# War, space, and the evolution of Old World complex societies

Peter Turchin[a,1], Thomas E. Currie[b], Edward A. L. Turner[c], and Sergey Gavrilets[d]

[a]Department of Ecology and Evolutionary Biology, University of Connecticut, Storrs, CT 06235-3042; [b]Centre for Ecology and Conservation, Department of Biosciences, University of Exeter, Cornwall TR10 9EZ, United Kingdom; [c]South Woodham Ferrers, CM3 5GU, England; and [d]Department of Ecology and Evolutionary Biology and Department of Mathematics, National Institute for Mathematical and Biological Synthesis, University of Tennessee, Knoxville, TN 37996

How did human societies evolve from small groups, integrated by face-to-face cooperation, to huge anonymous societies of today, typically organized as states? Why is there so much variation in the ability of different human populations to construct viable states? Existing theories are usually formulated as verbal models and, as a result, do not yield sharply defined, quantitative predictions that could be unambiguously tested with data. Here we develop a cultural evolutionary model that predicts where and when the largest-scale complex societies arose in human history. The central premise of the model, which we test, is that costly institutions that enabled large human groups to function without splitting up evolved as a result of intense competition between societies—primarily warfare. Warfare intensity, in turn, depended on the spread of historically attested military technologies (e.g., chariots and cavalry) and on geographic factors (e.g., rugged landscape). The model was simulated within a realistic landscape of the Afroeurasian landmass and its predictions were tested against a large dataset documenting the spatiotemporal distribution of historical large-scale societies in Afroeurasia between 1,500 BCE and 1,500 CE. The model-predicted pattern of spread of large-scale societies was very similar to the observed one. Overall, the model explained 65% of variance in the data. An alternative model, omitting the effect of diffusing military technologies, explained only 16% of variance. Our results support theories that emphasize the role of institutions in state-building and suggest a possible explanation why a long history of statehood is positively correlated with political stability, institutional quality, and income per capita.

cultural evolution | social complexity | ultrasociality

**H**umans have the ability to live and cooperate in huge groups of genetically unrelated individuals (what can be termed "ultrasociality") (1, 2). The central conceptual issue that this paper addresses is what mechanisms facilitate the spread of the necessary norms and institutions that enable human groups to function at the scale of millions of individuals (3–5). Social scientists have proposed a number of theories to explain the emergence of large-scale societies, emphasizing such factors as population growth, warfare, information management, economic specialization, and long-distance trade (6–10). However, because existing theories are usually formulated as verbal models, the causal mechanisms underlying these theories are not always made explicit. Understanding how ultrasocial norms and institutions spread is not a simple matter of their benefits for large-scale societies. Collective action problems, which stem from the tension between public nature of benefits yielded by cooperation and private costs borne by cooperating agents (11), inevitably arise when large groups of people need to cooperate in the production of public goods. Any theory that does not explain how societies find ways to solve these problems must be incomplete.

## Ultrasocial Norms and Institutions

Social norms and institutions are among the most important ways of solving the collective action problem (4, 12, 13). Although much theory building has focused on solving cooperative dilemmas within groups of individuals, collective action problems can arise at all levels of organization (14). For example, an archaic state may arise when several chiefdoms are unified (by conquest, by dynastic marriage, etc.). In order for the state to function well and preserve its integrity, its constituent units (formerly chiefdoms, now provinces) have to cooperate with each other (at the very least, the regional elites need to cooperate with the center).

As an example of an ultrasocial norm, consider generalized trust (14). Propensity to trust and help individuals outside of one's ethnic group has a clear benefit for multiethnic societies, but ethnic groups among whom this ultrasocial norm is widespread are vulnerable to free-riding by ethnic groups that restrict cooperation to coethnics (e.g., ethnic mafias). An example of an ultrasocial institution, much discussed by historians and political scientists, is government by professional bureaucracies (15). Other examples include systems of formal education, with the Mandarin educational system in China as the most famous example, and universalizing religions. World religions first appeared during the Axial Age (16) and provided a basis for integrating multiethnic populations within first mega-empires, such as Achaemenid Persia (Zoroastrianism), Han China (Confucianism), and Maurya Empire (Buddhism).

Our theoretical framework for understanding the evolution of social norms and institutions is provided by cultural multilevel selection (CMLS) (5, 17). Because the benefits of ultrasocial institutions are only felt at larger scales of social organization, and costs are born by lower-level units, fragmentation into lower-level units often leads to a loss of such institutions. For example, when a territorial state fragments into a multitude of province-sized political units, ultrasocial institutions such as governance by professional bureaucracies or education systems producing literate elites may be gradually lost (as happened, e.g., in parts of

---

**Significance**

How did human societies evolve from small groups, integrated by face-to-face cooperation, to huge anonymous societies of today? Why is there so much variation in the ability of different human populations to construct viable states? We developed a model that uses cultural evolution mechanisms to predict where and when the largest-scale complex societies should have arisen in human history. The model was simulated within a realistic landscape of the Afroeurasian landmass, and its predictions were tested against real data. Overall, the model did an excellent job predicting empirical patterns. Our results suggest a possible explanation as to why a long history of statehood is positively correlated with political stability, institutional quality, and income per capita.

western Europe after the collapse of the Roman Empire). Costly ultrasocial institutions can evolve and be maintained as a result of competition between societies: societies with traits that enable greater control and coordination of larger numbers will outcompete those that lack such traits (2, 18–20). Although societies can compete in many ways, here we focus entirely on warfare. Thus, our theoretical prediction is that selection for ultrasocial institutions and social complexity is greater where warfare between societies is more intense.

Historically one of the most important factors determining the intensity of Afroeurasian warfare was proximity to grasslands inhabited by horse-riding nomads (21–24). Steppe nomads influenced the dynamics of agrarian societies both directly, by eliminating weaker and less cohesive states (25), and indirectly, by innovating and spreading technologies that intensified warfare—most notably, chariots, horse-riding, and stirrup/heavy cavalry (26). These innovations were eagerly adopted by agrarian states so that new, intense forms of offensive warfare diffused out from the steppe belt. Our hypothesis, therefore, focuses on the interaction between ecology/geography and the historically attested development of military innovations. To test this idea, in this paper we develop a cultural evolutionary model that predicts where and when the largest-scale complex societies arose in human history.

## The Model
We developed a spatially explicit, agent-based simulation that translates these theoretical principles into quantitative predictions. Our approach is therefore somewhat different from the traditional method of inquiry that historians use. Mathematical models are an important part of any mature science and serve a number of useful purposes. First, by testing the logic of the proposed mechanisms and making the assumptions explicit, such models allow us to evaluate whether our theory provides a possible explanation of the emergence of large-scale complex societies. Second, the model can yield sharply defined, quantitative predictions that can be unambiguously tested against data. By comparing data from our simulations with real data on the historical distributions of large states and empires, we can test whether the model offers a plausible explanation. Most importantly, we can also investigate whether alternative hypotheses are equally as good at explaining the observed data.

We build on our earlier theoretical work (27), making it more realistic by explicit consideration of culturally transmitted traits and geography; this enables us to assess how well our model explains observed historical distributions of large-scale societies. The modeled landscape is the Afroeurasian landmass divided into a grid of 100 × 100-km squares (*SI Appendix*). Each grid cell is characterized by existence of agriculture, biome (e.g., desert), and elevation. At the beginning of the simulation, each agricultural square is inhabited by an independent polity, and the cells adjacent to the steppe are "seeded" with military technology (MilTech) traits, which gradually diffuse out to the rest of the landmass.

As explained above, the core of the model is the dynamics of ultrasocial traits (norms and institutions) (13). Each cell is inhabited by a community that has a "cultural genome," a vector taking values of 1 or 0, depending on whether an ultrasocial trait is present. An ultrasocial trait can be gained in a community. However, because such traits are costly, the probability of losing an ultrasocial trait is much greater. Thus, in the absence of other evolutionary forces, ultrasocial traits would be present in the landscape at a very low frequency.

The force that favors the spread of ultrasocial traits is warfare. Agricultural cells can conquer other such squares, building multicell polities. The probability of winning depends on relative powers of the attacking and defending polities, with power determined by the polity size (number of cells) and the average number of ultrasocial traits. When a cell from the defeated polity is annexed, the losing cell may copy the cultural genome of the victor. This change reflects either the victorious society imposing its culture on the defeated (e.g., by religious conversion, linguistic assimilation, or replacing literate elites of the defeated group) or the physical removal of individuals (e.g., genocide, expulsion); however, this is not essential in the case of culturally transmitted traits. The probability of such replacement increases with the number of MilTech traits; more effective forms of offensive warfare make victory more decisive. The conceptual core of the model invokes the following causal chain: spread of military technologies→intensification of warfare→evolution of ultrasocial traits→rise of large-scale societies.

Our simulations are run on a map that includes other important aspects of real-world ecology. Mountainous terrain (proxied by elevation) is easier to defend and less likely to be effectively controlled (28, 29), which increases the probability of more mountainous locations successfully repelling attacks and decreases the probability that defeated cells will copy the traits of their conquerors (*SI Appendix*).

