Supporting Information

Ceddia et al. 10.1073/pnas.1317967111

SI Text

SI Materials and Methods

Panel data is formed by a repeated cross-section, consisting of individual units $i = 1...N$, over a period $t = 1...T$ (1, 2). The use of panel data allows controlling for a number of unobserved factors, including time-invariant factors (i.e., that vary across individuals but not over time) and individual-invariant factors (i.e., that vary across time but are the same for all individual units). The starting point is the following statistical model

$$y_{it} = \mu + \beta_1 x_{it1} + \ldots \beta_k x_{itk} + \varepsilon_{it} \quad \textbf{[S1a]}$$

$$\varepsilon_{it} \sim N\left(0, \sigma_v^2\right). \quad \textbf{[S1b]}$$

To account for time-invariant (α_i) and individual-invariant (λ_t) unobserved effects, expressions **S1a** and **S1b** can be rewritten assuming that $\varepsilon_{it} = \alpha_i + \lambda_t + v_{it}$,

$$y_{it} = \mu + \alpha_i + \lambda_t + \beta_1 x_{it1} + \ldots \beta_k x_{itk} + v_{it} \quad \textbf{[S2a]}$$

$$v_{it} \sim N\left(0, \sigma_v^2\right). \quad \textbf{[S2b]}$$

Expression **S2** can be estimated either through the two-way Fixed Effect (FE) model or through the two-way Random Effect (RE) model. The FE model assumes that the time-invariant factors α_i and individual-invariant factors λ_t are just fixed constants. The model is estimated through an ordinary least squares (OLS) regression of $(y_{it} - \bar{y}_{it})$ on $(x_{itk} - \bar{x}_{itk})$, where $\bar{y}_{it}$ and $\bar{x}_{itk}$ are the individual-specific mean of y_{it} and x_{itk}, respectively, and subsequently recovering the α_i and λ_t intercepts. The RE specification implies that the time-invariant effects α_i and the individual-invariant effects λ_t are stochastic with $\alpha_i \sim N(0, \sigma_\alpha^2)$ and $\lambda_t \sim N(0, \sigma_\lambda^2)$. The RE model is estimated through a generalized least squares procedure, which requires an OLS regression of $(y_{it} - \vartheta \bar{y}_{it})$ on $(x_{itk} - \vartheta \bar{x}_{itk})$, thus removing from the data a fraction ϑ (this parameter is also estimated) of the individual-specific means. The choice between a simple OLS or FE and RE model is made on the basis of the Breusch–Pagan Lagrange multiplier (LM) test and the Hausman test (1, 2).

The Breusch–Pagan LM test works on the null hypothesis $H_0 : \sigma_\alpha^2 = \sigma_\lambda^2 = 0$ and is formed as

$$LM = LM_1 + LM_2 \quad \textbf{[S3a]}$$

$$LM_1 = \frac{NT}{2(T-1)}\left\{1 - \frac{\tilde{\varepsilon}'(\mathbf{I}_N \otimes \mathbf{J}_T)\tilde{\varepsilon}}{\tilde{\varepsilon}'\tilde{\varepsilon}}\right\}^2 \otimes \quad \textbf{[S3b]}$$

$$LM_2 = \frac{NT}{2(T-1)}\left\{1 - \frac{\tilde{\varepsilon}'(\mathbf{J}_N \otimes \mathbf{I}_T)\tilde{\varepsilon}}{\tilde{\varepsilon}'\tilde{\varepsilon}}\right\}^2. \quad \textbf{[S3c]}$$

The vector $\tilde{\varepsilon}$ represents the residual from the OLS regression (corresponding to **[S1]**); N is the number of individuals; T is the number of time periods; $\mathbf{I}_N$ and $\mathbf{I}_T$ are identity matrices of dimensions N and T, respectively; $\mathbf{J}_N$ and $\mathbf{J}_T$ are respectively the $N \times N$ and $T \times T$ matrices with all elements equal to 1; and the symbol $\otimes$ denotes the Kronecker product between two matrices. The LM statistic is distributed as $\chi^2(2)$. Large values of LM allow rejection of the null hypothesis, therefore indicating that the models accounting for the existence of individual and time effects (either FE or RE) should be preferred to the OLS.

