Supporting Information

War and Space: Explaining the Evolution of Old World Complex Societies

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I. Model Description

I.1 The modeled period, area, and spatial units

The model simulates social evolution during the period between 1500 BCE and 1500 CE. All modeled interactions take place within a two-dimensional rectangular grid of cells, each representing a 100 km × 100 km square of the Earth's surface. This grid was created in ArcGIS v9.3 using Hawth's Analysis Tools (Beyer 2004) under a conic equidistant projection. The modeled area includes Eurasia and Africa (the 'Old World'). Each cell is classified as either sea or land. Land cells are characterized by average elevation, and are further classified into desert, steppe, or agriculture categories. Agricultural cells are non-desert and non-steppe areas to which agriculture has spread during the current period (thus, the extent of the area where agriculture is practiced expands during the simulation). Additionally, as explained above, desert cells through which major rivers flow are treated as agricultural cells.

Assessment of the extent of the Eurasian Steppe was made according to the World Wildlife Fund's (WWF) global map of terrestrial ecosystems[1]. The biome labeled, "*Temperate grasslands, savannas, and shrublands (temperate, semiarid)*" was used to designate grid cells as being Steppe or not (see figure S1). These vast grasslands run almost contiguously from Northeastern China, through Asia and Europe to the Black Sea and down into the region of Syria and even some places in Turkey. A small region in the Eastern part of the Arabian Peninsula also belongs to this biome. However, this is far removed from the other grasslands and was not involved in the historical development and spread of horse-based military technology that we focus on in this paper, and is therefore not designated as steppe in our simulations. The mean distance to the Steppe (in kilometers) was also calculated for use in spatially explicit statistical analyses (see below). The grid was overlaid on high resolution climate maps (resolution ~ 1 km^2),[2] in order to assess precipitation, and topography. Cells were classified as 'desert' and therefore non-agricultural if their mean annual rainfall was less than 250 mm. For each cell the mean elevation (in meters) was calculated.
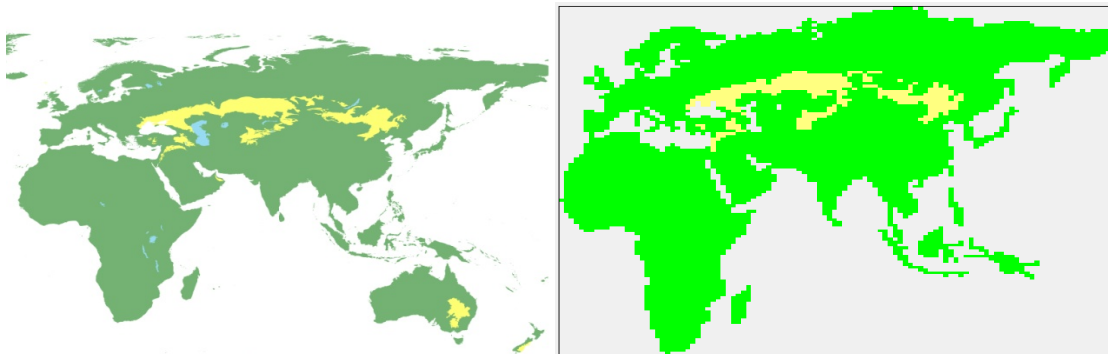

Figure S1. *Classification of the Steppe in our simulation (right) is based on the WWF map of terrestrial ecosystems (left). The grassland regions in Eastern Arabia, are not classified as Steppe for the purposes of this model, and those in New Zealand and Australia do not form part of the Afro-Eurasian region we focus on in this paper. Steppe regions are shown in yellow in both figures.*

36   Our map of the extent of agriculture at the beginning of the simulation (1500 BCE), is based on
37   Bellwood (3: figure 0.1), with the following areas excluded: (1) the Bantu expansion over subequatorial
38   Africa, which probably occurred sometime after 500 BCE; and (2) Japan, again after 500 BCE.
39   Additionally, we have taken into account the *terrestrial plant threshold* (TPT) occurring at Effective
40   Temperatures of 12.75°C (4: Table 4.02 and figure 4.12). The TPT marks the northern boundary of the
41   area where plant productivity is sufficiently high to permit plant-dominated subsistence strategies by
42   hunter-gatherers. This is also the area where intensification of production leads to the domestication and
43   diffusion of plant cultivars (5). When plants were first domesticated (in regions south of the isotherm)
44   they spread readily West and East (6). The northward spread, especially across the TPT, was much slower
45   and required a lengthy period of adaptation to colder climates. For example, Bronze Age populations in
46   the European forest belt north of the TPT practiced agropastoralism with a heavy emphasis on animal-
47   dominated strategies (7). Productive agriculture, capable of sustaining complex societies, appeared in
48   Northern and later Eastern Europe only during the first millennium CE. Thus, the extent of agriculture,
49   and therefore the modeled area increases throughout the simulation (see below for details, Figure S2).
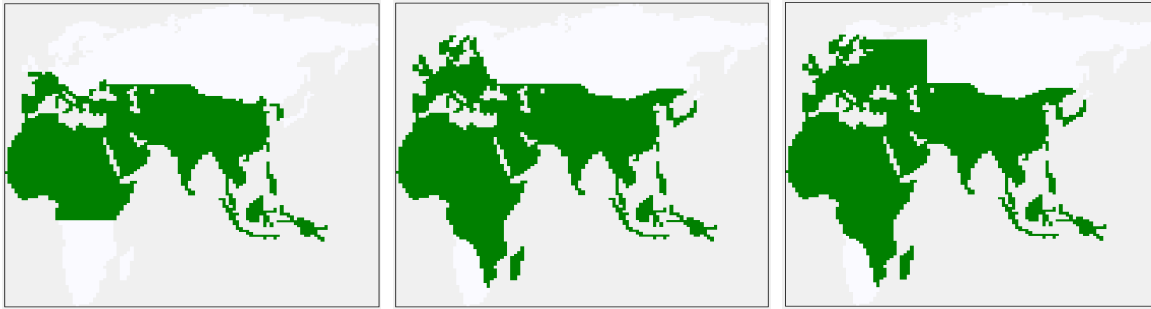
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52   **Figure S2.** *The extent of agriculture in the simulation (green) increases throughout the simulation*
53   *(earliest period, left; final period, right)*

54   Only agricultural cells are explicitly modeled. Each agricultural cell is occupied by a
55   'community.' Each community is characterized by two binary vectors of cultural traits. The first one, U,
56   contains n_{ultra} "ultrasociality traits" and the second one, M, contains n_{mil} of military technology (MilTech)
57   traits. Thus, $u_{i,x,y}$ is the value of the i-th ultrasociality trait for the community located at (x, y) coordinates,
58   and $m_{i,x,y}$ is the same for MilTech traits. Both ultrasociality and MilTech traits take values of either 0
59   (absent) or 1 (present).

60   Each community (agricultural cell) has up to four land neighbors (thus, cells touching corners
61   diagonally are not considered to be neighbors). Cells neighboring on sea ("littoral cells") can also interact
62   with other nearby littoral cells (this will be explained below). Time is discrete.

63   Communities are aggregated within multicell 'polities.' A polity can also consist of a single
64   community. At the beginning of the simulation all polities start with just one cell. Polities engage in
65   warfare which, if successful, can result in victors conquering cells from other polities. Polities can also
66   disintegrate. Ultrasociality traits characterizing each community can change by mutation, or by cultural
67   assimilation ('ethnocide'), while MilTech traits change by diffusion. These processes are described in
68   greater detail below.

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70   **I.2 Model parameters: estimating initial values**

71   Model parameters were estimated in a two-stage process. In the first stage, we came up with a parameter
72   'reference set' using a variety of *a priori* reasoning. The purpose of this exercise was to arrive not at
73   precise values of parameters, but to estimate their orders of magnitude. In the second phase, we used the

74   direct grid search approach to explore the parameter space. Again, our goal was not to obtain point
75   estimates (we are not interested in parameter values *per se*), but to locate the region within the parameter
76   space for which the model dynamics exhibits a good fit with the data. Here we describe the logic
77   underlying initial estimates of parameters, and in Section III.1 we provide details of the search of the
78   parameter space.

79   The time step in the model was set to 2 years. Thus, the duration of the simulation was 1500 steps
80   (or 3,000 years, corresponding to the period from 1500 BCE to 1500 CE).

81   The number of ultrasocial traits was set to 10, and MilTech traits to 5. The probability of a
82   MilTech diffusing to a nearby cell without one was 0.25 per time step. This diffusion rate was chosen so
83   that MilTech traits would diffuse throughout the simulated area by the end of simulation.

