-1.219***
								(0.0726)
South Asia								-0.950***
								(0.0494)
M.E.&N.Afr.								-0.693***
								(0.0427)
L.Am.&Cari.								-0.701***
								(0.0414)
E.Asia&Pac.								-0.795***
								(0.0505)
Eur.&C.Asia								-0.446***
								(0.0614)
Constant	-5.7172***	8.3782***	-0.2491	-2.4299***	-6.0660***	8.2737***	-0.6996	-0.654**
	(0.3550)	(0.2414)	(0.4812)	(0.2444)	(0.3563)	(0.2328)	(0.4879)	(0.2823)
“R-sq”	0.68	0.83	0.64	0.83	0.67	0.83	0.64	0.91
Observations	1665	1665	1665	1665	1665	1665	1665	1665

Notes: Standard errors in parentheses. Asterisks indicate * significant at 10%; ** significant at 5%; *** significant at 1%. All models estimated by three-stage least squares regression. Variables are defined in the text. All regional dummies are based on World Bank, WDI 1999 classifications and include only low- and middle-income countries. The omitted “region” is the high income countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, U.K. and USA).

Table 5. Reduced-form parameters for all endogenous variables

	Endogenous variables (in logs):			
Exogenous variables	R&D/ha	labor/ha	fert./ha	output/ha
income [ln(rgdpch)]	-0.222	-1.603	-0.190	-0.576
inst.qual. [icrge80]	0.058	0.027	0.037	0.029
statehood [years]	0.485	0.228	0.308	0.240
literacy [ln(pct)]	-0.157	-0.313	-0.200	-0.156
sec.ed. [ln(years)]	-0.161	-0.321	-0.205	-0.160
irrig. [ln(irrig.pct.)]	0.002	0.002	0.015	0.002
LQI [ln(lqiigbp2)]	0.027	0.026	0.242	0.027
coastal [ln(lt100cr)]	0.002	0.002	0.017	0.002
frost [ln(plfst5)]	0.013	0.012	0.082	0.013
lvstk/ha [ln(lvstk/ha)]	0.817	0.770	1.042	0.813
precip (mm)	0.00031	0.00029	0.00039	0.00031
Sub-Sah.Af	-3.748	-3.533	-4.782	-3.730
South Asia	-2.921	-2.754	-3.727	-2.907
M.E.&N.Afr.	-2.131	-2.009	-2.719	-2.120
L.Am.&Cari.	-2.155	-2.032	-2.750	-2.145
E.Asia&Pac.	-2.444	-2.304	-3.119	-2.432
Eur.&C.Asia	-1.371	-1.293	-1.750	-1.365
Constant	-6.313	8.041	-1.014	-0.246

Note: Variables are defined in the text. All regional dummies are based on World Bank, WDI 1999 classifications and include only low- and middle-income countries. The omitted “region” is the high income countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, U.K. and USA).

Table 6. Mean values and reduced-form effect of exogenous variables on output

	Mean values by sub-sample				Effects on output		
	Whole Sample	Low- & Middle Income	Sub-Saharan Africa	High-Income Countries	Whole Sample	Low- & Middle Income	Sub-Saharan Africa
Endogenous variables							
ag. output ($/ha)	193	112	53	642			
ag. labor (#/ha)	0.13	0.17	0.17	0.07			
fertilizer use (kg/ha)	6.24	1.98	0.38	75.87			
ag. R&D/ha ($/ha)	0.011	0.005	0.003	0.052			
Exogenous variables							
income ($/cap)	2542	1427	789	8956	-51.6%	-65.3%	-75.3%
ICRG index(0-10)	5.8	4.4	4.5	9.0	9.5%	14.2%	13.8%
statehood (0-2)	0.9	1.2	1.9	0.2	-1.8%	-2.6%	-4.7%
literacy (%)	56.4	44.0	27.3	96.9	-8.1%	-11.6%	-18.0%
sec. ed. (yrs)	0.38	0.23	0.10	1.16	-16.2%	-22.7%	-32.9%
irrigation (%)	2.9	2.9	0.5	3.0	0.00%	0.01%	0.32%
land qual. index (%)	12.3	9.1	3.9	24.1	1.9%	2.7%	5.1%
coastal location (%)	11.4	5.6	0.2	55.0	0.3%	0.4%	1.0%
frost prevalence (%)	3.1	0.7	0.2	87.4	4.4%	6.5%	8.5%
livestock (units/ha)	391	307	148	661	53.3%	86.5%	237.0%
precipitation (mm)	1183	1343	1081	834	-10.1%	-14.4%	-7.3%

Note: Variables shown are the underlying observations, not their log forms. Effects on output are the changes due to setting each exogenous variable at its mean value for the subsample of high-income countries, to eliminate that source of difference between the regions. The subsample of high-income countries is Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, U.K. and USA.