The Hausman statistic is constructed as

$$H = \left(\hat{\beta}_{RE} - \tilde{\beta}_{FE}\right)' \left[\mathrm{var}\left(\tilde{\beta}_{FE}\right) - \mathrm{var}\left(\hat{\beta}_{RE}\right)\right]^{-1} \left(\hat{\beta}_{RE} - \tilde{\beta}_{FE}\right). \quad \textbf{[S4]}$$

The vectors $\hat{\beta}_{RE}$ and $\tilde{\beta}_{FE}$ represent the estimated parameters under the RE and FE hypothesis, respectively, whereas $\mathrm{var}(\hat{\beta}_{RE})$ and $\mathrm{var}(\tilde{\beta}_{FE})$ are the estimated variances. The statistic H is distributed as $\chi^2(k)$, where k is the dimension of the parameter vector β. A large value of this statistic argues in favor of the FE over the RE model.

SI Results and Discussion

Governance Quality Indicators and Descriptive Statistics of the Sample. The governance quality indicators and the descriptive statistics for the sample are presented in Tables S1 and S2, respectively.

Controlling for the Effect of Land Quality. Drawing on data from the Global Agro-Ecological Zones (GAEZ 3.0), a set of proxies for the quality of available land resources in a country (LQ_i) are included. In particular, for intermediate levels of inputs, the average potential yield of rain-fed wheat ($LQ_i = AWY_i$) and rain-fed maize ($LQ_i = AMY_i$) over the baseline period 1961–1990 are considered. Finally the weighted average of wheat and maize potential yields is formed as $AMWY_i = (PW_i \times AWY_i + PM_i \times AMY_i)/(PW_i + PM_i)$, where PW_i and PM_i respectively represent the wheat and maize output in the ith country over the baseline period. This average wheat and maize potential yield is also used as a land quality proxy ($LQ_i = AMWY_i$).

On the basis of the linear expression

$$\begin{aligned}\log(ALit) = {} & \alpha(LQ_i) + \gamma_1(GOV_i \times AOHA_{it}) + \beta_1 \log(AOHA_{it}) \\ & + \beta_2 \log^2(AOHA_{it}) + \theta_1 \log(POP_{it}) + \theta_2 \log^2(POP_{it}) \\ & + \theta_3 \log(GDPC_{it}) + \theta_4 \log^2(GDPC_{it}) + \theta_5 \log^3(GDPC_{it}) \\ & + \theta_6 \log(EX_{it}) + \theta_7 \log^2(EX_{it}) + \theta_8 \log(PEDS_{it}) \\ & + \theta_9 \log^2(PEDS_{it}) + \theta_{10} \log(AVA_{it}) \\ & + \theta_{11}\left[\log(PEDS_{it}) \times \log(AVA_{it})\right] + v_{it},\end{aligned} \quad \textbf{[S5]}$$

a set of 18 different models, with 3 different land quality proxies, and 6 different governance quality indicators are estimated. Note that as the land quality proxy varies across countries but not over time, the OLS estimation of expression **S5** is equivalent to a weighted fixed-effect model (1). The results are presented in Tables S3–S8.

When wheat potential yields are considered as a proxy of land quality ($LQ_i = AWY_i$), the coefficient associated with it is negative and significant for all six models (corresponding to the six different governance measures). This suggests that better land quality promotes land sparing. The effect of governance quality and intensification is generally consistent with the models presented in Tables 1 and 2 (models 1–6), except in the case where $GOV_i = ACC_i$ (the coefficient associated with $GOV \times AOHA$ has the right sign but is not significant) and where $GOV_i = EPI_i$ (the coefficient associated with $GOV \times AOHA$ has the wrong sign but is not significant). However, when land quality is approximated through maize potential yields ($LQ_i = AMY_i$) and combined wheat and maize yields ($LQ_i = AWMY_i$), the coefficient associated with it is positive. This suggests that better land quality promotes agricultural expansion. In general, the other coefficients are consistent with models 1–6 in the main text, except in the case where $GOV_i = ACC_i$ and $GOV_i = EPI_i$ (the coefficients associated with $GOV \times AOHA$ have the wrong sign but are not significant).