84   As explained above, at the start of simulation (1500 BCE) only cells within the set Agri1 are
85   allowed to build multicell polities by attacking and annexing other agricultural cells. We also assume that
86   by the second half of the first millennium agriculture has spread to all cells within Agri3. In the
87   simulation this occurs at time step = 1100 (corresponding to 700 CE). The timing of agriculture spread to
88   cells within Agri2 is earlier, but it is unclear when this happened. We estimated the onset of Agri2
89   empirically, by running the model for the value of this parameter equal to 100, 200, … 1000. The value
90   that yielded the highest R^2 (the coefficient of determination) for the fit of model predictions to data was
91   900 (300 CE), and this is the value that we used.

92   Parameter β measures the effect of the product of average ultrasociality and the size (number of
93   cells) of the polity on its military power. This parameter was set to 1. The related parameter γ translates
94   elevation of the defending cell (in km) into its defensive power. This parameter was set to 4, so that 1,000
95   m of elevation in a mountainous cell with no ultrasocial traits makes its power the same as a plains cell
96   with four ultrasocial traits.

97   Parameters regulating ethnocide were set as follows. The maximum probability of ethnocide, ε_{max},
98   was set to 1, and the baseline probability ε_{min} was 1/20th of it, or 0.05. The effect of elevation, γ_1, was set
99   to 1.

100   Baseline disintegration probability δ_0 was set to 0.05, which corresponds to the assumption that
101   even smaller polities with a lot of ultrasocial traits collapse on average every 20 time steps (or 40 years,
102   corresponding to 2 ruler generations). Parameter δ_s was also set to 0.05. Thus, a polity without any
103   ultrasocial traits collapses with probability = 1 when it reaches the size of 19 cells. Parameter δ_a was set to
104   2. This means that each additional unit of average ultrasociality extends the threshold size by 2/0.05 = 40
105   cells. Thus, even with all ultrasocial traits present polities cannot exceed the size of approx. 400 cells
106   without collapsing.

107   Parameters setting mutation rates were $\mu_{01} = 0.0001$ and $\mu_{10} = 0.002$. Thus, at the mutation
108   equilibrium the frequency of ultrasocial traits is less than 0.05.

109   Finally, the distance of sea-based attack, d_{sea}, was set to 1 at the beginning of the simulation and
110   then was incremented by $\Delta = 0.025$ every time step. Model parameters are summarized in Table SM1.

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118   **Table SM1.** Model parameters.

Parameter	Reference value	Explanation
β	1	effect of average ultrasociality on power
ε_{min}	0.05	minimum probability of ethnocide (with all MilTech = 0)
ε_{max}	1	maximum probability of ethnocide (with all MilTech = 1)
δ_0	0.05	baseline probability of disintegration (for $S = 0$ and $U = 0$
δ_s	0.05	effect of polity size on probability of disintegration
δ_a	2	effect of average ultrasociality on probability of disintegration
μ_{01}	0.0001	probability of mutation to an ultrasocial trait
μ_{10}	0.002	probability of ultrasocial trait mutating to non-ultrasocial trait
γ	4	effect of elevation on defensive power
γ_1	1	effect of elevation on the probability of ethnocide

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II. Estimation of Imperial Density Maps from Historical Data

122   In order to test the simulation model, data were collected on the distributions of large-scale polities during
123   the time frame 1500 BCE to 1500 CE in the Afro-Eurasia region described above. One of us (E.T.) used a
124   variety of historical atlases and other sources (see below) to create hand-drawn reference maps of the
125   geographic distribution of large, well-attested polities at 100-year time-steps (1500 BCE, 1400 BCE,...,
126   1500 CE). Using ArcGIS v9.3 information from these maps were then integrated into a geographical
127   information system (by T.C.) based on the same grid map used for the simulations. As the original maps
128   used to create our reference maps were created in a manner blind to the particular hypothesis being tested
129   here, where possible these original maps were used to determine the boundaries and extent of the polities
130   identified in the reference maps. All these maps were geo-referenced to ensure they were projected in the
131   same way as the grid map. The grid was overlaid on to these maps. For each time slice, if a polity covered
132   10 or more grid cells (Figure S3 gives an example of one such time slice), then this polity was entered
133   into our database and the appropriate grid cells were indicated as belonging to this polity. Obviously, the
134   borders of a polity rarely coincide exactly with the rigid, straight lines of our grid cells. Therefore a grid
135   cell was assigned to a particular polity if that covered approximately 50% or more of the grid cell.
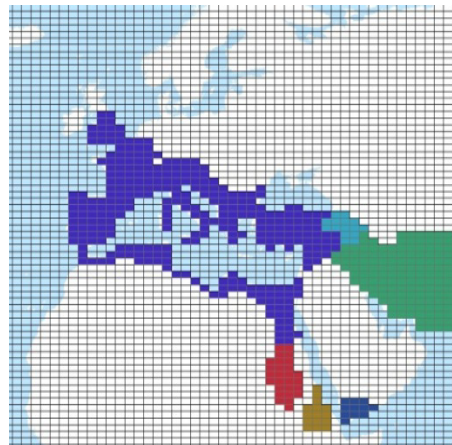
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138   **Figure S3.** Estimated distributions of the Roman Empire (blue) and other large-scale polities from one
139   time slice.

140   Therefore for each cell we have a record of the number of time steps in which that cell was
141   inhabited by a polity large enough to meet the cut-off criteria. This enabled the construction of an
142   imperial density map for the entire time period showing the regions in which large polities occurred more
143   often (Figure S4). To assess the time dynamics of polity distributions we calculated imperial densities for
144   each thousand-year period (this relates to the following time slice maps (A) 1500 BCE - 400 BCE, (B)
145   500 BCE - 400 CE, and (C) 500 CE - 1500 CE (Figure S5).
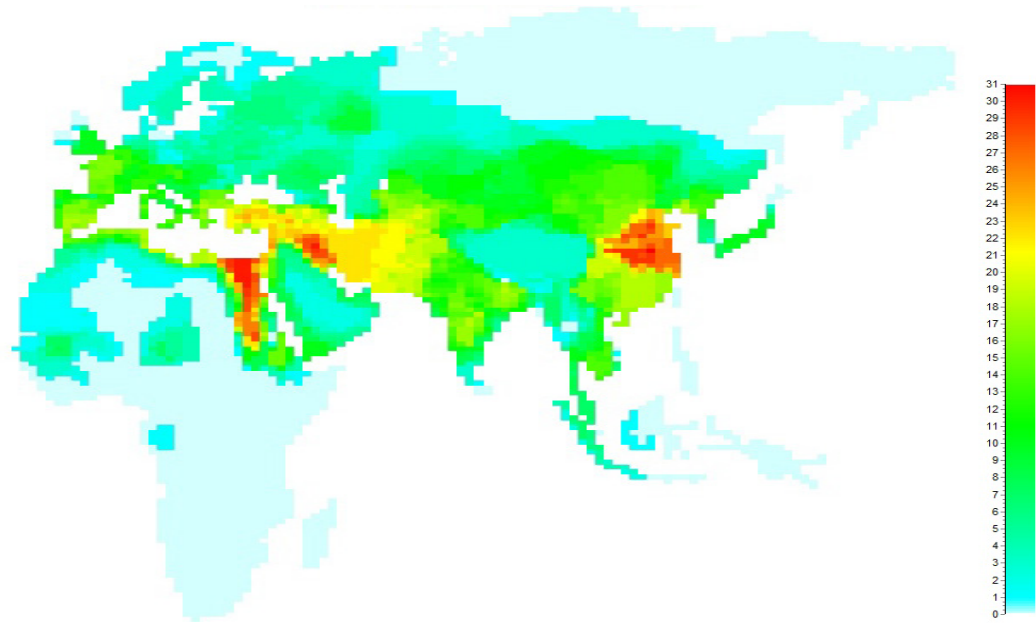
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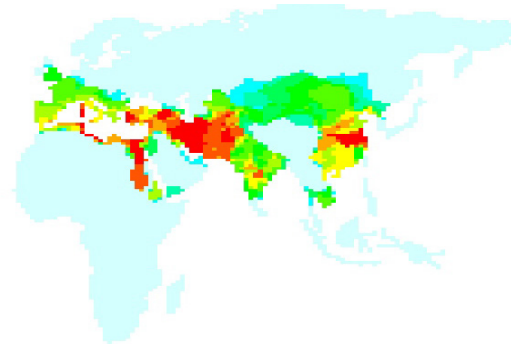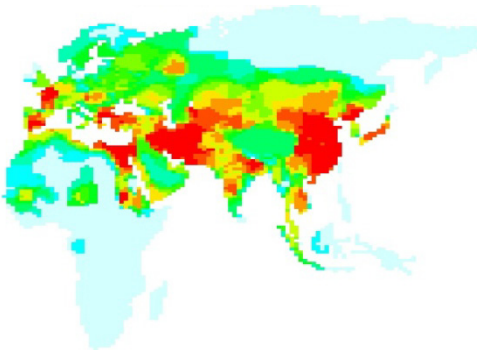148   **Figure S4.**   Imperial Density Map 1500 BCE – 1500 CE. Scale shows how many time slices polities
149   were present in each cell. Red cells indicate regions that were more frequently inhabited by large-scale
150   polities. Cyan cells show where large polities were less common. The lightest blue regions indicate the
151   absence of large polities during the time-span considered in this paper.