Table A1. Summary statistics for variables used in Tables 1 and 1a

Variable	Obs	Mean	Std. Dev.	Min	Max
popdense	12442	35.754	102.344	0.000	1840.645
cultland	12408	12.629	27.620	0.000	100.000
frost	12442	16.418	13.112	0.000	30.000
frost2	12442	441.462	408.134	0.000	900.000
precip	12442	53.948	49.674	0.000	478.250
precip2	12442	5377.694	10879.160	0.000	228723.100
cstriv	12442	967.966	1011.684	9.000	4953.000

Table A2. Summary statistics for variables used in Table 2

Variable	Obs	Mean	Std. Dev.	Min	Max
loutph	2325	-1.943076	1.464344	-5.902598	1.585661
llaborph	2325	-1.968343	1.43612	-7.014574	1.275922
frlabp5	2325	-.8096875	1.198079	-4.826296	.9441409
llvstkph	2325	5.759999	1.20497	1.307853	8.250638
lfertph	2325	.9726121	3.396713	-17.68983	5.952837
frfertp5	2325	1.110936	1.922109	-3.53898	5.952837
rain	2325	1135.168	666.4489	37.20422	3674.137
frrain5	2325	287.4454	407.8006	0	2045.359
lirrigpc	2325	.9609139	2.331885	-6.907755	4.60518
frirrig5	2325	.5770148	1.365372	-6.907755	4.126962
llqiigb2	2325	1.846693	2.841527	-6.907755	4.329594
frlqi_5	2325	.7982185	1.763974	-5.843103	4.085755
llt100cr	2325	1.625491	4.017284	-6.907755	4.60518
lranddph	2325	-4.823065	1.877291	-10.67668	.5629358
frlrndp5	2325	-1.376003	1.872583	-10.00679	.5629358
lplfst5	2325	-3.65691	3.174796	-6.907755	.0009995

Note: “rain” variable is expressed in mm, and so rain*frost variable is zero when frost is zero.

Table A3. Summary statistics for variables used in Table 3

Variable	Obs	Mean	Std. Dev.	Min	Max
loutph	1725	-1.634547	1.363087	-5.604633	1.585661
lranddph	1725	-4.539398	1.860363	-10.67668	.5629358
llaborph	1725	-2.022974	1.462629	-7.014574	1.197914
lfertph	1725	1.836593	2.79226	-16.36496	5.952837
llvstkph	1725	5.965548	1.002921	2.95633	8.250638
lirrigpc	1725	1.103777	2.153752	-6.907755	4.348019
llqiigb2	1725	2.50626	1.938058	-6.907755	4.329594
llt100cr	1725	2.399485	3.499172	-6.907755	4.60518
lplfst5	1725	-3.445067	3.207851	-6.907755	.0009995
rain	1725	1183.907	662.2453	110.6843	3674.137
syr1565l	1725	-.9585292	1.204244	-4.828314	1.255046
llitercy	1725	4.027194	.6752277	-.1972326	4.60517
icrge80	1725	5.77342	2.434175	2.27083	9.98437
state	1725	.8985507	.9655452	0	2

Table A4. Summary statistics for variables used in Table 4

Variable	Obs	Mean	Std. Dev.	Min	Max
loutph	1665	-1.648923	1.347093	-5.604633	1.585661
lranddph	1665	-4.543399	1.85529	-10.67668	.5629358
llaborph	1665	-2.074353	1.430719	-7.014574	1.197914
lfertph	1665	1.830171	2.769477	-16.36496	5.878091
llvstkph	1665	5.965316	.998663	2.95633	8.250638
lirrigpc	1665	1.072928	2.117127	-6.907755	4.348019
llqiigb2	1665	2.518118	1.927094	-6.907755	4.329594
llt100cr	1665	2.413322	3.464542	-6.907755	4.60518
lplfst5	1665	-3.46052	3.204509	-6.907755	.0009995
rain	1665	1181.712	664.036	110.6843	3674.137
syr1565l	1665	-.9568192	1.202813	-4.828314	1.255046
llitercy	1665	4.033769	.6710518	-.1972326	4.60517
icrge80	1665	5.804328	2.451347	2.27083	9.98437
state	1665	.8768769	.9619441	0	2

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