The relative performance of the models, against models 1–6 in the main text, is assessed on the basis of the Akaike Information Criterion (AIC). Models 1–6 outperform the 18 models associated with **[S5]** as they all present lower AIC scores.

Controlling for the Simultaneous Effect of Multiple Governance Dimensions. An additional model accounting for the simultaneous effect of all six governance indicators is estimated on the basis of the following expression:

$$\begin{aligned}\log(ALit) = {} & \mu + \alpha_i + \lambda_t + \sum_{n:1}^{6} \gamma_n (GOV_{ni} \times AOHA_{it}) + \beta_1 \log(AOHA_{it}) \\ & + \beta_2 \log^2(AOHA_{it}) + \theta_1 \log(POP_{it}) + \theta_2 \log^2(POP_{it}) \\ & + \theta_3 \log(GDPC_{it}) + \theta_4 \log^2(GDPC_{it}) + \theta_5 \log^3(GDPC_{it}) \\ & + \theta_6 \log(EX_{it}) + \theta_7 \log^2(EX_{it}) + \theta_8 \log(PEDS_{it}) \\ & + \theta_9 \log^2(PEDS_{it}) + \theta_{10} \log(AVA_{it}) \\ & + \theta_{11} \left[\log(PEDS_{it}) \times \log(AVA_{it})\right] + v_{it}.\end{aligned} \quad \textbf{[S6]}$$

The Breusch–Pagan LM test indicates that the simple OLS (with $\alpha_i = \lambda_t = 0$) is the best estimator for **[S6]**. The results are presented in Table S9.

When all governance aspects are accounted for simultaneously, results appear less clear. Regarding environmental governance aspects, the coefficients are either not significant ($GOV = PA$ and $GOV = ESI$) or have a positive sign ($GOV = EPI$), thus indicating that better environmental governance promotes agricultural expansion when agricultural productivity increases. Concerning conventional governance, only the effect of rule of law ($GOV = ROL$) is consistent with the resulted reported in the main text, whereas the coefficients associated with the remaining governance indicators ($GOV = CORC$ and $GOV = ACC$) are negative, thus suggesting that better governance when combined with increased productivity promotes land sparing. However, on the basis of the AIC criterion, this model is statistically inferior to the ones presented in *Results* and *Discussion*, particularly Tables 1 and 2.

The Role of Socioeconomic Factors. On the basis of the results obtained through models 1–6, the following considerations about the role of socioeconomic factors, can be made. The relationship between per capita gross domestic product (GDP) and agricultural expansion is highly nonlinear but ultimately implies that higher GDP leads to agricultural expansion. The elasticity of the agricultural area with respect to per capita GDP is $\varepsilon_{GDPC} = \theta_3 + 2\theta_4 \log(GDPC) + 3\theta_5 \log^2(GDPC)$. In all models (with the exception of model 3) the relevant parameters are significantly different from zero and point to the existence of two turning points $\tau_1 = \exp\{[-2\theta_4 - (4\theta_4^2 - 12\theta_3\theta_5)^{1/2}]/6\theta_5\}$ and $\tau_2 = \exp\{[-2\theta_4 + (4\theta_4^2 - 12\theta_3\theta_5)^{1/2}]/6\theta_5\}$. The estimated values for τ_1 are US\$1,208, US\$1,091, US\$997, US\$1,063, and US\$1,071 *per annum* (p.a.) for models 1, 2, 4, 5, and 6, respectively. The estimated values for τ_2 are US\$3,184, US\$3,630, US\$4,032, US\$3,491, and US\$3,519 p.a., respectively, for the same set of models.

For per capita GDP levels, up to τ_1 an increase in per capita GDP is associated with an expansion of agricultural area. When per capita GDP lies between τ_1 and τ_2, a negative relationship with agricultural area emerges. Finally, when per capita GDP exceeds τ_2, the relationship with agricultural expansion returns positive.