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153   (A)

154   (B)

155   (C)

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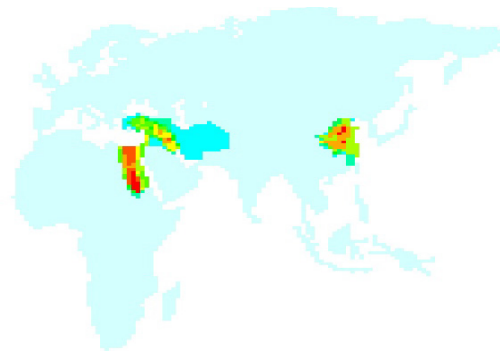
157   **Figure S5.** Imperial Density Maps for (A) 1500 BCE - 400 BCE, (B) 500 BCE - 400 CE, and (C) 500 CE
158   - 1500 CE.

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160   *References used for creating Imperial Density Maps:*

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189   Beginning of Recorded Time to the Present Day*. Millennium House Pty Ltd.

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III. Supplementary Results

III.1 Exploration of the Parameter Space

193   Imperial density data, $Z(x,y,t)$, is the frequency (measured with a century step) with which a cell at spatial
194   coordinates x,y finds itself in a polity with territory greater than 10 grid cells during era t. In comparisons
195   with model predictions we only look at the set of spatial coordinates of cells with agriculture,
196   $\{x, y\} \in \text{AGRI}$. Era t = 1, 2, 3 refers to (1) 1500–500 BCE, (2) 500 BCE–500 CE, or (3) 500–1500 CE.

197   The model is sampled in the same way as data. Thus, the model prediction $\hat{Z}(x, y, t)$ is the frequency
198   with which a cell at x,y is found within a multicell polity with 10 cells or more during era t.

199   Our measure of model accuracy is the coefficient of determination (R^2, the proportion of variance
200   explained by the model) in the linear regression of Z on $\hat{Z}$. We calculate both the overall R^2 for all three
201   eras, and R^2 for each era separately, to determine in which eras the model performs better at explaining
202   the observed empirical patterns. In explorations of parameter space we used as the objective function the
203   overall R^2 that tells us how well the model captures both the spatial and temporal dynamics of macrostate
204   incidence in the historical record (the era-specific R^2 capture spatial, but not temporal variation in the
205   data). There was a substantial variation between different realizations of the model, which resulted in
206   coefficients of determination changing by 0.02–0.03 between different runs. Experimentation showed that
207   by averaging $\hat{Z}$ over 5 replicates the estimate of R^2 can be stabilized to within 0.01. Accordingly, during

208   parameter explorations we replicated each parameter combination 5 times. For key results (the reference
209   set, the 'best set', etc.) we used 20 replicates.

210   Figure S6 shows the comparison between the data (left column) and model predictions for the
211   reference set of parameters. During Era 1 the model predicts the same three 'imperiogenesis hotspots' (in
212   Mesopotamia, Egypt, and North China) as in data, although within these three regions the actual
213   distributions of macrostate incidence are not well captured. In Era 2 the model correctly captures the
214   spread of large-scale societies into the central Mediterranean/Western Europe, North India, South China,
215   and the beginnings of state formation in continental Southeast Asia. The model misses nomadic polities
216   northwest of China because it only simulates agrarian societies. Additionally, the model does not predict
217   the observed dense concentration of macrostates in Iran, because most of the Iranian plateau is desert, and
218   the model assumes that desert cells cannot support complex societies. Finally, in Era 3 the model predicts
219   the spread to northern and eastern Europe, Japan, and southeast Asia, matching the empirical pattern.

220   The match between model predictions and data calculated separately for each era is $R^2 = 0.54$,
221   0.35, and 0.34, while the overall $R^2 = 0.47$. One obvious reason for a relatively poor model performance
222   for Era II is the predicted spread of macrostates into Northern Europe, which anticipates the actual rise of
223   complex societies there by a thousand years. A grid search over possible values of τ_2 indicated that
224   increasing the value of this parameter from 500 to 900 dramatically improves the fit for Era 2, raising R^2
225   from 0.35 to 0.52 (Figure S7), and overall R^2 to 0.51.

226   Next we investigate how sensitive model performance is to specific values of parameters by
227   varying each parameter, in turn, from a value one-half to double the reference values (Table SM2). The
228   results show that the model is not unduly sensitive to any parameter. For about half of them the
229   coefficient of determination hardly changes, and for all values of parameters R^2 stays within relatively
230   narrow bounds, 0.41–0.56. In other words, the model explains roughly one-half of variance in the data for
231   a broad band of parameter values around the reference set.

232   The grid search of the parameter space indicated that an improvement of the overall R^2 to 0.65
233   can be achieved by changing the values of only three parameters, ε_{max}, δ_0, and γ (in addition to τ_2 that we
234   have fitted in the first step). This 'best parameter set' also improves the degree of fit as judged by visual
235   inspection of data and model-predicted patterns (Figure S8). Again, the close match between the observed
236   and predicted values is relatively insensitive to the variation in model parameters (Table SM3).

237   **Table SM2.** Results of varying model parameter on the match between model predictions and data,
238   measured by prediction R^2. The simulation was run by varying each parameter in turn, by multiplying its
239   reference value with the 'factor' (0.5, 0.75, … 2). This exploration is centered on the reference set
240   estimates with $\tau_2 = 900$.

Parameter	Factors				
	0.5	0.75	1	1.5	2
β	0.42	0.48	0.51	0.54	0.56
ε_{min}	0.51	0.52	0.51	0.51	0.50
ε_{max}	0.41	0.48	0.51	0.56	0.56
δ_0	0.54	0.52	0.51	0.49	0.45
δ_s	0.54	0.52	0.51	0.49	0.47
δ_a	0.48	0.51	0.51	0.52	0.54
μ_{01}	0.47	0.50	0.51	0.50	0.49
μ_{10}	0.49	0.50	0.51	0.52	0.50
γ	0.56	0.53	0.51	0.44	0.45
γ_1	0.54	0.52	0.51	0.48	0.44

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243   **Table SM3.** Results of varying model parameter on the match between model predictions and data,
244   measured by prediction R^2. The simulation was run by varying each parameter in turn, by multiplying its
245   reference value with the 'factor' (0.5, 0.75, ... 2). This exploration was centered on the 'best' estimates of
246   parameters.

Parameter	Factors				
	0.5	0.75	1	1.5	2
B	0.61	0.62	0.65	0.65	0.64
ε_{min}	0.64	0.65	0.65	0.64	0.63
ε_{max}	0.59	0.63	0.65	0.63	0.63
δ_0	0.65	0.64	0.65	0.63	0.62
δ_s	0.60	0.64	0.65	0.64	0.64
δ_a	0.64	0.63	0.65	0.63	0.62
μ_{01}	0.64	0.65	0.65	0.61	0.56
μ_{10}	0.60	0.64	0.65	0.65	0.65
Γ	0.67	0.65	0.65	0.63	0.60
γ_1	0.63	0.64	0.65	0.63	0.60
d_{sea}	0.64	0.65	0.65	0.62	0.62
Δ	0.66	0.65	0.65	0.62	0.59