## Empirical Tests of the Model Predictions
We tested how good the model was at predicting the historical distributions of large-scale societies in Afroeurasia during 1,500 BCE–1,500 CE. Using a geographic information system and the same grid as in the simulation (we sampled model output in precisely the same way as data), we compiled information from a variety of historical atlases and other sources to draw maps at 100-y intervals of all polities that controlled territories greater than ~100,000 km² (*SI Appendix*) Next, we created imperial density maps indicating the frequency and distribution of large-scale societies; i.e., we calculated how often each grid cell was found within a large-scale polity. To capture changes through time, we examined imperial density maps for each of the three millennia. Thus, the model was tested for its ability to predict a large dataset—7,941 empirical points (each of the 2,647 agricultural cells for three eras).

As Fig. 1, *SI Appendix*, and Movie S1 show, our model is able to produce outputs that are remarkably similar to the observed data. As in the real data, the first imperiogenesis hotspots appear in Mesopotamia, Egypt, and North China because these areas are situated near the steppe frontier, and that is where MilTech diffuse first, tipping the selection in favor of ultrasocial traits. A sufficient frequency of ultrasocial traits, then, enables the rise of large and relatively stable states. Fig. 2 shows that the density of ultrasocial traits is closely correlated with imperial density. Macrostate formation then occurs when MilTech traits diffuse to the central Mediterranean/western Europe, north India, and South China, and yet later to northern and eastern Europe, Japan, Southeast Asia, and Sub-Saharan Africa. Model dynamics, thus, reflect the historical pattern of such innovations as chariots and cavalry first spreading to regions proximate to the steppe, and later to more distant regions. It should be noted that though Egypt is not directly adjacent to the Eurasian steppe belt (which extends into central Anatolia), it is close enough that MilTech traits diffuse there by the middle of the first era (1,500–500 BCE); historically, this corresponds to the spread of chariot warfare to Egypt by the Hyksos, and later the spread of cavalry, which first appears with the raiding Scythians (30). Furthermore, there is also a close correlation between the appearance of such innovations and subsequent rise of large-scale states (25) (Fig. 3*A*).

We assessed quantitatively how well our model fits the historical data, and investigated whether simpler processes could generate these patterns. A quantitative measure of fit suggests that under certain parameter values the model can explain two-thirds of the variance in overall imperial density (Table 1 and *SI Appendix*). $R^2$ values are also substantial for each era. This is a striking result, given that the model with 12 parameters (of which only four have substantial effects on model performance) is predicting 7,941 data points. Model predictions do not depend sensitively on precise parameter values ($R^2 \sim 0.5$ or better for a broad range of parameters; *SI Appendix*). However, turning off the effect of elevation reduces model accuracy, whereas making

**Fig. 1.** Comparison between data (*A*, *C*, and *E*) and prediction (*B*, *D*, and *F*) for three historical eras. Model predictions are averages over 20 realizations. Red indicates regions that were more frequently inhabited by large-scale polities, yellow shows where large polities were less common, and green indicates the absence of large polities during the period.

warfare equally intense everywhere (no effect of MilTech) or seeding MilTech randomly (instead of on the steppe interface) results in an almost complete loss of predictability (Table 1). This result shows that the match between the model and the historical data is not simply an artifact of the particular shape of the grid in which we run our model. It appears that the diffusion of MilTech and its effect on warfare intensity did indeed create an important selective force favoring the emergence of larger-scale societies. Not including these processes in the model produces results that do not match the historical data.

The importance of the steppe frontier in the evolution of ultrasociality is supported by spatially explicit statistical analyses of imperial density maps. Simultaneous autoregressive models (SAR), which account for spatial autocorrelations in the data

(31), show that the distance from the steppe is the strongest predictor of total imperial density in agricultural cells (Fig. 3*B*), followed by a measure of the long-term presence of agriculture in these cells, and elevation (*SI Appendix*). These three variables predict 42% of the variance in these models. Interestingly, the estimated historical distribution of horse-based warfare involving chariots and cavalry is also a good predictor of imperial density, which is consistent with our assumption that more intense forms of warfare act as an evolutionary driver of social complexity.

## Discussion

Historians have traditionally focused on reconstructing the specific historical development of individual polities or regions. Our approach here is very different. We have made use of historical
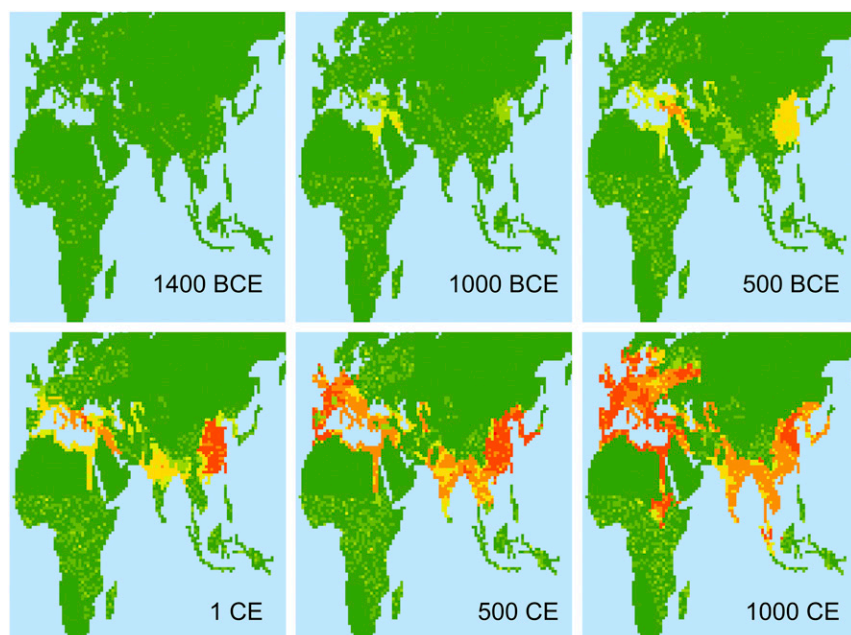
**Fig. 2.** Dynamics of ultrasocial trait density in one realization of the model. Note the initially random distribution of ultrasociality traits. As in Fig. 1, red indicates high density of ultrasocial traits and green their absence.

information to build up a more general, composite picture of the historical and geographical locations of large-scale societies. The model developed here does well at predicting the broad outlines of where and when such societies have traditionally formed and persisted. This is a remarkable result, given the limitations of historical data and a rudimentary representation of the environment and the causal mechanisms in the model. 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. However, it is important to note that these errors are not biased toward providing support for our particular hypothesis. Our use of a regular sampling strategy is a strength that 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 chosen to focus on agrarian societies during a particular timeframe and in a particular part of the world. Future work will extend this approach to examine the evolution of social complexity in the Americas and in the Old World after 1,500 CE (*SI Appendix, Supporting Discussion*).

Despite the current dominance of societies with origins in western Europe, our data indicate that for most of recorded history, Egypt, the Near East, Central Asia, and China were the predominant imperial hotspots. We have argued here that this pattern was due to the emergence and spread of technologies enabling more intense forms of warfare that, in turn, created selection pressures for the cultural evolution of norms and institutions, making possible cooperating groups numbering in the millions. In our model, the key mechanism is the elimination of groups and societies that fail to acquire/retain ultrasocial institutions via a process of CMLS. Because the intensity of between-group competition varies in space and time, we were able to test the model's predictions empirically. Recent research indicates that there are strong empirical patterns linking history and geography to the current distribution of world wealth and political stability (*SI Appendix, Supporting Discussion*). Our model provides a possible explanation of how history and geography can interact in enabling the spread and persistence of ultrasocial institutions. For example, the presence of agriculture is partly due to the suitability of external environmental conditions, and partly due to the development and spread of agricultural techniques and technologies through population expansion and cultural transmission. Military technology spreads via cultural transmission, yet the most important aspect of this factor was that the location of its initial development was on the ecological boundary of the Eurasian steppe (which itself was due to a historical contingency—availability of wild horses for domestication). In turn, this may explain why factors relating to countries' economic and political development, including institutional quality and even income per capita, show positive associations with a long history of statehood (32).

More generally, the present study highlights the role that evolutionary theory in combination with suitable data can play in addressing questions about human history and cultural evolution. Undoubtedly, the rise and fall of individual states and empires will be complex, involving idiosyncratic and contingent events. Our analyses, however, also provide support for the idea that the story of the past is not just a case of "one damned thing after another" (33), but that there are general mechanisms at play in shaping the broad patterns of history (34–36).

## Methods

**General Logic of the Model.** The goal of the model is to understand under what conditions ultrasocial norms and institutions will spread. The theoretical framework is provided by CMLS (5, 17). As explained previously, within-group forces cause ultrasocial traits to collapse and to be replaced with noncooperative traits. However, ultrasocial traits increase the competitive ability of groups. Thus, if selection between groups is strong enough, ultrasocial traits should spread despite being disadvantaged within groups.