These results allow us to reject the environmental Kuznets curve (EKC) hypothesis for agricultural expansion. The EKC is very appealing to policymakers as it suggests the possibility of growing out of environmental degradation (3). Our results suggest that the relationship between agricultural contraction and increase in per capita GDP is only temporary, as it holds only for moderate income levels (i.e., when average per capita income rests between τ_1 and τ_2). These considerations are particularly important for countries like Brazil and Venezuela, where per capita GDP levels are substantially above the estimated values for τ_2.

Although the existence of the first turning point (τ_1) may reflect structural changes in the economy (e.g., as a country becomes more affluent the service sector expands at the expenses of agriculture and manufacturing), the second turning point (τ_2) is more difficult to explain. One possibility is that in a growing economy demand for agricultural land may increase as a result of increasing energy demand (e.g., biofuels production) and increasing integration into international commodities markets because more affluent countries tend to trade more. The fact that the coefficients associated with agricultural exports (EX) are generally positive and significant (except in models 1 and 5), supports this hypothesis.

The elasticity of agricultural area with respect to population is $\varepsilon_{POP} = \theta_1 + 2\theta_2 \log(POP)$. The effect of population on agricultural area is positive although not always significant. This is not entirely surprising, since changes in total population may hide important dynamics related to internal migration which can more accurately explain agricultural expansion/contraction (4).

Finally, the elasticity of agricultural area with respect to the service on external debt ($PEDS$) is given by $\varepsilon_{PEDS} = \theta_8 + 2\theta_9 \log^2(PEDS) + \theta_{11} \log(AVA)$. In all models, an increase in the service on external debt leads to agricultural expansion in those countries with a sufficiently large agricultural sector, as measured by the agricultural value added AVA, indicating a sort of path dependence by which countries with a relatively large agricultural sector are more likely to expand agriculture to service external debt (5). Unlike internal debt, which can often be serviced by either acting directly on the money supply or by borrowing on the internal bond market, servicing the external debt requires access to foreign currency. For this reason, countries with large external debt tend to more quickly degrade their natural resources to meet their international obligations (6).

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Table S1. Conventional and environmental governance indicators

Countries	Conventional governance			Environmental governance		
	CORC	*ROL*	*ACC*	*PA*	*ESI*	*EPI*
Bolivia	−0.63405	−0.53152	0.02175	15.08474	59.5	54.5
Brazil	−0.02463	−0.39595	0.31840	15.51659	62.2	57.7
Colombia	−0.25474	−0.795	−0.44246	19.63689	58.9	60.3
Paraguay	−1.27461	−1.05883	−0.4	4.26264	59.7	50.65
Uruguay	−0.27984	−0.65612	−0.17086	7.493	60.4	48.5
Venezuela	−0.90662	−1.10801	−0.42026	52.7373	48.1	54.5

Table S2. Descriptive statistics for the sample for 215 cases

Variables	Description	Mean	Standard	Minimum	Max	Source
AL	Agricultural land (1,000 ha)	63,784.949	80,609.512	11,417	264,500	FAO
AOHA	Value of agricultural output (at constant prices) per hectare (US dollars per hectare)	152.231	99.412	16.536	465.105	FAO
POP	Population	38,164,522.3	50,404,994.1	2,484,739	187,958,211	WB
EX	Index of agricultural exports (as percent of the volume in 2004–2006)	62.781	46.203	4	254	FAO
GDPC	GDP per capita (at US$2,000)	2,533.705	1,526.928	775.533	6,521.484	WB
PEDS	Service on external debt as percent of GDP	5.264	2.469	0.923	12.111	WB
AVA	Agricultural value added as percent of GDP	14.639	8.045	4.023	37.702	WB
CORC	Index of corruption control	−0.569	0.432	−1.275	−0.025	WB
ROL	Index of rule of law	−0.759	0.264	−1.108	−0.396	WB
ACC	Index of voice and accountability	−0.181	0.283	−0.442	0.318	WB
PA	Percent of terrestrial area under environmental protection	19.290	15.904	4.263	52.737	WDPA
ESI	Environmental Sustainability Index	58.117	4.625	48.100	62.200	YCELP
EPI	Environmental Performance Index	54.512	3.920	48.500	60.300	YCELP

FAO, Food and Agriculture Organization; WB, World Bank; WDPA, World Database on Protected Areas; YCELP, Yale Center for Environmental Law and Policy. All data has been retrieved from the following databases: FAOSTAT (http://faostat3.fao.org/faostat-gateway/go/to/home/E), WB (http://data.worldbank.org/indicator), WB governance indicators (http://info.worldbank.org/governance/wgi/), and WDPA (www.wdpa.org/Statistics.aspx).