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248   **Figure S6.** Comparison between data (left column) and model (right column) for three historical eras
249   (top: 1500–500 BCE, middle: 500 BCE–500 CE; bottom: 500–1500 CE). Reference parameter set
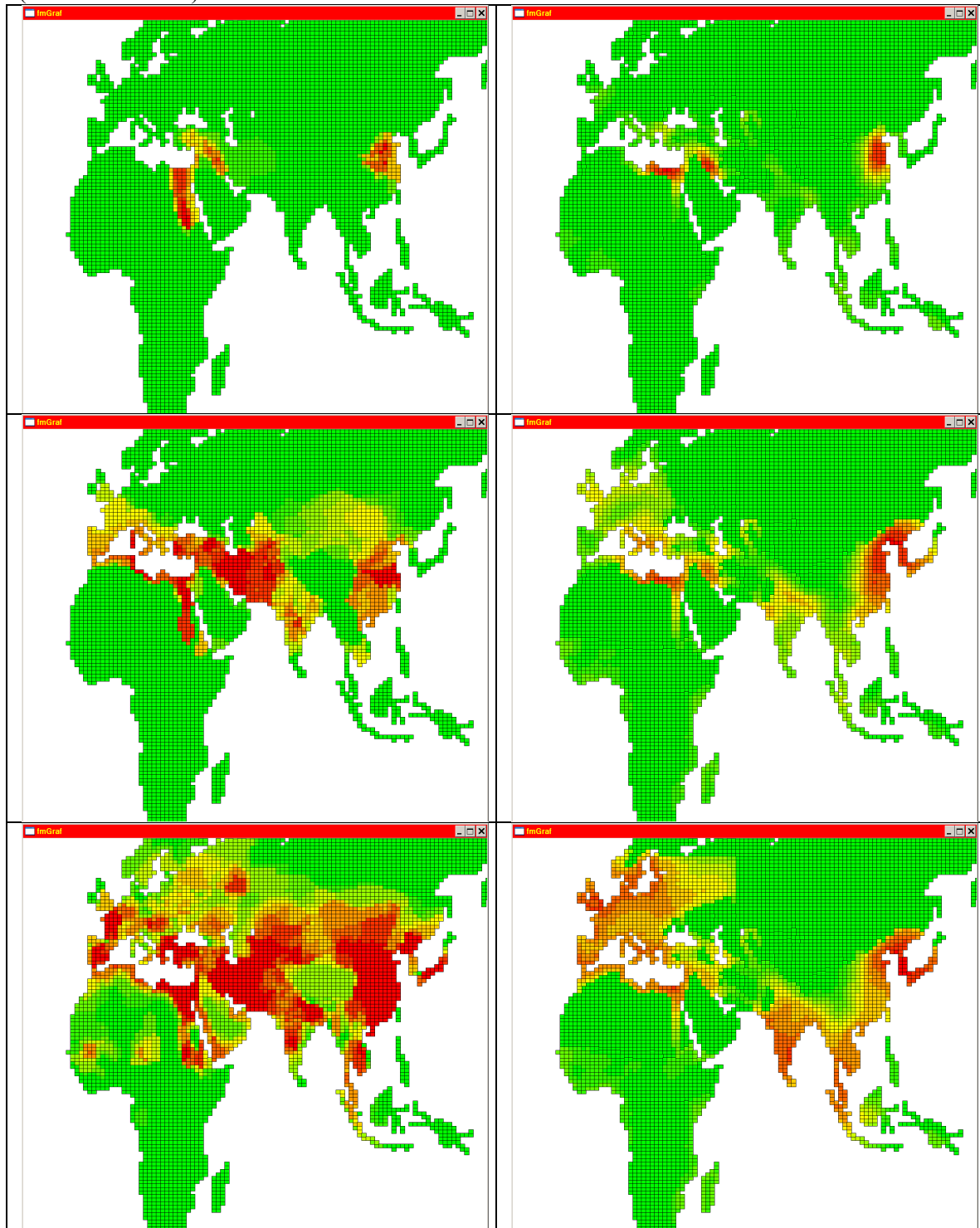250   (overall $R^2 = 0.47$).

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253   **Figure S7.** Comparison between data (left column) and model (right column) for three historical eras
254   (top: 1500–500 BCE, middle: 500 BCE–500 CE; bottom: 500–1500 CE). Reference parameter set with τ_2
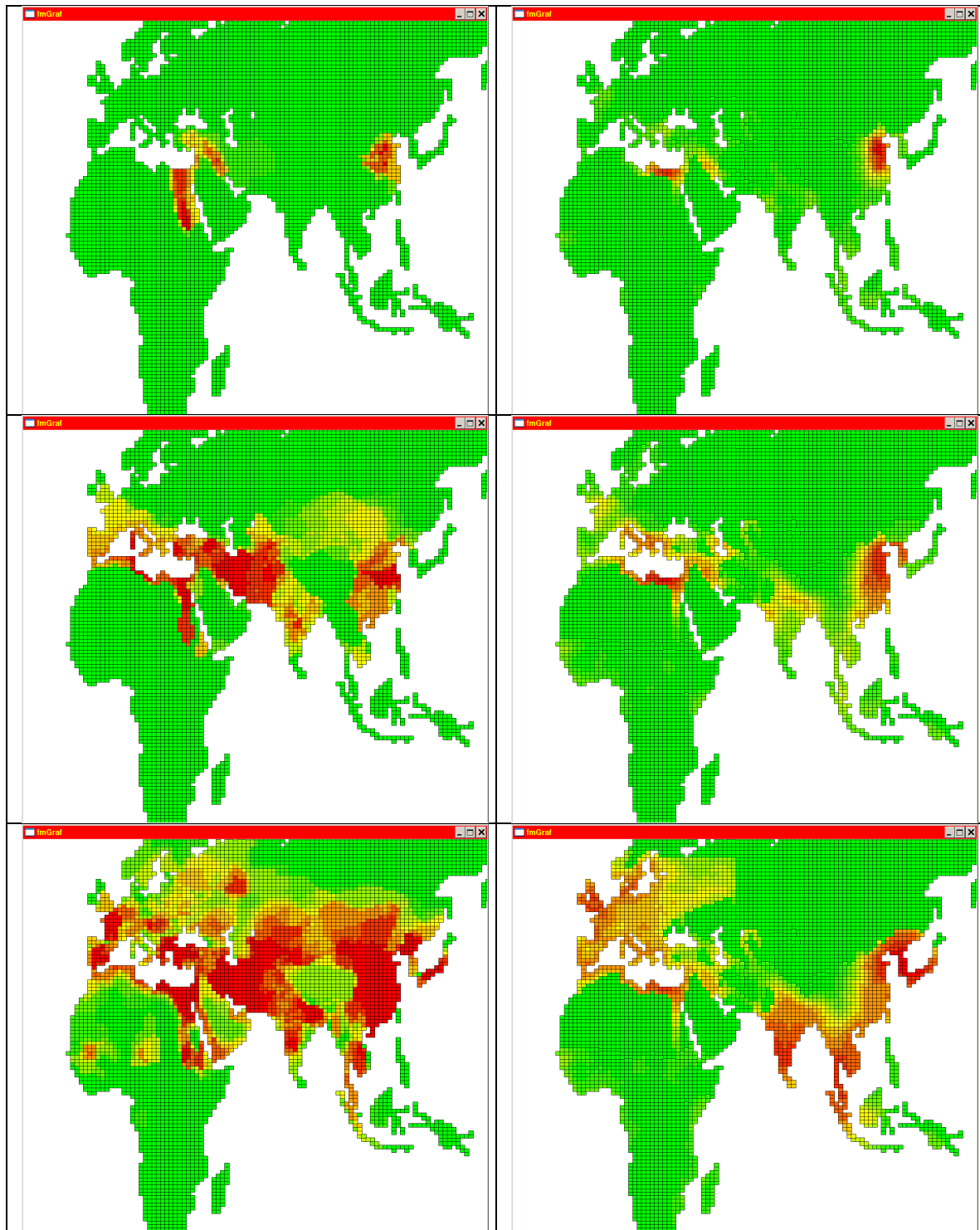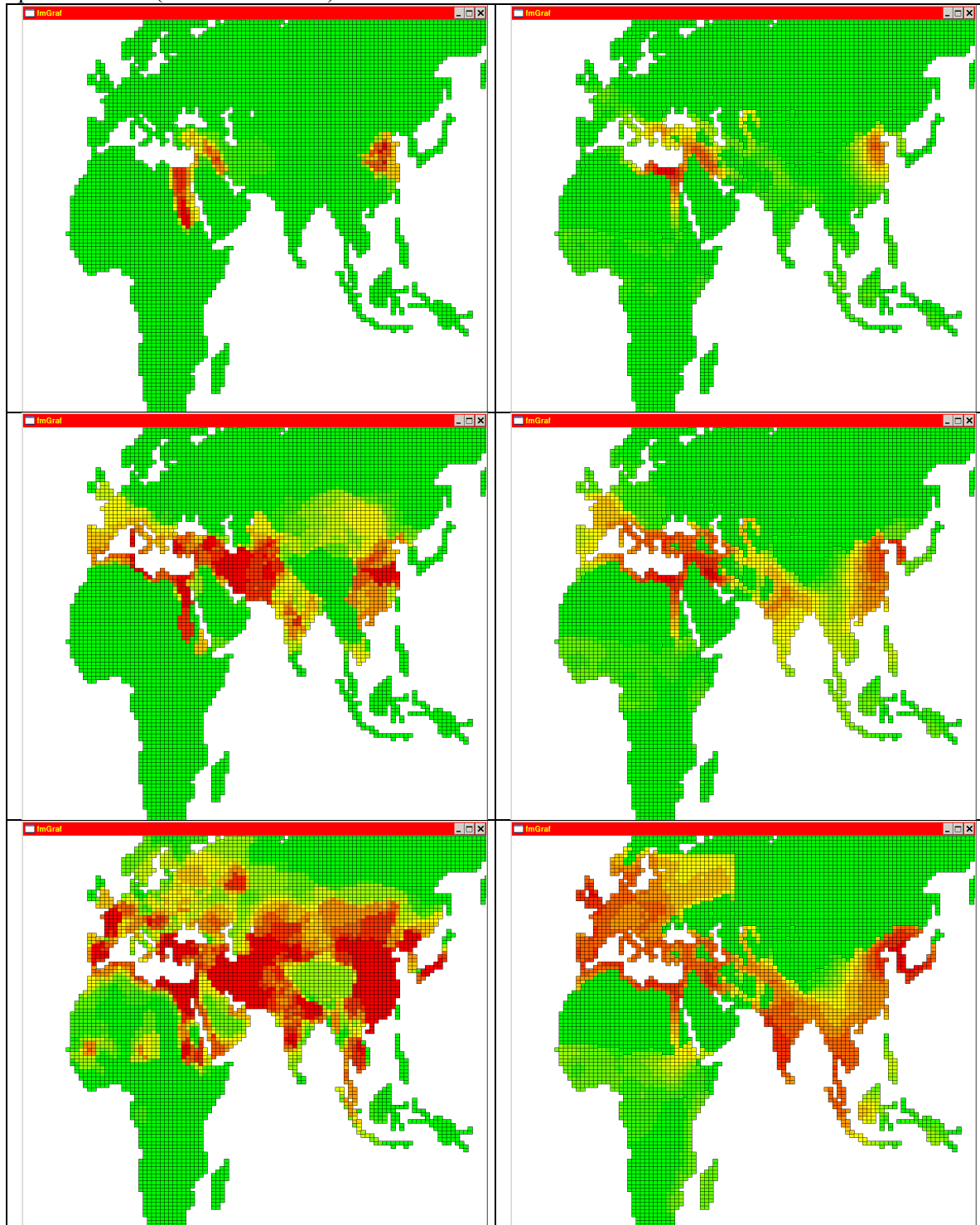255   = 900 (overall R^2 = 0.51).