The strength of between-group competition is assumed to be affected by two broad groups of factors: technology and geography. The two technological factors that we consider explicitly are productive (agricultural) technologies and military technologies. For simplicity, agriculture is modeled as a binary variable (presence or absence of intensive agriculture capable of supporting a complex society). Presence of agriculture is a necessary condition for a cell to attack or be attacked and potentially annexed.

Military technologies (note the plural) directly affect the strength of between-group competition; each is also modeled as a binary variable. The more such technologies are present in an area, the greater the probability that a successful attack will be decisive enough to result in cultural extinction of the losing group, and cultural domination by the victorious group.

The model assumes that military technologies arise on the interface between the Eurasian steppe belt and agrarian societies living next to it. This assumption is meant to capture the pattern of invention and spread of military innovations during the era when horse-related military innovations dominated warfare within Afroeurasia (after the introduction of the chariots and before the widespread use of gunpowder; thus, roughly 1,500 BCE to 1,500 CE). As military historians have documented (26, 37), these innovations included chariots, mounted archery, heavy cavalry, and stirrups, among others. We are not arguing that horse-related innovations were the only

ANTHROPOLOGY

**Fig. 3.** Strong temporal and spatial patterns in the data. (*A*) Invention of chariots and cavalry revolutionized warfare and led to lasting increases in the scale of social integration (pre-1,500 BCE data from ref. 25). (*B*) Imperial density decreases with increasing distance from the steppe (distance classes: 0 = within the steppe; 1 = 1–1,000 km, and so on; error bars indicate 95% confidence interval).

ones important in premodern warfare; rather, the argument is that the arrival of such technologies in an area significantly elevates the intensity of between-polity competition above existing levels. Thus, the model focuses not on the evolution of any kind of state, but on the rise and spread of very large states: macrostates. Our hypothesis is that the diffusion of horse-related military technologies from the steppe-sown interface to the rest of Afroeurasia results in a characteristic spatiotemporal pattern of spread of intense forms of warfare, leading to macrostate forms of political organization.

Other military innovations, such as the use of metals for weapons and armor, were often "bundled" with horse-based technologies. For example,

**Table 1. Effect of turning off various components of the model on its ability to predict data ($R^2$ for each era, and overall $R^2$)**

| Model | Era 1 | Era 2 | Era 3 | Overall |
|---|---|---|---|---|
| Full model | 0.56 | 0.65 | 0.47 | 0.65 |
| No elevation effect ($\gamma = \gamma_1 = 0$) | 0.31 | 0.46 | 0.35 | 0.48 |
| No effect of MilTech on ethnocide ($\varepsilon_{min} = \varepsilon_{max}$) | 0.08 | 0.08 | 0.02 | 0.16 |
| No effect of the steppe (MilTech seeded randomly) | 0.03 | 0.11 | 0.00 | 0.17 |

the use of iron arrowheads significantly increased the killing power of mounted archers, and better metal-working techniques (and, later, the spread of the stirrup) led to heavy cavalry. All such innovations are modeled simply as abstract "military technologies."

Unlike technology, the geographic variables we model do not change with time (we assume that the climate change over the modeled period can be safely ignored). The features of geography that are explicitly taken into account are (*i*) deserts and steppes (modeled as lacking agriculture in the time period considered here), (*ii*) mountains (elevation), (*iii*) rivers (make agriculture possible when flowing through deserts), and (*iv*) sea coasts (coastal cells can also initiate attacks against other coastal cells within a certain distance). The extent of agriculture is modeled as changing during the simulation to reflect the historical spread of agricultural populations and technologies (*SI Appendix*).

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

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

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

**Warfare.** Warfare between polities occurs at the boundaries between them. Border cells (cells with at least one neighbor belonging to a different polity) are randomly sampled to select an attacker, which attempts attack in a randomly chosen direction. If the defending cell belongs to a different polity, warfare between the two polities is initiated with probability $P$. All border cells receive one chance to initiate attack in a year, but the order in which they are chosen is randomized every time-step. This sampling scheme implies that the probability of attack by one polity on another is proportional to the length of the boundary between them.

Littoral cells can also initiate a seaborne attack. If such a cell attempts to attack a sea cell on which it borders, the simulation checks whether there are any other littoral cells within the distance $d_{sea}$, and if yes, proceeds to attack such a cell in the usual manner.

The success of attack is determined by the relative powers of the attacking and defending polities. The power of attacker depends on its average level of ultrasociality (the average number of ultrasociality traits in its communities):

$$\overline{U}_{att} = \frac{\sum_j \sum_i u_{ij}}{S_{att}},$$

where $u_{ij}$ is the value (0 or 1) of ultrasociality trait in the *i*th locus of *j*th community belonging to the polity and $S_{att}$ is the polity size (the number of communities).

Both average ultrasociality level and size increase a polity's power:

$$P_{att} = 1 + \beta \overline{U}_{att} S_{att}.$$

Here, $\beta$ is the coefficient that translates ultrasociality traits into the polity's power. Thus, if no community within the polity has any ultrasocial traits, the polity's power will be at the minimum, 1. If, however, all communities have all possible ultrasociality traits, then the polity power will be at maximum, or $1 + \beta\, n_{ultra}\, S_{att}$, where $n_{ultra}$ is the number of traits (length of the ultrasociality vector).

The power of the defending polity similarly increases with its size and average number of ultrasociality traits. Because mountainous areas are easier to defend, the defender's power is increased by the elevation of the defending cell:

$$P_{def} = 1 + \beta \overline{U}_{def} S_{def} + \gamma E_{def},$$

where $E_{def}$ is the elevation (in kilometers) of the defending cell found at spatial coordinates $x$ and $y$, and $\gamma$ is the coefficient translating elevation into defensive power.

Turchin et al.

The probability of successful attack is then calculated according to the following formula:

$$P_{success} = \frac{P_{att} - P_{def}}{P_{att} + P_{def}}.$$

If $P_{success} < 0$ (that is, $P_{att} < P_{def}$), the attack fails by definition. A failed attack results in no changes. When attack is successful, the defending cell is annexed by the attacking polity. Annexation can also result in ethnocide, as explained below.

**Diffusion of Military Technology.** The dynamics of spread of MilTech traits are very simple. At the beginning of the simulation, technological traits in all cells bordering on the steppe are set to 1. Subsequently, these traits diffuse out by the process of local diffusion. At each time step, the model samples all agricultural cells and randomly selects a particular locus. If the value of the trait at this locus is 0, nothing happens. If it is 1, the simulation randomly chooses one of four directions and checks whether the neighbor cell in this direction has the particular technology trait. If not, then the technology trait spreads to the neighbor with probability $\sigma$. Thus, the value of $\sigma$ controls the rate of diffusion of technology traits. Once a technology trait spreads to a cell, it is never lost (unlike ultrasocial traits). Note that technological diffusion is exogenous to other processes in the model (it is not affected by warfare or ethnocide). It is essentially a pacesetter determining how fast intense forms of warfare spread from the steppe interface to the rest of Afroeurasia.

**Sociocultural Evolution.** The dynamics of ultrasociality traits are governed by two processes: local cultural shift (mutation) and ethnocide. A cultural shift process operates as follows: at each time step, 0-valued ultrasociality traits change to 1-valued traits with probability $\mu_{01}$, and 1-valued traits change to 0-valued ones with probability $\mu_{10}$. The assumption of the model is that ultrasociality traits (1s) are greatly disadvantaged, compared with non-ultrasociality traits (0s); we model this simply by assuming that $\mu_{01} << \mu_{10}$. Thus, if only the local cultural shift process was operating, ultrasociality traits would be present at a very low level. More precisely, at the equilibrium, the average proportion of loci having 1s is

$$\overline{u} = \frac{\mu_{01}}{\mu_{01} + \mu_{10}}.$$

Ethnocide can occur when a defeated cell is annexed by the winning polity. The probability of ethnocide is increased by the number of MilTech traits possessed by the attacker and decreased by the mountainous terrain (elevation) of the defender:

$$P_{ethnocide} = \varepsilon_{min} + (\varepsilon_{max} - \varepsilon_{min})\overline{M}_{att} - \gamma_1 E_{def},$$

where $\overline{M}_{att}$ is the sum of technology trait values in the attacking cell divided by $n_{mil}$ (thus, this quantity varies between 0 and 1), and $E_{def}$ is the elevation of the defending cell. Parameter $\varepsilon_{min}$ specifies the probability of ethnocide in the situation when the attacker possesses none of the technology traits, and $\varepsilon_{max}$ the probability when the attacker has all technology traits, assuming that the defender cell is a flatland (elevation = 0). Parameter $\gamma_1$ measures the effect of elevation on decreasing the probability of ethnocide. If $P_{ethnocide} < 0$, nothing happens. If ethnocide occurs, then the values of the ultrasociality vector in the losing cell are set to the values of the attacking cell. Note that this copying process does not directly favor ultrasociality traits (1s). Both 0s and 1s in the winning cell's vector are copied. However, warfare benefits ultrasocial traits indirectly, because polities with more ultrasociality traits have a greater chance of defeating polities with fewer such traits and spreading their traits via ethnocide.