Table S3. Regression results for the models accounting for land quality and *GOV* = *CORC*

Variables	*LQ* = *AWY*	*LQ* = *AMY*	*LQ* = *AWMY*
Log(*AOHA*)	−2.0279§ (0.1136)	−1.2028§ (0.1271)	−0.5517§ (0.1141)
Log^2(*AOHA*)	0.1996§ (0.01419)	0.1098§ (0.0158)	0.0412§ (0.0137)
Log(*POP*)	4.7038§ (0.3696)	2.2484§ (0.3754)	0.2007 (0.2513)
Log^2(*POP*)	−0.1199§ (0.01129)	−0.0318‡ (0.0108)	0.0274§ (0.0072)
Log(*GDPC*)	−9.5542§ (1.1886)	−7.0663§ (1.4769)	−1.6846 (1.0800)
Log^2(*GDPC*)	1.1113§ (0.1720)	0.8524§ (0.2183)	0.3011* (0.1704)
Log^3(*GDPC*)	−0.0419§ (0.0083)	−0.0323‡ (0.0107)	−0.0157* (0.0088)
Log(*EX*)	0.2120§ (0.0046)	0.1323† (0.0581)	0.0387 (0.0540)
Log^2(*EX*)	0.0228§ (0.0063)	−0.0193† (0.0078)	−0.0065 (0.0072)
Log(*PEDS*)	−0.1062* (0.0640)	−0.2483† (0.00794)	−0.2666§ (0.0729)
Log^2(*PEDS*)	−0.0026 (0.0177)	0.0260 (0.0222)	0.0093 (0.0202)
Log(*AVA*)	0.1220§ (0.0310)	0.4440§ (0.0395)	0.3396§ (0.0351)
Log(*PEDS*) × log(*AVA*)	0.0479‡ (0.0172)	0.0556† (0.0214)	0.0845§ (0.0193)
CORC × *AOHA*	0.0027§ (0.00227)	0.0022§ (0.0003)	0.0021§ (0.0002)
LQ	−0.00176§ (0.00007)	0.0006§ (0.00004)	0.0007§ (0.00004)
Adjusted R^2	0.994	0.991	0.993
Log-likelihood	275.9662	229.2167	247.6384
Pr > F	0.000	0.000	0.000
AIC	−2.428	−1.993	−2.164

Dependent variable: log(*AL*); *10% s.l.; †5% s.l.; ‡1% s.l.; §0.1% s.l. s.l., significance level.

Table S4. Regression results for the models accounting for land quality and *GOV* = *ROL*

Variables	*LQ* = *AWY*	*LQ* = *AMY*	*LQ* = *AWMY*
Log(*AOHA*)	−2.8669§ (0.1819)	−1.7577§ (0.1995)	−1.2394§ (0.1661)
Log^2(*AOHA*)	0.3187§ (0.0246)	0.1855§ (0.0274)	0.1359§ (0.0229)
Log(*POP*)	5.3171§ (0.4397)	2.4039§ (0.4471)	0.8049† (0.3117)
Log^2(*POP*)	−0.1365§ (0.0133)	0.0361‡ (0.0129)	0.0101 (0.0090)
Log(*GDPC*)	−10.8590§ (1.3511)	−6.6442§ (1.6354)	−2.7815† (1.2193)
Log^2(*GDPC*)	1.2195§ (0.1897)	0.7340‡ (0.2350)	0.3829† (0.1851)
Log^3(*GDPC*)	0.0441§ (0.0090)	−0.0247† (0.0113)	−0.0167* (0.0093)
Log(*EX*)	0.2545§ (0.0495)	0.1622‡ (0.0621)	0.0779 (0.0564)
Log^2(*EX*)	−0.0296§ (0.0067)	−0.0231‡ (0.0084)	−0.0121 (0.0076)
Log(*PEDS*)	−0.1406† (0.0664)	−0.2787‡ (0.0832)	−0.2889§ (0.0749)
Log^2(*PEDS*)	0.0117 (0.0184)	0.0333 (0.0234)	0.0196 (0.0208)
Log(*AVA*)	0.2299§ (0.0333)	0.4910§ (0.0455)	0.4096§ (0.0392)
Log(*PEDS*) × log(*AVA*)	0.0415† (0.0183)	0.0595‡ (0.0228)	0.0797§ (0.0202)
ROL × *AOHA*	0.0036§ (0.0003)	0.0025§ (0.0004)	0.0027§ (0.0004)
LQ	−0.0017§ (0.00007)	0.0006§ (0.00003)	0.0007§ (0.00004)
Adjusted R^2	0.994	0.990	0.992
Log-likelihood	266.6518	218.3686	241.0475
Pr > F	0.000	0.000	0.000
AIC	−2.341	−1.892	−2.103