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259   **Figure S8.** Comparison between data (left column) and model (right column) for three eras. Best
260   parameter set (overall $R^2 = 0.65$).

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264 **III.2 Null Models: Effects of Turning off CMLS and Elevation**

265 The observation that model performance (ability to predict spatio-temporal distribution of imperial
266 density) is not sensitive to precise values of parameters raises the question of what will happen if we
267 selectively turn off certain structural components of the model. This allows us to assess whether
268 alternative, simpler processes could account for the observed data. For example, the match between the
269 simulated data and the empirical data could be due to the particular shape of the grid (reflecting the
270 geography of the old world landmass) on which we are running the model.

271 The conceptual core of the model is the effect of MilTech traits on the intensity of cultural
272 multilevel selection (CMLS). We can eliminate the influence of MilTech on the probability of ethnocide
273 by setting parameters ε_{min} and ε_{max} to the same value. Running the model for several values of ε_{min} and ε_{max}
274 we observe a dramatic reduction in the overall R^2 (Table SM4). Note that warfare between polities and
275 ethnocide in conquered cells are simulated in exactly the same way as in the full model; it is the
276 connection between MilTech and ethnocide that is broken. The MilTech-independent intensity of
277 ethnocide ($\varepsilon_{min} = \varepsilon_{max}$= 0.2, 0.5, or 1) has a very slight effect on the results. The somewhat positive values
278 of the overall R^2 (0.15–0.17) are probably due to the effect of long-term presence of agriculture (this is
279 supported by the regression analyses in the next section).

280 Another key assumption of the model is that MilTech traits diffuse out from the Steppe, creating
281 a geographical pattern of variation in the CMLS intensity. We can eliminate the effect of distance from
282 the Steppe on CMLS intensity by seeding initial MilTech traits randomly within agricultural cells, rather
283 than on the Steppe frontier. When MilTech traits are seeded randomly, the results are essentially the same
284 as with breaking the connection between MilTech and ethnocide – most of predictability is lost (Table
285 SM4).

286 We also investigated the effect of turning off the influence of elevation on defensive power and
287 on the probability of ethnocide. Setting $\gamma = 0$ (no elevation effect on defensive power) reduces R^2 for the
288 first era, but also results in slightly better predictabilities for Eras 2 and 3, and no change in the overall R^2.
289 On the other hand, setting $\gamma_1 = 0$ (no elevation effect on ethnocide) has a measurably negative effect on all
290 R^2. Setting both γ and $\gamma_1 = 0$ further decreases the ability of the model to predict data. This exercise
291 suggests that the main effect of elevation in the model is the one mediated by cultural selection on
292 ultrasocial traits.

293 Finally, eliminating elevation effects in addition to the effect of MilTech on ethnocide results in
294 the same overall R^2 as in the model only lacking MilTech-ethnocide connection (Table SM4).

295 **Table SM4.** Effect of turning off various components of the model on its ability to predict data (R^2 for
296 each era, and overall R^2). All results based on 20 replicate model runs.

Model	Era 1	Era 2	Era 3	Overall
Full model	0.56	0.65	0.47	0.65
No elevation effect on defensive power ($\gamma = 0$)	0.43	0.68	0.53	0.65
No elevation effect on ethnocide ($\gamma_1 = 0$)	0.45	0.59	0.40	0.59
No elevation effects ($\gamma = \gamma_1 = 0$)	0.31	0.46	0.35	0.48
No effect of MilTech on ethnocide ($\varepsilon_{min} = \varepsilon_{max}$= 0.2)	0.09	0.10	0.02	0.17
No effect of MilTech on ethnocide ($\varepsilon_{min} = \varepsilon_{max}$= 0.5)	0.08	0.08	0.02	0.16
No effect of MilTech on ethnocide ($\varepsilon_{min} = \varepsilon_{max}$= 1)	0.04	0.10	0.00	0.15
No effect of the Steppe (MilTech seeded randomly)	0.03	0.11	0.00	0.17
Null model (no effects of MilTech* and elevation)	0.04	0.17	0.00	0.16

297 * $\varepsilon_{min} = \varepsilon_{max}$= 0.5

298

299

300   **III.3 Spatially-Explicit Regression Analyses**

301   To complement the results of the simulation model we performed statistical analyses of the data on the
302   historical distribution of empires. We examined the effect of the same ecological and historical factors
303   discussed above as predictors of imperial density. As the data take the form of a grid the data points may
304   show a substantial degree of spatial autocorrelation (Figure S9). The assumptions of standard statistical
305   procedures such as Ordinary Least Squares regression may not hold in cases such as this, running the risk
306   of inaccurate parameter estimation, and inflated type I errors (i.e., falsely rejecting the null hypothesis of
307   no association between the predictor and response variables) (8). To control for spatial autocorrelation in
308   the data we ran a series of Simultaneous Autoregressive Models (SAR) models in the package SAM v4.0
309   (Spatial Analysis in Macroecology) (9). This approach explicitly models spatial autocorrelation in the
310   residualswith the effects of surrounding cells being weighted according to how far away they are
311   (specifically $\frac{1}{d^{\alpha}}$, where d is distance). The α parameter, therefore, affects the extent to which spatial
312   autocorrelation is modeled as occurring. By choosing a suitable value for alpha, spatial autocorrelation in
313   the error term of the model can be removed, and the unique effects of the predictor variables can be
314   assessed. In these analyses initial explorations of the data indicated that value of $\alpha = 3$ was suitable for
315   effectively reducing spatial autocorrelation in the error term. In all cases the autoregressive parameter,
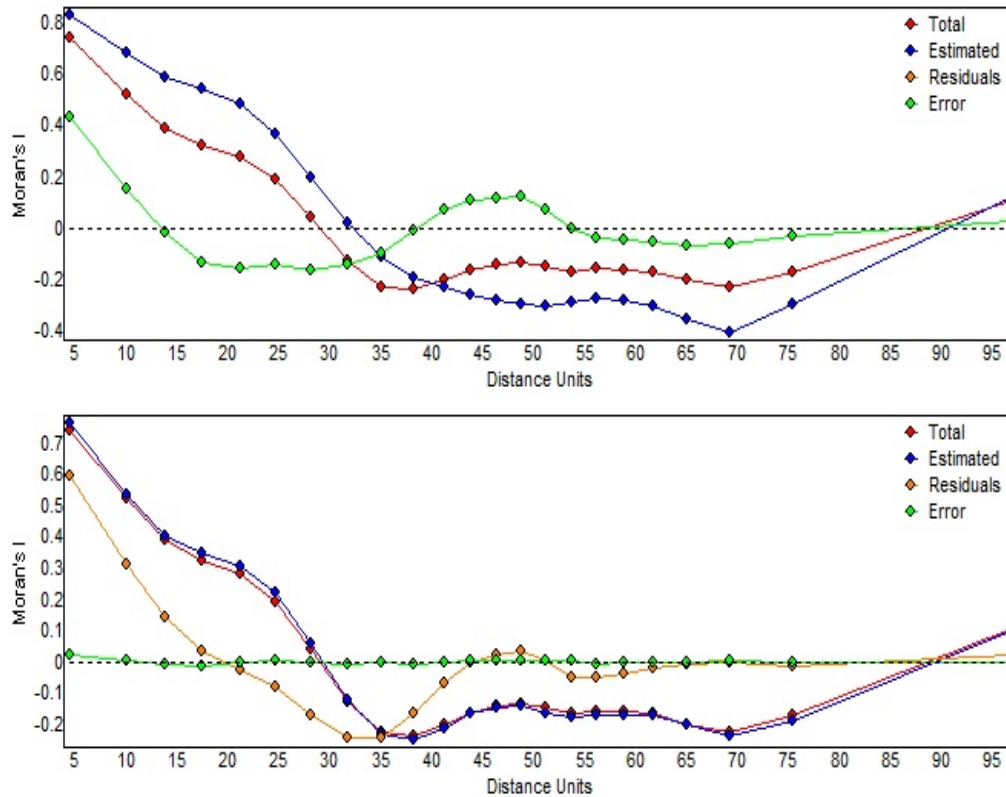316   *rho*, was estimated.