**Polity Disintegration.** Historical processes of social evolution involved scaling-up dynamics, resulting in larger and more complex societies, and scaling-down dynamics, resulting in social dissolution. The model handles disintegrative process in a highly parsimonious manner. Every time-step, each polity can dissolve into the constituent communities with the probability $P_{disint}$. Probability of disintegration increases with the polity size ($S$) and decreases with the average complexity level ($\overline{U}$):

$$P_{disint} = \delta_0 + \delta_s S - \delta_a \overline{U}.$$

The probability of disintegration is constrained to be between 0 and 1.

1. Campbell DT (1983) The two distinct routes beyond kin selection to ultrasociality: Implications for the humanities and social sciences. *The Nature of Prosocial Development: Theories and Strategies*, ed Bridgeman D (Academic, New York), pp 11–39.
2. Richerson PJ, Boyd R (1998) The evolution of human ultrasociality. *Ethnic Conflict and Indoctrination*, eds Eibl-Eibesfeldt I, Salter FK (Berghahn, Oxford), pp 71–95.
3. Bowles S (2004) *Microeconomics: Behavior, Institutions, and Evolution* (Princeton Univ Press, Princeton, NJ).
4. Fukuyama F (2011) *The Origins of Political Order: From Prehuman Times to the French Revolution* (Farrar, Straus, and Giroux, New York).
5. Richerson P, Henrich J (2012) Tribal social instincts and the cultural evolution of institutions to solve collective action problems. *Cliodynamics* 3:38–80.
6. Carneiro RL (1970) A theory of the origin of the state: Traditional theories of state origins are considered and rejected in favor of a new ecological hypothesis. *Science* 169(3947):733–738.
7. Johnson AW, Earle T (2000) *The Evolution Of Human Societies: From Foraging Group to Agrarian State* (Stanford Univ Press, Stanford, CA), 2nd Ed.
8. Spencer CS, Redmond EM (2004) Primary state formation in Mesoamerica. *Annu Rev Anthropol* 33:179–199.
9. Wright HT (2006) Early state dynamics as political experiment. *J Anthropol Res* 62:305–319.
10. Flannery K, Marcus J (2012) *The Creation of Inequality: How Our Prehistoric Ancestors Set the Stage for Monarchy, Slavery, and Empire* (Harvard Univ Press, Cambridge, MA).
11. Olson M (1965) *The Logic of Collective Action: Public Goods and the Theory of Groups* (Harvard Univ Press, Cambridge, MA).
12. Henrich N, Henrich J (2007) *Why Humans Cooperate: A Cultural and Evolutionary Explanation* (Oxford Univ Press, New York).
13. Bowles S, Gintis H (2011) *A Cooperative Species: Human Reciprocity and Its Evolution* (Princeton Univ Press, Princeton, NJ).
14. Turchin P (2013) The puzzle of human ultrasociality: How did large-scale complex societies evolve? *Cultural Evolution,* Strüngmann Forum Report, eds Richerson PJ, Christiansen MH (MIT Press, Cambridge, MA), Vol 12, pp 61–73.
15. Mann M (1986) *The Sources of Social Power. I. A History of Power from the Beginning to A.D. 1760* (Cambridge Univ Press, Cambridge, UK).
16. Bellah RN (2011) *Religion in Human Evolution: From the Paleolithic to the Axial Age* (Harvard Univ Press, Cambridge, MA).
17. Wilson DS, Wilson EO (2007) Rethinking the theoretical foundation of sociobiology. *Q Rev Biol* 82(4):327–348.
18. Wilson DS (2002) *Darwin's Cathedral: Evolution, Religion, and the Nature of Society* (Univ of Chicago Press, Chicago).
19. Bowles S (2009) Did warfare among ancestral hunter-gatherers affect the evolution of human social behaviors? *Science* 324(5932):1293–1298.
20. Henrich J, et al. (2010) Markets, religion, community size, and the evolution of fairness and punishment. *Science* 327(5972):1480–1484.
21. Chase K (2003) *Firearms: A Global History to 1700* (Cambridge Univ Press, Cambridge, UK).
22. Turchin P (2003) *Historical Dynamics: Why States Rise and Fall* (Princeton Univ Press, Princeton, NJ).
23. Lieberman V (2010) *Strange Parallels: Southeast Asia in Global Context, c. 800–1830. Volume II: Mainland Mirrors, Europe, China, South Asia, and the Islands* (Cambridge Univ Press, Cambridge, UL).
24. Levy JS, Thompson WR (2011) *The Arc of War: Origins, Escalation, and Transformation* (Univ of Chicago Press, Chicago).
25. Turchin P (2009) A theory for formation of large empires. *J Global Hist* 4:191–207.
26. Gat A (2008) *War in Human Civilization* (Oxford Univ Press, New York).
27. Gavrilets S, Anderson D, Turchin P (2010) Cycling in the complexity of early societies. *Cliodynamics* 1:58–80.
28. Scott JC (2009) *The Art of Not Being Governed: An Anarchist History of Upland Southeast Asia* (Yale Univ Press, New Haven, CT).
29. Michaud J (2010) Zomia and beyond. *J Global Hist* 5:187–214.
30. Christian D (1998) *A History of Russia, Central Asia, and Mongolia* (Blackwell, Oxford).
31. Dormann CF, et al. (2007) Methods to account for spatial autocorrelation in the analysis of species distributional data: A review. *Ecography* 30:609–628.
32. Bockstette V, Chanda A, Putterman L (2002) States and markets: The advantage of an early start. *J Econ Growth* 7:347–369.
33. Toynbee AJ (1957) *A Study of History* (Oxford Univ Press, London), Vol 2.
34. Diamond J (1997) *Guns, Germs, and Steel: The Fates of Human Societies* (Norton, New York).
35. Turchin P (2008) Arise 'cliodynamics' *Nature* 454(7200):34–35.
36. Currie TE, Greenhill SJ, Gray RD, Hasegawa T, Mace R (2010) Rise and fall of political complexity in island South-East Asia and the Pacific. *Nature* 467(7317):801–804.
37. Nefedov SA (2009) *War and Society* (Territoriya Buduschego, Moscow). Russian.

**ANTHROPOLOGY**

# Supporting Information

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

### P. Turchin, T. Currie, E. Turner, & S. Gavrilets

## 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.
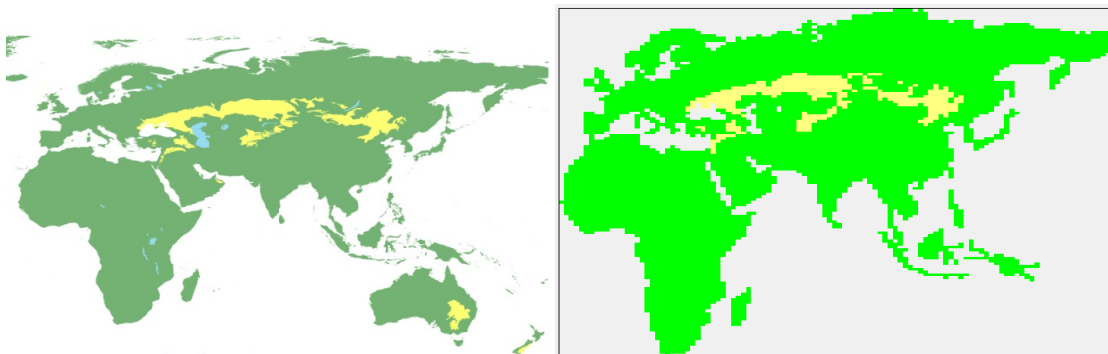


**Figure S1.** *Classification of the Steppe in our simulation (right) is based on the WWF map of terrestrial ecosystems (left). The grassland regions in Eastern Arabia, are not classified as Steppe for the purposes of this model, and those in New Zealand and Australia do not form part of the Afro-Eurasian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

50



51
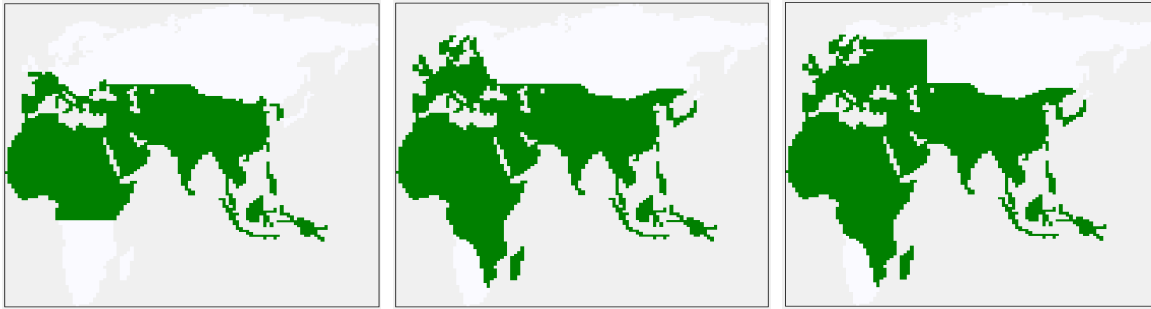
52 **Figure S2.** *The extent of agriculture in the simulation (green) increases throughout the simulation*
53 *(earliest period, left; final period, right)*

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.