Dependent variable: log(*AL*); *10% s.l.; †5% s.l.; ‡1% s.l.; §0.1% s.l. s.l., significance level.

Table S5. Regression results for the models accounting for land quality and *GOV* = *ACC*

Variables	*LQ* = *AWY*	*LQ* = *AMY*	*LQ* = *AWMY*
Log(*AOHA*)	−1.3595§ (0.1720)	−0.6223§ (0.1717)	−0.2927* (0.1578)
Log^2(*AOHA*)	0.1036§ (0.0225)	0.0152 (0.0224)	−0.0137 (0.0204)
Log(*POP*)	2.3318§ (0.6022)	−0.1585 (0.5393)	−0.9537† (0.4419)
Log^2(*POP*)	−0.0442† (0.0182)	0.0395† (0.0157)	0.0623§ (0.0130)
Log(*GDPC*)	−2.8268 (1.9092)	1.6952 (1.9271)	3.2528† (1.6284)
Log^2(*GDPC*)	0.1886 (0.2644)	−0.3581 (0.2722)	−0.4467* (0.2373)
Log^3(*GDPC*)	−0.0002 (0.0124)	0.0224* (0.0129)	0.0209* (0.0116)
Log(*EX*)	0.1253† (0.0602)	0.0646 (0.0668)	0.0032 (0.0633)
Log^2(*EX*)	−0.0113 (0.0082)	−0.0052 (0.0091)	0.0022 (0.0085)
Log(*PEDS*)	−0.2868§ (0.0811)	−0.3405§ (0.0897)	−0.3634§ (0.0841)
Log^2(*PEDS*)	0.0113 (0.0230)	0.0233 (0.0254)	0.0162 (0.0236)
Log(*AVA*)	0.1615§ (0.0435)	0.3191§ (0.0500)	0.2775§ (0.0458)
Log(*PEDS*) × log(*AVA*)	0.1072§ (0.0214)	0.1073§ (0.0233)	0.1236§ (0.0218)
ACC × *AOHA*	0.0005 (0.0005)	−0.0007 (0.0005)	−0.0003 (0.0005)
LQ	−0.0011§ (0.00007)	0.0004§ (0.00003)	0.0005§ (0.00003)
Adjusted R^2	0.990	0.988	0.990
Log-likelihood	219.6215	200.7363	214.7177
Pr > F	0.000	0.000	0.000
AIC	−1.903	−1.728	−1.858

Dependent variable: log(*AL*); *10% s.l.; †5% s.l.; ‡1% s.l.; §0.1% s.l. s.l., significance level.