317

318

319   **Figure S9.** Moran's I spatial autocorrelation plots at increasing distances (hundreds of kilometers) for
320   total imperial density (red), predicted imperial density from SAR analysis (blue), SAR analysis residuals,
321   reflecting the spatial autocorrelation component of the model (orange), and SAR error term (green). The
322   two plots show models with the same predictor and response variables, but in the top plot no correction
323   has been made for spatial autocorrelation while in the second this correction has been made resulting in
324   an error term that is no longer spatially autocorrelated.

325

326   In all analyses the dependent variable is imperial density (number of times cell is
327 inhabited by large polity) over the full time span (1500 BCE – 1500 CE) and is treated as varying
328 continuously for the purposes of these analyses. The cells considered are the same as in the
329 simulation (i.e. only those cells in which agriculture was present at some point). Four predictor
330 variables were examined: (1) the long-term presence of agriculture, (2) distance from the Steppe,
331 (3) elevation, and (4) presence and duration of horse-based warfare. The long-term presence of
332 agriculture indicates whether cells had agriculture at the beginning of our period, 1500 BCE (as
333 opposed to acquiring it at a later date). Distance from the Steppe was calculated as mean distance
334 (in hundreds of kilometers) from cells designated as Steppe. The elevation (in kilometers)
335 variable is the same as in the simulation. Finally, the approximate distribution of horse-based
336 forms of warfare in each era was estimated from several sources (Figure S10)(10-22). In the first
337 era, this was primarily chariot-based warfare, but later involved mounted cavalry. This variable
338 can take one of four values (0, 1, 2, 3) depending on the number of eras a cell had horse-based
339 warfare present. It is treated as continuous for the purposes of these analyses. Each predictor
340 variable was entered alone and in combination with others to assess their relative importance and
341 contribution to the overall model. Table SM5 shows the standardized SAR coefficients (i.e. after
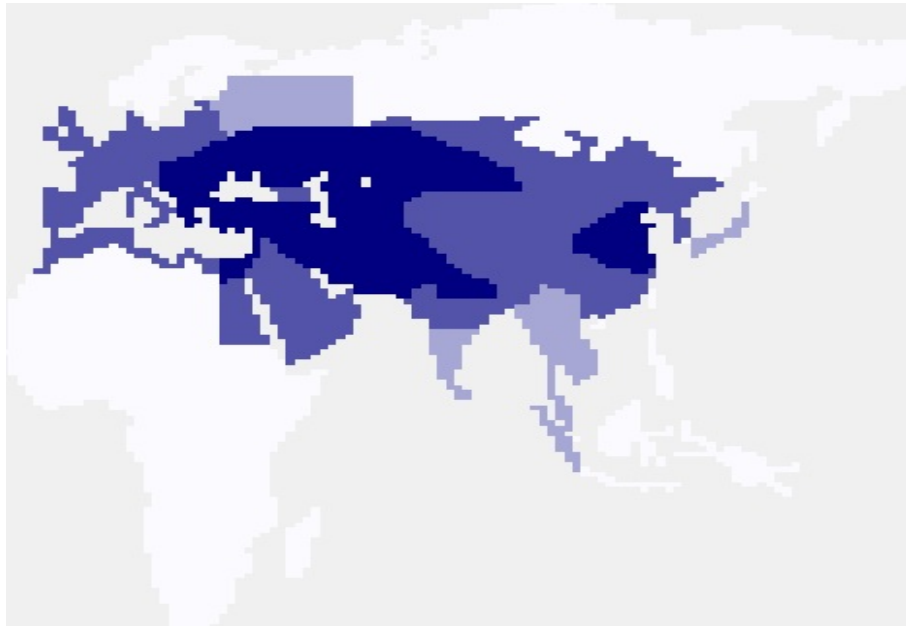342 taking into account the effects of spatial autocorrelation).
343

344
345

346 *Figure S10. Estimated distribution of horse-based warfare across eras: All eras (dark blue), Era II & III*
347 *(mid-blue), Era III only (light blue).*

348

349 **Table SM5.** Standardized parameter estimates, AIC (Akaike Information Criterion adjusted for small
350 sample size, AICc), and R^2 values of predictor variables in different SAR models. 'Agriculture' = long-
351 term presence of agriculture; 'Steppe' = distance from the Steppe; 'Elevation' = average elevation (in
352 km), 'Horse' = horse based warfare (chariots for Era I, cavalry for Eras II and III). All parameter
353 estimates are significant at *P* < 0.001.

Model	AIC	R^2	Agriculture	Steppe	Elevation	Horse
Full	16519.0	0.53	0. 09	–0.28	–0.09	0.27
Only horse warfare	17031.6	0.43	–	–	–	0.38
Full without horse	17103.5	0.42	0.10	–0.47	–0.10	–
Steppe & agriculture	17184.7	0.40	0. 09	–0.44	–	–
Steppe & elevation	17323.7	0.36	–	–0.48	–0.10	–
Only steppe	17365.2	0.35	–	–0.45	–	–
Agricult. & elevation	18346.0	0.06	0.12	–	–0.07	–
Only agriculture	18351.7	0.06	0.11	–	–	–
Only elevation	18518.9	<0.001	–	–	–0.07	–

354

355   The best-fitting model is one in which all predictor variables are present. The model explains
356 around 53 percent of the variance in total imperial density over the time period we have considered here.
357 Distance from the Steppe and the presence and duration of horse-based warfare are the two best predictors
358 of total imperial density. This is in line with our theoretical model, which stresses the proximity to the
359 Steppe and intense forms of warfare in selecting for large-scale forms of organization.The long-term
360 presence of agriculture is a weaker predictor of imperial density (however, remember that the analysis
361 considers only cells that did acquire agriculture by 1500 CE). This suggests that while agriculture is
362 certainly a pre-condition for the evolution of large, complex societies variation in the timing of the
363 introduction of agriculture itself may be less important in explaining why some areas have consistently
364 been home to the largest-scale societies while others have not. Compare, for example, China and the
365 Middle East, with New Guinea and Sub-Saharan Africa; all regions in which agriculture has been
366 practiced for long periods but with very different histories with respect to the emergence of large-scale
367 societies. Creation and retention of norms/institutions of large-scale organization is important – some
368 regions into which agriculture expanded rapidly developed complex societies (e.g. East Europe), while
369 others did not (e.g. southern Africa).