69

## 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 $\beta$ 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 $\gamma$ 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, $\varepsilon_{max}$,
98   was set to 1, and the baseline probability $\varepsilon_{min}$ was 1/20th of it, or 0.05. The effect of elevation, $\gamma_1$, was set
99   to 1.

100   Baseline disintegration probability $\delta_0$ 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 $\delta_s$ 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 $\delta_a$ 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.

111

112

113

114

115

116

117

118    **Table SM1.** Model parameters.

| Parameter | Reference value | Explanation |
|-----------|-----------------|-------------|
| $\beta$ | 1 | effect of average ultrasociality on power |
| $\varepsilon_{min}$ | 0.05 | minimum probability of ethnocide (with all MilTech = 0) |
| $\varepsilon_{max}$ | 1 | maximum probability of ethnocide (with all MilTech = 1) |
| $\delta_0$ | 0.05 | baseline probability of disintegration (for $S = 0$ and $U = 0$ |
| $\delta_s$ | 0.05 | effect of polity size on probability of disintegration |
| $\delta_a$ | 2 | effect of average ultrasociality on probability of disintegration |
| $\mu_{01}$ | 0.0001 | probability of mutation to an ultrasocial trait |
| $\mu_{10}$ | 0.002 | probability of ultrasocial trait mutating to non-ultrasocial trait |
| $\gamma$ | 4 | effect of elevation on defensive power |
| $\gamma_1$ | 1 | effect of elevation on the probability of ethnocide |

119

120

# 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.

136



137
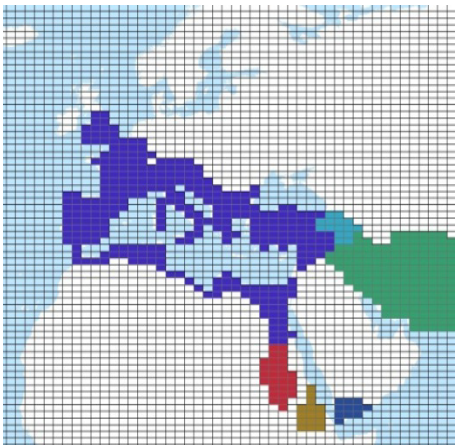
138    **Figure S3.** Estimated distributions of the Roman Empire (blue) and other large-scale polities from one
139    time slice.

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).

146



147
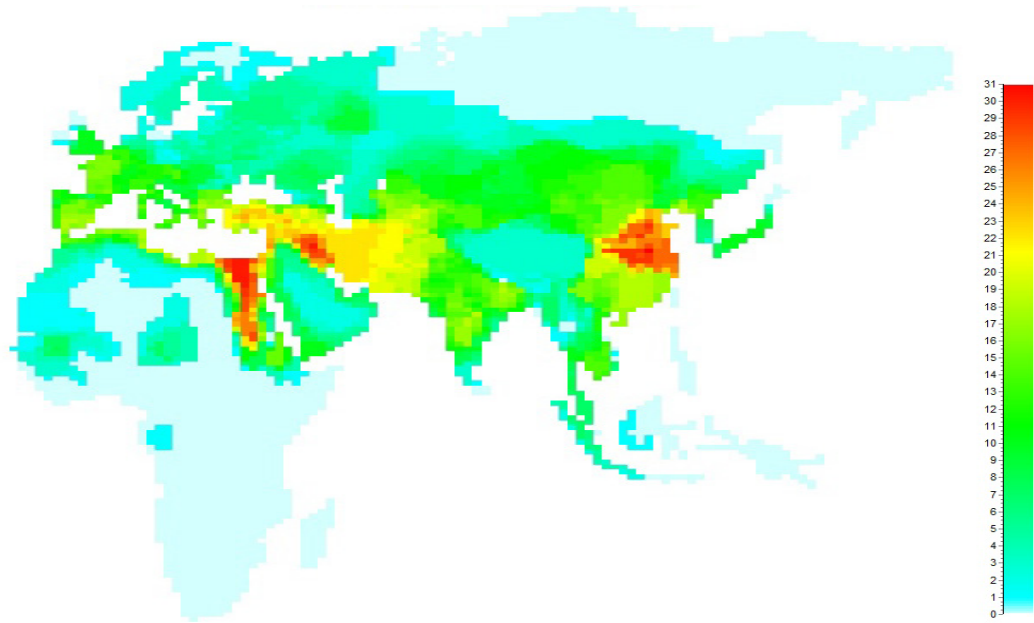
148    **Figure S4.**   Imperial Density Map 1500 BCE – 1500 CE. Scale shows how many time slices polities
149    were present in each cell. Red cells indicate regions that were more frequently inhabited by large-scale
150    polities. Cyan cells show where large polities were less common. The lightest blue regions indicate the
151    absence of large polities during the time-span considered in this paper.

152

153    (A)



154    (B)



155    (C)

156
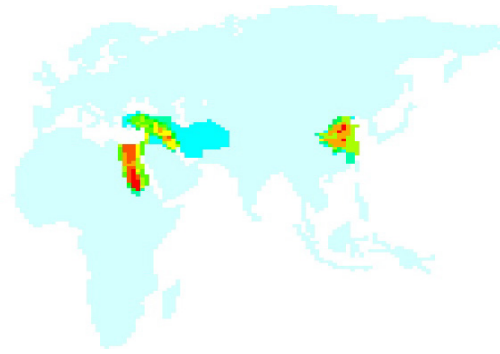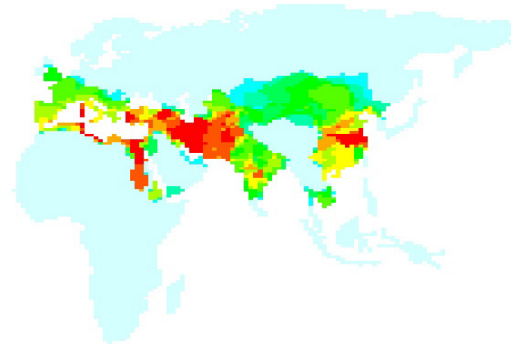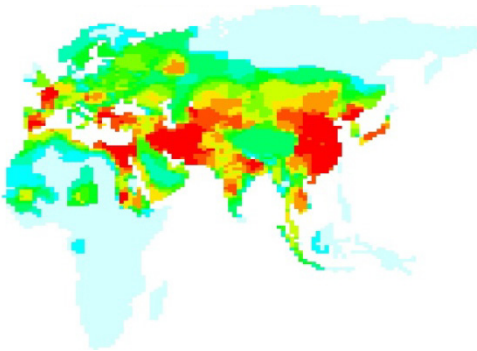
157    **Figure S5.** Imperial Density Maps for (A) 1500 BCE - 400 BCE, (B) 500 BCE - 400 CE, and (C) 500 CE
158    - 1500 CE.

159

160    *References used for creating Imperial Density Maps:*

161    Barnes, I. and Hudson, R. (1998) *Historical Atlas of Asia: From the Word's Oldest Civilizations to*
162       *Emerging Superpower.*  Wiley.

163    Barraclough, G. ed. (1994) *The Times Atlas of World History* (Fourth Edition). BCA.

164    Black, J. ed. (2008) *World History Atlas* (Third Edition).  Dorling Kindersley.

165    Bregel, Y. (2003) *An Historical Atlas of Central Asia.*  Brill Academic.

166    Cussans, T., Parker, P., Winkleman, B., and Oliver, C. ed. (1994) *The Times Atlas of European History.*
167       Times Books.

168    Davidson, P. (2011) *Atlas of Empires.*  New Holland Publishers (UK) Ltd.

169   Encyclopedia Britannica (2011) *Encyclopedia Britannica* (http://www.britannica.co.uk).  Encyclopedia
170       Britannica UK Ltd

171   Euratlas-Nüssli (2011) *Euratlas* (euratlas.com).  Euratlas-Nüssli.

172   Hammond World Atlas Corporation (2007) *Historical World Atlas* (Revised Edition).  Hammond World
173       Atlas Corporation.

174   Haywood, J. (2000) *The Cassell Atlas of World History: The Ancient & Classical Worlds* (Volume One).
175       Cassell

176   Haywood, J. (2000) *The Cassell Atlas of World History: The Medieval & Early Modern Worlds* (Volume
177       Two).  Cassell

178   Haywood, J. (2011) *The New Atlas of World History*.  Thames & Hudson Ltd.

179   Kinder, H., and Hilgemann, W. (1974) *The Anchor Atlas of World History From the Stone Age to the Eve
180       of the French Revolution* (Volume I).  Anchor Books.

181   Lessman, T. (2011) *Talessman's Atlas of World History*.  Thomas Lessman. downloaded 25/3/2011.
182       These maps are free to download from worldhistorymaps.info.

183   Nelson, J. (2010) *World History Maps Interactive Historical Atlas One Map for Every Year The Old
184       World Since 500 BCE* (worldhistorymaps.com). World History Maps Inc.