Table S6. Regression results for the models accounting for land quality and *GOV* = *PA*

Variables	*LQ* = *AWY*	*LQ* = *AMY*	*LQ* = *AWMY*
Log(*AOHA*)	−2.1636§ (0.1622)	−1.4732§ (0.1729)	−1.0399§ (0.1470)
Log^2(*AOHA*)	0.2026§ (0.0196)	0.1292§ (0.0210)	0.0884§ (0.0179)
Log(*POP*)	3.9215§ (0.4233)	1.9732§ (0.4166)	0.6688† (0.2979)
Log^2(*POP*)	−0.0920§ (0.0126)	−0.0223* (0.0119)	0.0156* (0.0085)
Log(*GDPC*)	−6.7267§ (1.3188)	−4.9265‡ (1.5211)	−1.9547* (0.1721)
Log^2(*GDPC*)	0.6088† (0.1843)	0.4425† (0.2164)	0.1923 (0.1721)
Log^3(*GDPC*)	−0.0141 (0.0088)	0.0089 (0.0104)	−0.0044 (0.0086)
Log(*EX*)	0.2500§ (0.0555)	0.1835‡ (0.0641)	0.1126* (0.0572)
Log^2(*EX*)	−0.0276§ (0.0075)	−0.0247‡ (0.0087)	−0.0158† (0.0077)
Log(*PEDS*)	−0.1413* (0.0740)	−0.2497‡ (0.0852)	−0.2497‡ (0.0755)
Log^2(*PEDS*)	0.0201 (0.0203)	0.0398* (0.0237)	0.0303 (0.0208)
Log(*AVA*)	0.2499§ (0.0383)	0.4991§ (0.0476)	0.4407§ (0.0408)
Log(*PEDS*) × log(*AVA*)	0.0357* (0.0212)	0.0433* (0.0244)	0.0536† (0.0214)
PA × *AOHA*	−0.00003§ (0.000004)	−0.00003§ (0.000005)	−0.00004§ (0.000005)
LQ	−0.0014§ (0.00007)	0.0005§ (0.00003)	0.0007§ (0.00003)
Adjusted R^2	0.992	0.990	0.992
Log-likelihood	245.9078	215.7991	241.6368
Pr > F	0.000	0.000	0.000
AIC	−2.148	−1.868	−2.108

Dependent variable: log(*AL*); *10% s.l.; †5% s.l.; ‡1% s.l.; §0.1% s.l. s.l., significance level.

Table S7. Regression results for the models accounting for land quality and *GOV* = *ESI*

Variables	*LQ* = *AWY*	*LQ* = *AMY*	*LQ* = *AWMY*
Log(*AOHA*)	−2.1374§ (0.3873)	−1.9405§ (0.4272)	−1.3477‡ (0.4093)
Log^2(*AOHA*)	0.2261§ (0.0590)	0.2186§ (0.0646)	0.1489† (0.0615)
Log(*POP*)	1.2530‡ (0.4336)	−0.2403 (0.4134)	−1.2914§ (0.3310)
Log^2(*POP*)	−0.0111 (0.0130)	0.0422§ (0.0120)	0.0726§ (0.0096)
Log(*GDPC*)	1.1830 (1.6233)	2.9144* (1.7520)	5.1799§ (1.4859)
Log^2(*GDPC*)	−0.3366 (0.2307)	−0.5238† (0.2522)	−0.7056‡ (0.2199)
Log^3(*GDPC*)	0.0221† (0.0109)	0.0292† (0.0120)	0.0318‡ (0.0108)
Log(*EX*)	0.1154* (0.0586)	0.0821 (0.0649)	0.0121 (0.0619)
Log^2(*EX*)	−0.0065 (0.0079)	−0.0062 (0.0087)	0.0026 (0.0083)
Log(*PEDS*)	−0.2835§ (0.0799)	−0.3495§ (0.0881)	−0.3660§ (0.0825)
Log^2(*PEDS*)	0.0077 (0.0227)	0.0221 (0.0250)	0.0142 (0.0232)
Log(*AVA*)	0.1351§ (0.0399)	0.3334§ (0.0433)	0.2735§ (0.0402)
Log(*PEDS*) × log(*AVA*)	0.1108§ (0.0211)	0.1103§ (0.0230)	0.1263§ (0.0215)
ESI × *AOHA*	0.00005† (0.00002)	−0.00007‡ (0.00002)	−0.00006* (0.00002)
LQ	−0.0011§ (0.00006)	0.0004§ (0.00003)	0.0005§ (0.00003)
Adjusted R^2	0.991	0.988	0.990
Log-likelihood	222.2488	203.9027	218.0805
Pr > F	0.000	0.000	0.000
AIC	−1.928	−1.757	−1.889

Dependent variable: log(*AL*); *10% s.l.; †5% s.l.; ‡1% s.l.; §0.1% s.l. s.l., significance level.