370   The weakest predictor was elevation, which, although a statistically significant predictor, does not
371 contribute greatly to the amount of variation explained in these models. However, visual inspection of the
372 data (Figure S11) indicate that elevation appears to be acting as a constraining factor rather than an active
373 driver of imperial density. In other words, although complex societies tend not to form or spread to
374 regions of high altitude and rugged topography, there are many flat, low-altitude regions where large-
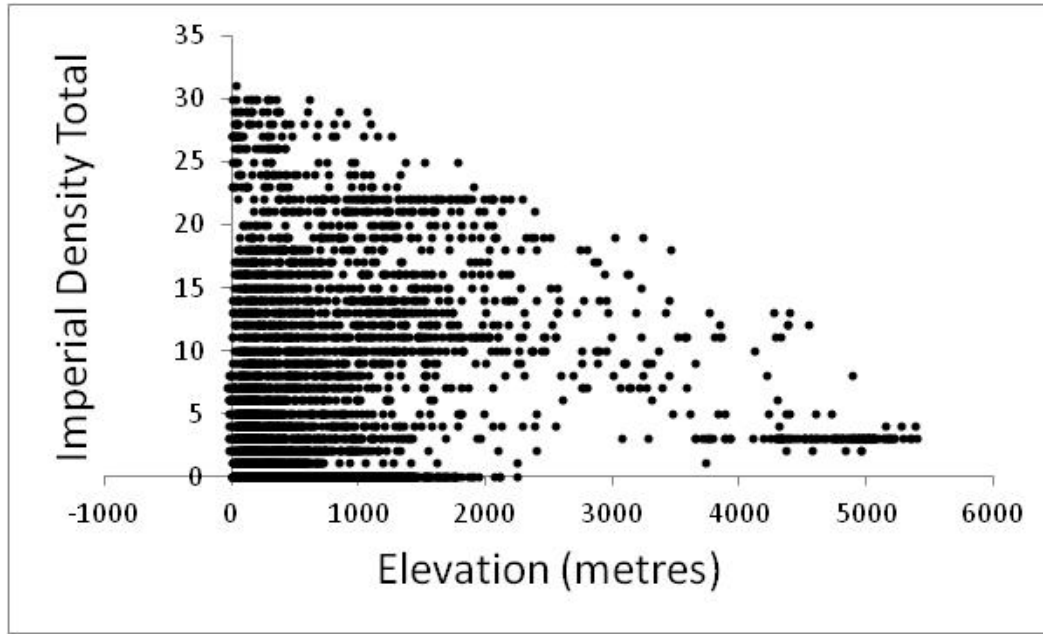375 scale societies did not form.

376

377

378   ***Figure S11.*** *The maximum value of imperial density decreases with increasing elevation. Many regions*
379   *of lower elevation did not consistently develop large polities. This indicates that high elevation acts as a*
380   *limiting factor on the creation of complex societies.*

381

382   Although in these analyses our horse-based warfare variable is a slightly better predictor than
383   distance from the steppe, both variables appear to explain similar parts of the variance and it should be
384   stressed that our estimation of the distributions of these military technologies is only approximate. Future
385   work will improve the temporal and spatial resolution of this variable and can even look at the
386   development of particular aspects of military technology. This may allow a stronger test of the order in
387   which warfare intensity and the development of large-scale organization develop. However, regardless of
388   the precise times at which these technologies developed and spread, the broad outlines represented in our
389   estimated distributions are expected to be reasonable in relative terms (i.e. chariots developing first in
390   regions adjacent to the steppe, with cavalry spreading out later).

391

392   If we plot the estimated values based on the SAR coefficients from the best analysis (Figure S12)
393   we can see that the SAR model does well at predicting which regions were more frequently home to large
394   societies and in which region such societies did not form. It is important to point out that although the
395   SAR model is predicting areas in which empires were more frequent relative to other areas, the maximum
396   absolute values of these predicted scores (~13) do not reach the maximum observed values (i.e. 31).
397   Plotting the residuals from the SAR analysis we can see that although the SAR model does well at
398   predicting values for much of the area considered, it under-predicts the values for imperial density in the
399   hotspots of empire formation (the middle east, Egypt, and China), while slightly over-predicting some
400   regions such as eastern Europe, and Scotland and Northern Ireland.

401

A. Total Imperial Density   B. Predicted Density   C. Residual
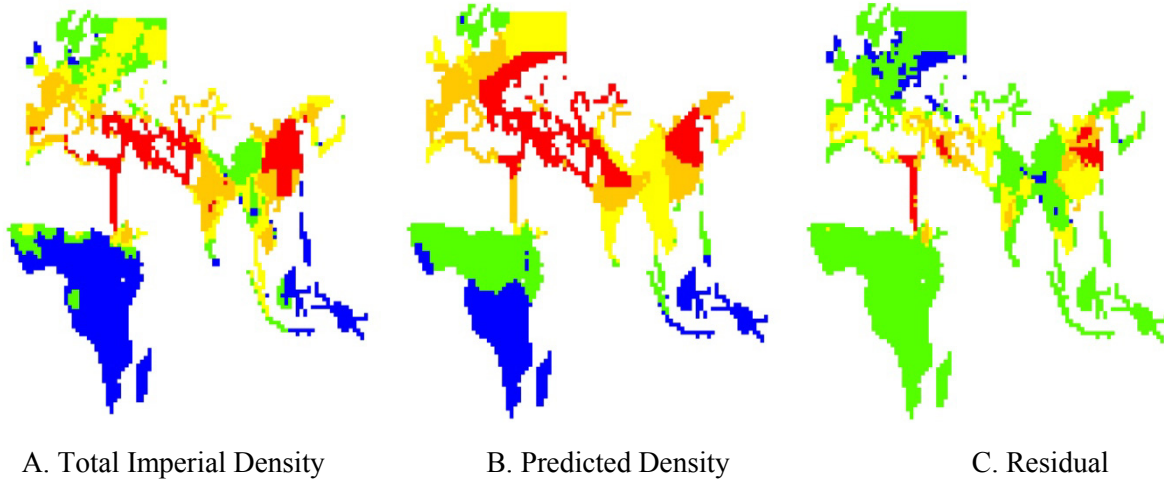
Figure S12. *Comparison of observed imperial density against SAR predicted values show the model does well at predicting regions of relatively high and relatively low imperial density. Observed and predicted category designations were based on portioning the data into quintiles. The five quintiles, from lowest to highest are blue, green, yellow, orange, and red. Predicted density categories are depicted in the same way. Residuals from the SAR analysis show most regions are well estimated (key blue:-10.2 to -5, green: - 5 to 5, yellow: 5 to 10, orange: 10 to 15, red: 15 to 20.2, i.e green cells are those where predictions match observed values within 5 points). The model generally under-predicts the frequency with which cells were occupied in regions that were actually hotspots of empire formation.*

In order to assess how important is the spatial autocorrelation component in explaining the fit between the simulated and historical data we also ran SAR analyses using the simulated data from the best parameter set as a predictor of the historical data. We ran analyses looking at 1) the total imperial density over the entire time span, and 2) imperial densities within each of three eras. The results of these analyses are summarized in table SM6. The results show that even factoring out the effect of spatial autocorrelation, the simulation still explains almost half the variance in our estimates of overall imperial density, compared to an estimate of 66% from OLS regression. Considering each era in turn also sees the R^2 value drop between 15 and 24%. Taking spatial autocorrelation into account does not, thus, affect the qualitative pattern of results with the simulation being a better predictor of imperial density in era 2 than in eras 1 and 3. We continue to use the OLS R^2 as our metric for the match between model predictions and data because spatial autocorrelations are not simply noise to be tuned out, but a result of processes explicitly built into the model (spatial diffusion of MilTech traits, spread of ultrasocial traits from a cell to a neighboring cell when it is conquered and undergoes ethnocide).

Table SM6. Comparison of R^2 values between OLS regression and SAR analyses for the simulated data from the best parameter set as a predictor of imperial density for each era and overall.

Time Frame	OLS	SAR
Overall	0.66	0.47
Era 1	0.52	0.29
Era 2	0.67	0.52
Era 3	0.49	0.25

IV. Supporting Discussion

IV.1 Limitations of the Approach

Due to the nature of the question addressed in our study, there are inevitably several sources of error in historical and geographical data we have used. Our decision to collect historical data only at 100-year time-slices means that the model 'misses' peaks of some substantial polities such as the Empire of Alexander the Great, or Attila's Hunnic Empire. This could be seen as a limitation for traditional historical analyses because we have not included a few polities known to be historically influential. However, for the purposes of our analyses this is actually strength. Using a regular sampling strategy allows us to collect data in a systematic way independent of the hypothesis being tested rather than cherry-picking examples that support our ideas.

We have also only focused on the largest polities, i.e those that were approximately greater than 100,000 km^2. This means that some complex societies, such as the Ancient Greek city states, are not included in our database. The focus on territorial extent is also a result of our attempt to be systematic and minimize bias, and this large threshold was chosen for practical considerations. Historical information about the world varies partly in the degree to which modern societies can invest in uncovering it. Our information about the history of western civilization, thus, is disproportionately good compared to some other parts of the world. Employing a relatively large cut-off minimizes the risk of "missing" polities with large populations in less well-documented regions and time-frames, because the larger the polity the more likely it is to have left some trace in the historical record. At a smaller threshold there are simply too many polities about which we have very little information, including their territories, and the effects of a bias in our access to the historical record is increased. Despite the complications involved in trying to estimate the historic distributions of complex societies, the broad, qualitative pattern identified in our dataset is likely to hold. Large societies first arose in Egypt, the Middle East, and Northern China, and then spread later to Europe, Central, South and Southeast Asia. Such societies were largely absent in sub-Saharan Africa (except for the Sahel region), and in other tropical regions, such as New Guinea. Finally, because we have focused on the largest polities in this model we have operated at quite a coarse grain of analysis. It would of course be possible to use smaller grid cells, however, this would be of limited value given the nature of these data and the goals of our present analysis. Adjusting the size of the grid cells may affect particular estimates of parameter values and overall model fit, there is no reason to suspect that it would affect the overall pattern of our model's predictions, as long as model parameters are scaled appropriately as the resolution is increased. In other words, models without the effect of warfare intensity diffusing from the Steppe, and elevation would still do worse regardless of the cell dimensions.