185   O'Brien, P. ed. (2007) *Atlas of World History* (Concise Edition).  Oxford University Press.

186   Shepherd, W. (1911) *Historical Atlas.* Henry Holt and Company.

187   Shepherd, W. (1923) *Historical Atlas*. Henry Holt and Company.

188   Wawro, G. ed. (2008) *Historical Atlas A Cartographic History of Our Lives and History from the
189       Beginning of Recorded Time to the Present Day*.  Millennium House Pty Ltd.

190

# 191   III. Supplementary Results

## 192   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 $\tau_2$ 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, $\varepsilon_{max}$, $\delta_0$, and $\gamma$ (in addition to $\tau_2$ 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 |
| $\beta$ | 0.42 | 0.48 | 0.51 | 0.54 | 0.56 |
| $\varepsilon_{min}$ | 0.51 | 0.52 | 0.51 | 0.51 | 0.50 |
| $\varepsilon_{max}$ | 0.41 | 0.48 | 0.51 | 0.56 | 0.56 |
| $\delta_0$ | 0.54 | 0.52 | 0.51 | 0.49 | 0.45 |
| $\delta_s$ | 0.54 | 0.52 | 0.51 | 0.49 | 0.47 |
| $\delta_a$ | 0.48 | 0.51 | 0.51 | 0.52 | 0.54 |
| $\mu_{01}$ | 0.47 | 0.50 | 0.51 | 0.50 | 0.49 |
| $\mu_{10}$ | 0.49 | 0.50 | 0.51 | 0.52 | 0.50 |
| $\gamma$ | 0.56 | 0.53 | 0.51 | 0.44 | 0.45 |
| $\gamma_1$ | 0.54 | 0.52 | 0.51 | 0.48 | 0.44 |

241

242

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 |
| $\varepsilon_{min}$ | 0.64 | 0.65 | 0.65 | 0.64 | 0.63 |
| $\varepsilon_{max}$ | 0.59 | 0.63 | 0.65 | 0.63 | 0.63 |
| $\delta_0$ | 0.65 | 0.64 | 0.65 | 0.63 | 0.62 |
| $\delta_s$ | 0.60 | 0.64 | 0.65 | 0.64 | 0.64 |
| $\delta_a$ | 0.64 | 0.63 | 0.65 | 0.63 | 0.62 |
| $\mu_{01}$ | 0.64 | 0.65 | 0.65 | 0.61 | 0.56 |
| $\mu_{10}$ | 0.60 | 0.64 | 0.65 | 0.65 | 0.65 |
| $\Gamma$ | 0.67 | 0.65 | 0.65 | 0.63 | 0.60 |
| $\gamma_1$ | 0.63 | 0.64 | 0.65 | 0.63 | 0.60 |
| $d_{sea}$ | 0.64 | 0.65 | 0.65 | 0.62 | 0.62 |
| $\Delta$ | 0.66 | 0.65 | 0.65 | 0.62 | 0.59 |

247

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 $R^2 = 0.47$).



251
252

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 $\tau_2$
255   $= 900$ (overall $R^2 = 0.51$).



256
257
258
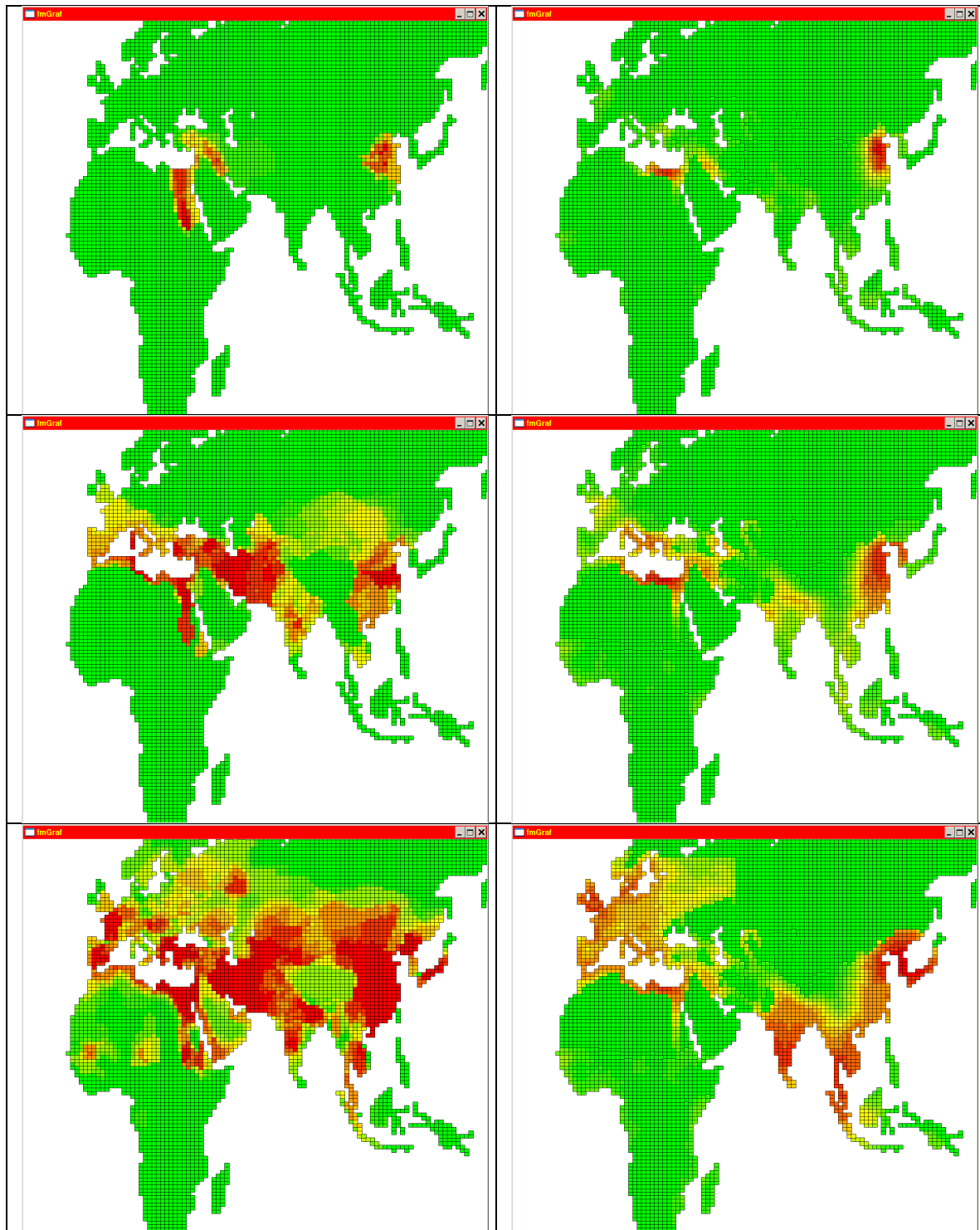
259     **Figure S8.** Comparison between data (left column) and model (right column) for three eras. Best
260     parameter set (overall $R^2 = 0.65$).



261
262

263
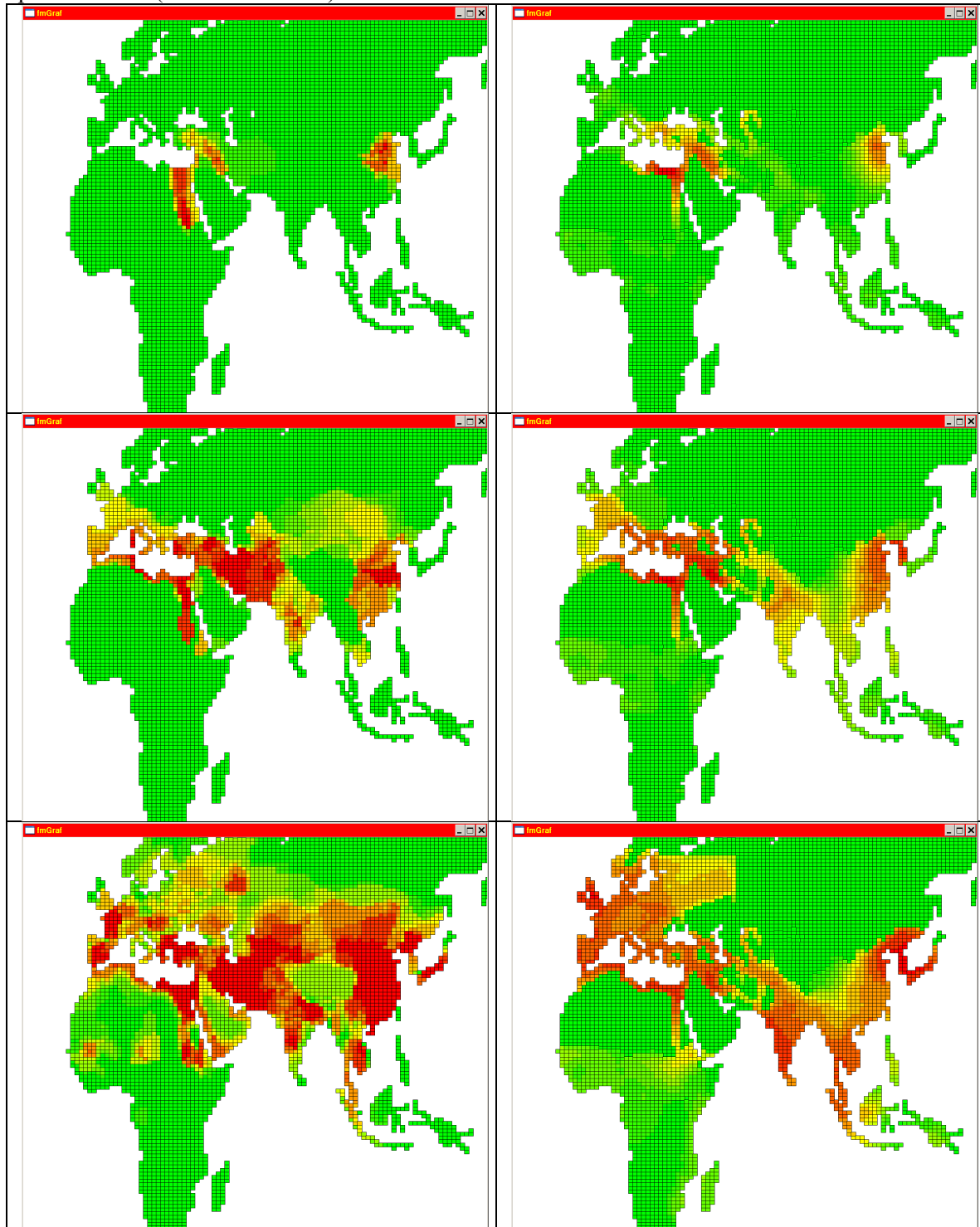
264   **III.2  Null Models: Effects of Turning off CMLS and Elevation**