Table S8. Regression results for the models accounting for land quality and *GOV* = *EPI*

Variables	*LQ* = *AWY*	*LQ* = *AMY*	*LQ* = *AWMY*
Log(*AOHA*)	−1.2091§ (0.3252)	−0.3809 (0.3361)	−0.3247 (0.3118)
Log^2(*AOHA*)	0.0819* (0.0456)	−0.0190 (0.0474)	−0.0083 (0.0444)
Log(*POP*)	1.8351§ (0.3962)	0.2882 (0.3624)	−0.7601‡ (0.2757)
Log^2(*POP*)	−0.0290† (0.0117)	0.0256* (0.0102)	0.0565§ (0.0077)
Log(*GDPC*)	−1.3637 (1.2722)	−0.0643 (1.3833)	2.5937† (1.1178)
Log^2(*GDPC*)	0.0002 (0.1878)	−0.1061 (0.2082)	−0.3580† (0.1769)
Log^3(*GDPC*)	0.0079 (0.0094)	0.0106 (0.0105)	0.0169* (0.0093)
Log(*EX*)	0.1132* (0.0624)	0.0547 (0.0688)	0.0065 (0.0649)
Log^2(*EX*)	−0.0079 (0.0084)	−0.0050 (0.0092)	0.0014 (0.0086)
Log(*PEDS*)	−0.2819§ (0.0812)	−0.3511§ (0.0895)	−0.3672§ (0.0839)
Log^2(*PEDS*)	0.0098 (0.0231)	0.0218 (0.0255)	0.0168 (0.0237)
Log(*AVA*)	0.1431‡ (0.0452)	0.3190§ (0.0516)	0.2880§ (0.0476)
Log(*PEDS*) × log(*AVA*)	0.1081§ (0.0218)	0.1121§ (0.0237)	0.1239§ (0.0222)
EPI × *AOHA*	0.000001 (0.00001)	0.00002 (0.00001)	0.0000008 (0.00001)
LQ	−0.0011§ (0.00007)	0.0004§ (0.00003)	0.0005§ (0.00003)
Adjusted R^2	0.990	0.988	0.990
Log-likelihood	219.0819	200.5198	214.5520
Pr > F	0.000	0.000	0.000
AIC	−1.898	−1.726	−1.856

Dependent variable: log(*AL*); *10% s.l.; †5% s.l.; ‡1% s.l.; §0.1% s.l. s.l., significance level.

Table S9. Regression results for the model including all of the governance variables

Variables	Coefficients
Log(*AOHA*)	−1.8766§ (0.3046)
Log^2(*AOHA*)	0.1773§ (0.0472)
Log(*POP*)	−0.083 (0.497)
Log^2(*POP*)	0.0321† (0.015)
Log(*GDPC*)	44.4959§ (9.7161)
Log^2(*GDPC*)	−6.000§ (1.2819)
Log^3(*GDPC*)	0.2692§ (0.0561)
Log(*EX*)	0.0686 (0.0464)
Log^2(*EX*)	−0.0112* (0.0064)
Log(*PEDS*)	−0.0110 (0.0621)
Log^2(*PEDS*)	0.0059 (0.0170)
Log(*AVA*)	0.2915§ (0.0408)
Log(*PEDS*) × log(*AVA*)	−0.0082 (0.0188)
CORC × *AOHA*	−0.0226§ (0.0027)
ROL × *AOHA*	0.0465§ (0.0079)
ACC × *AOHA*	−0.0152§ (0.0037)
PA × *AOHA*	0.00007 (0.00005)
ESI × *AOHA*	0.00004 (0.00008)
EPI × *AOHA*	0.0003§ (0.00004)
Constant	−102.8612§ (23.1652)
Adjusted R^2	0.995
Log-likelihood	296.3575
Pr > F	0.000
AIC	−2.571

Dependent variable: log(*AL*); *10% s.l.; †5% s.l.; ‡1% s.l.; §0.1% s.l. s.l., significance level.