A further limitation is the coarse grain at which we model the cultural traits, and the underlying ecology. We have deliberately kept our cultural traits quite abstract in order to facilitate model building; any simulation has to find a balance between attempting to be realistic, and being simple enough to understand the processes being modeled (23). Future work, will build on this simple model, introducing such extensions as explicit hierarchical organization, varying the strength of different traits, or having traits with more specific effects on group stability. Also, conceptually, cultural variation is often represented as a set of binary variables in cross-cultural analyses (24, 25). Complex variables, such as bureaucracy, can be 'binarized' by asking a series of yes/no questions: are bureaucrats full-time or part time? Is there an examination system? etc. This approach is especially useful in functional analyses, where cultural traits may

480 appear quite different, but actually perform similar underlying functions. Furthermore,
481 agriculture is treated simply as being present or absent and its extent only varies at three points.
482 However, some regions are more productive than others and, therefore, have a greater ability to
483 support large populations and complex societies. Nevertheless, the relationship between
484 agricultural productivity and social complexity is by no means straightforward, and agricultural
485 productivity itself will vary as a function of climatic factors, the type of crop being grown, and
486 the technology and techniques used in farming. Also we model desert cells as being unable to
487 support complex societies; however, the imperial density maps indicate certain desert regions,
488 particularly the Iranian plateau, actually having dense concentrations of macrostates. Although
489 the coarse-grain modeling of the environment is suitable for our present purposes, in future work
490 we will develop a more detailed picture of the resource base underpinning large-scale complex
491 societies (producing finer-grained maps with smaller cells—50 x 50 km, and even 10 x 10 km),
492 which will allow us to consider these and other complexities. It is important to note, as discussed
493 above, that these errors are not biased towards providing support for our particular hypothesis.
494 Indeed it is remarkable that our model is able to simulate data that match well the observed data
495 in spite of these limitations.
496   We have chosen to focus on agrarian societies during a particular time frame and in a
497 particular part of the world. We do not model the Americas, even though a number of large-scale
498 societies, such as the Aztecs and Incas, developed there historically. However, Turchin has
499 previously argued that similar processes, (i.e.interaction between groups on either side of an
500 ecological frontier, and increasing intensity of warfare) may also explain the emergence of large-
501 scale societies there (26). Recently, a group of anthropologists and archaeologists (reported
502 extensively in a special issue of *Evolutionary Anthropology*) have proposed that the diffusion of
503 bow-and-arrow technology had a major impact on the evolution of social complexity within
504 North America (27). In future work we can assess whether using our model, but substituting
505 archery in place of cavalry, may predict spatio-temporal patterns in the Americas. Furthermore,
506 as the Old and New Worlds were almost completely isolated from one another until just before
507 the end of the time frame we have considered in this study, examining the development of
508 complex societies in the Americas would represent an interesting "natural experiment" in history
509 (28). Our model performs very well in Afro-Eurasia for the period of 1500 BCE to 1500 CE,
510 when horse-based warfare was the most important factor in elevating the intensity of competition
511 between societies. The question arises, will a suitably updated version of the model do as well
512 for the post-1500 CE period? It is clear that the model would have to focus on such new military
513 technologies as gunpowder weapons and ocean-crossing ships (29, 30) and on economic
514 competition (31). Plans are underway for developing such a model and testing it with the post-
515 1500 data.
516
517 *IV.2 Broad Implications of our Research*

518 Our results potentially have implications for understanding the degree of inequality in wealth and
519 material security in the modern world. Recent research indicates that present-day economic
520 development and political stability have deep historical roots. Jared Diamond (6) argued that the
521 initial endowments of continents in terms of domesticable plants and animals, and East-West vs.
522 North- South orientation had determining impacts on subsequent political and economic
523 development. Olsson and Hibbs (32) analyzed empirical evidence from a large cross-section of
524 countries, and found that their results supported Diamond's hypothesis. They concluded that
525 geographic and initial biogeographic conditions exert decisive influence on transition to

526 sedentary agriculture, to complex social organization, and to modern industrial production. In
527 other words, events that happened as far back in history as 10,000 years ago (domestication of
528 plants and animals) shaped, and continue to affect the fates of modern nations. In a recent
529 analysis, Comin et al. (33) assembled a dataset on technology adoption in 1000 BC, 0 AD, and
530 1500 AD. They found that technology in 1500 AD was strongly correlated with per capita
531 income and technology adoption today. In turn, the situation in 1500 AD was strongly infuenced
532 by that in 0 AD, and 0 AD was correlated with 1000 BC. Bockstette et al. (34) broadened the
533 scope of analysis to political variables and found that 'state antiquity' (an index of the depth of
534 experience with state-level institutions) was significantly correlated with political stability,
535 institutional quality, and the rate of economic growth between 1960 and 1995. The ability of
536 populations to construct and maintain viable states is also strongly conditioned by history. For
537 example, the efficiency of provincial governments in Italy is strongly correlated with the
538 vibrancy of civic life in the province during the Renaissance (35). In fact, the roots of the North-
539 South split in the ability to cooperate may go all the way to the times of the Late Roman Empire
540 (36). The ability of different regions of Afghanistan to maintain local peace and order is similarly
541 strongly conditioned on the previous history of state building in the region (37). Furthermore,
542 ability to cooperate in the political and the economic spheres are probably interrelated (38).

543   It should not be surprising that political and economic development are closely
544 correlated, and, in fact, may be just two different manifestations of the same deep structural
545 process. Building viable states and vibrant economies requires huge numbers of people to
546 cooperate on a very large scale (39). In this paper we have followed the work of a number of
547 theorists who have argued that the human capacity for cooperation in huge groups of genetically
548 unrelated individuals, is due to the evolution of ultrasocial norms and institutions (40-42). Many
549 social scientists also stress the importance of institutions in explaining variation in modern-day
550 development. For example, Acemoglu et al. (43) pointed out that a number of areas that were
551 highly developed prior to 1500 AD experienced severe reversals as a result of European
552 colonization. They argue that in the unhealthy tropical regions, where Europeans could not settle,
553 they set up highly extractive institutions, which destroyed the future prospects for economic
554 growth and political development. They claim that "once the effect of institutions is controlled
555 for, countries in Africa or those closer to the equator do not have lower incomes." In a similar
556 vein, the analysis by Nunn and Puga (44) connected poor institutional development within Africa
557 to regions that historically were under the greatest pressure from slaver raids. Yet another
558 direction has been explored by Enrico Spolaore and co-workers, who have focused on the
559 ancestral composition of current populations (45). Institutional-based explanations are sometimes
560 contrasted with other theories that stress exogenous factors (38). Some authors, such as Jared
561 Diamond and Jeffrey Sachs, argue for a direct effect of geography on economic growth, focusing
562 on such mechanisms as disease burdens. For example, there is a striking correlation between
563 malaria and poverty (46).

564   These examples demonstrate that although there are strong empirical patterns linking
565 history and geography to the current distribution of world wealth and political stability, there is
566 as yet no agreement on the processes underlying these patterns. We argue that the dichotomy
567 between institutional explanations on the one hand and geographic or ecological on the other is a
568 false one. Our model encapsulates one set of mechanisms that may explain how geographic and
569 historical influences interact in enabling the evolution and persistence of ultrasocial institutions.
570 In our model the formation of large groups is a product of historical factors (e.g. the evolution of
571 cultural institutions), and geographic factors (e.g. terrain), while some factors have both

572 historical and geographic elements. For example, the presence of agriculture is partly due to the
573 suitability of external environmental conditions, and partly due to the development and spread of
574 agricultural techniques and technologies through population expansion and cultural transmission.
575 Military technology spreads via cultural transmission yet the most important aspect of this factor
576 was that the location of its initial development was on the ecological boundary of the Eurasian
577 steppe (which itself was due to a historical contingency – availability of wild horse for
578 domestication). In our model the key mechanism is the elimination of groups and societies that
579 fail to acquire, or lose ultrasocial institutions via a process of cultural multilevel selection
580 (CMLS). Because the intensity of between-group competition varies in space and time, we were
581 able to test the model's predictions empirically.

582

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