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 $\varepsilon_{min}$ and $\varepsilon_{max}$ to the same value. Running the model for several values of $\varepsilon_{min}$ and $\varepsilon_{max}$
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 $\gamma$ 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

### III.3  Spatially-Explicit Regression Analyses

300  

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 $\alpha$ 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
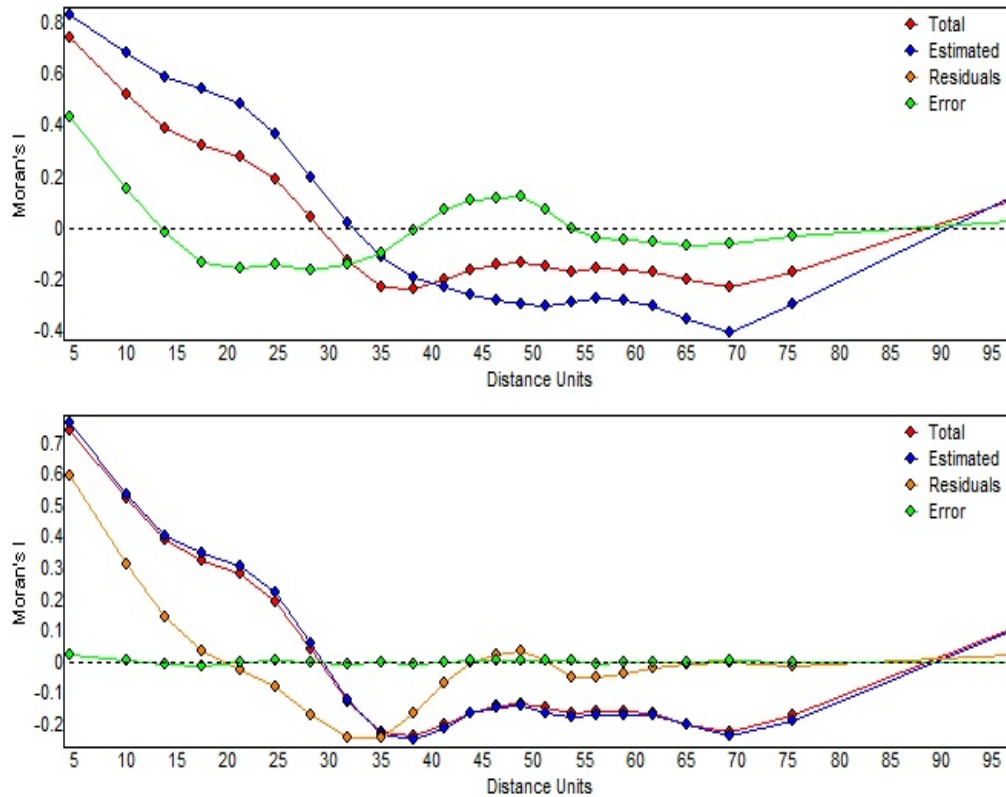
319  **Figure S9.** Moran's I spatial autocorrelation plots at increasing distances (hundreds of kilometers)  for
320  total imperial density (red), predicted imperial density from SAR analysis (blue), SAR analysis residuals,
321  reflecting the spatial autocorrelation component of the model (orange), 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
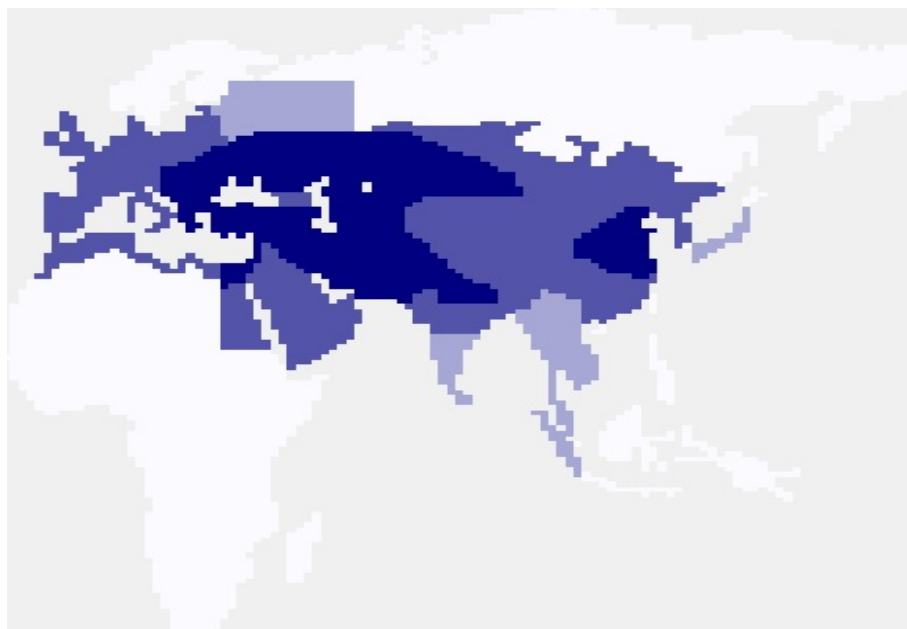
346  **Figure S10.** *Estimated distribution of horse-based warfare across eras: All eras (dark blue), Era II & III*
347  *(mid-blue), Era III only (light blue).*

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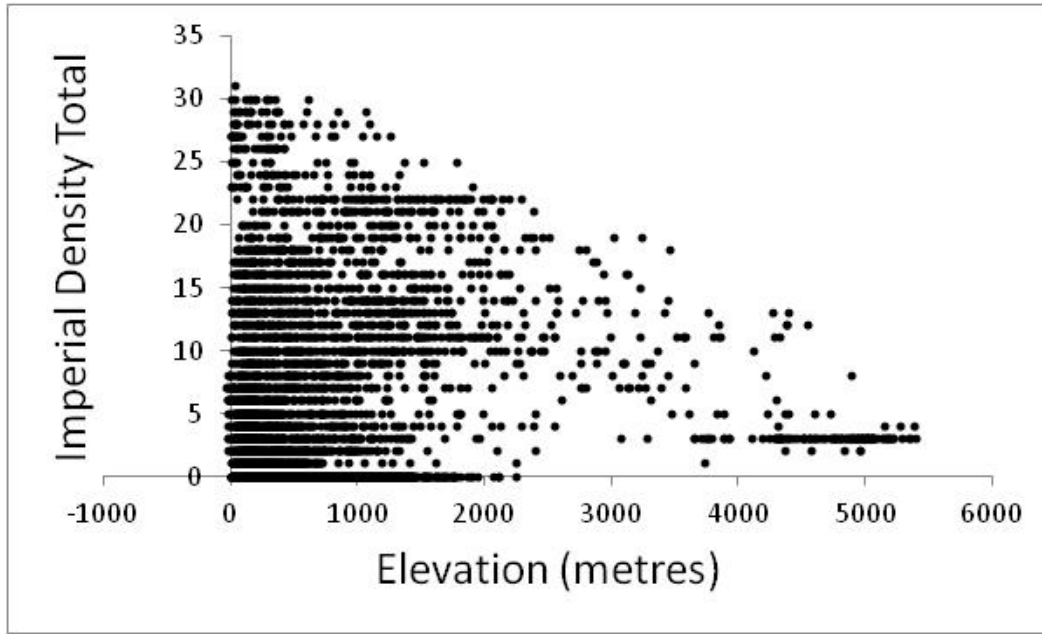
**Figure S11.** *The maximum value of imperial density decreases with increasing elevation. Many regions of lower elevation did not consistently develop large polities. This indicates that high elevation acts as a limiting factor on the creation of complex societies.*

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
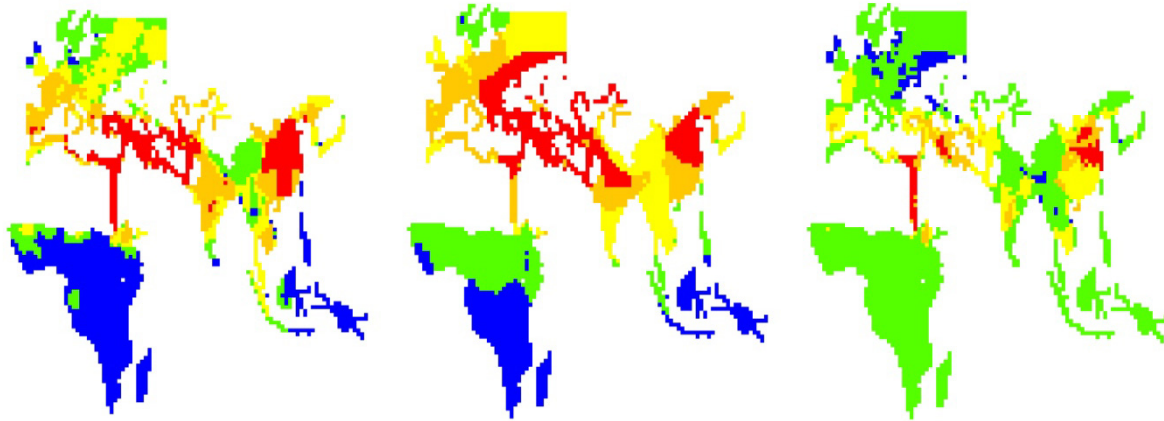
| A. Total Imperial Density | B. Predicted Density | C. Residual |

*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

# References

584   1.   Olson DM*, et al.* (2001) Terrestrial Ecoregions of the World: A New Map of Life on Earth. *BioScience*
585         51:933-938.
586   2.   Hijmans RJ, Cameron SE, Parra JL, Jones PG, & Jarvis A (2005) Very high resolution interpolated climate
587         surfaces for global land areas   *International Journal of Climatology* 25:1965-1978.
588   3.   Bellwood P (2005) *First Farmers: The Origins of Agricultural Societies* (Blackwell, Oxford).
589   4.   Binford LR (2001) *Constructing Frames of Reference* (University of California Press, Berkeley).
590   5.   Johnson AL & Hard RJ (2008) Exploring Texas Archaeology with a Model of Intensification. *Plains*
591         *Anthropologist* 53:135-151.
592   6.   Diamond J (1997) *Guns, Germs, and Steel: The Fates of Human Societies* (W. W. Norton, New York).
593   7.   Peregrine PN (2003) Atlas of Cultural Evolution. *World Cultures* 14(1):2-88.
594   8.   Dormann CF*, et al.* (2007) Methods to account for spatial autocorrelation in the analysis of species
595         distributional data: a review. *Ecography* 30:609-628.
596   9.   Rangel TF, Diniz-Filho JAF, & Bini LM (2010) SAM: a comprehensive application for Spatial Analysis in
597         Macroecology. *Ecography* 33:46-50.
598   10.  Jankovich M (1971) *They Rode into Europe* (Harrap, London).
599   11.  Fisher HJ (1972) 'He Swalloweth the Ground with Fierceness and Rage': The Horse in the Central Sudan. I.
600         Its Introduction. *Journal of African History* 13:367-388.
601   12.  Law R (1980) *The Horse in West African History* (Oxford University Press, Oxford).
602   13.  Munson PJ (1980) Archaeology and the Prehistoric Origins of the Ghana Empire. *Journal of African*
603         *History* 21:457-466.
604   14.  Beckwith CI (1987) *The Tibetan Empire in Central Asia* (Princeton University Press, Princeton).
605   15.  Gladitz C (1997) *Horse Breeding in the Medeival World* (Four Courts Press, Dublin).
606   16.  Heidorn LA (1997) The Horses of Kush. *Journal of Near Eastern Studies* 56:105-114.
607   17.  Hyland A (1998) *The Warhorse: 1250-1600* (Sutton, Phoenix Mill, UK).
608   18.  Di Cosmo N (2002) *Ancient China and Its Enemies: The Rise of Nomadic Power in East Asian History*
609         (Cambrdige University Press, Cambridge).
610   19.  Drews R (2004) *Early Riders: The Beginnings of Mounted Warfare in Asia and Europe* (Routledge, New
611         York).
612   20.  Bachmann D (2005) Historical spread of the chariot.  (Wikipemedia Commons
613         http://en.wikipedia.org/wiki/File:Chariot_spread.png ).
614   21.  Potts DT (2007) Cataphractus and kamandar: Some Thoughts on the Dynamic Evolution of Heavy Cavalry
615         and Mounted Archers in Iran and Central Asia *Bulletin of the Asia Institute* 21:149-158.
616   22.  DiMarco LA (2008) *War Horse: A History of the Military Horse and Rider* (Westholme, Yardley, PA).
617   23.  Miller JH & Page SE (2007) *Complex Adaptive Systems: An Introduction to Computational Models of*
618         *Social Life* (Princeton University Press, Princeton).
619   24.  Murdock GP & White DR (1969) Standard Cross-Cultural Sample. *Ethnology* 8(4):329–369.
620   25.  Turchin P, Whitehouse H, Francois P, Slingerland E, & Collard M (2012) A Historical Database of
621         Sociocultural Evolution. *Cliodynamics* 3:271-293.
622   26.  Turchin P (2009) A Theory for Formation of Large Empires. *Journal of Global History* 4:191-207.

623   27.   Bingham PM, Souza J, & Blitz JH (2013) Introduction: Social Complexity and the Bow in the Prehistoric
624           North American Record. *Evolutionary Anthropology* 22(3):81-88.
625   28.   Diamond J & Robinson JA (2010) *Natural Experiments of History* (Belknap, Cambridge, MA).
626   29.   Roberts M (1956) *The Military Revolution, 1560–1660* (Belfast).
627   30.   Gat A (2008) *War in Human Civilization* (Oxford University Press, New York).
628   31.   Kennedy P (1987) *The Rise and Fall of the Great Powers: Economic Change and Military Conflict from
629           1500 to 2000* (Random House, New York).
630   32.   Olsson O & Hibbs DA (2005) Biogeography and Long-run Economic Development. *European Economic
631           Review*  49:909-938.
632   33.   Comin D, Easterly W, & Gong E (2010) Was the Wealth of Nations Determined in 1000 BC?" American
633           Economic Journal: Macroeconomics  2: 65-97. *American Economic Journal: Macroeconomics* 2:65-97.
634   34.   Bockstette V, Chanda A, & Putterman L (2002) States and Markets: The Advantage of an Early Start.
635           *Journal of Economic Growth* 7:347-369.
636   35.   Putnam RD, Leonardi R, & Nanetti RY (1993) *Making Democracy Work: Civic Traditions in Modern Italy*
637           (Princeton University Press, Princeton, NJ).
638   36.   Turchin P (2006) *War and Peace and War: The Life Cycles of Imperial Nations* (Pi Press, NY).
639   37.   Barfield T (2010) *Afghanistan: A Cultural and Political History* (Princeton University Press, Princeton,
640           NJ).
641   38.   Acemoglu D & Robinson J (2012) *Why Nations Fail: The Origins of Power, Prosperity, and Poverty*
642           (Crown, New York).
643   39.   Seabright P (2004) *The Company of Strangers* (Princeton University Press, Princeton).
644   40.   Bowles S (2004) *Microeconomics: Behavior, Institutions, and Evolution* (Princeton University Press,
645           Princeton).
646   41.   Fukuyama F (2011) *The Origins of Political Order: From Prehuman Times to the French Revolution*
647           (Farrar, Straus and Giroux, New York).
648   42.   Richerson P & Henrich J (2012) Tribal Social Instincts and the Cultural Evolution of Institutions to Solve
649           Collective Action Problems. *Cliodynamics* 3:38-80.
650   43.   Acemoglu D, Johnson S, & Robinson JA (2001) The Colonial Origins of Comparative Development: An
651           Empirical Investigation. *The American Economic Review* 91(5):1369-1401.
652   44.   Nunn N & Puga D (2009) Ruggedness: The Blessing Of Bad Geography In Africa. NBER Working Paper
653           14918 http://www.nber.org/papers/w14918.
654   45.   Spolaore E & Wacziarg R (2013) How deep are the roots of economic development? *Journal of Economic
655           Literature*:forthcoming.
656   46.   Sachs J & Malaney P (2002) The economic and social burden of malaria. *Nature* 415:680-685.
657
658

# Supporting Information

## Turchin et al. 10.1073/pnas.1308825110
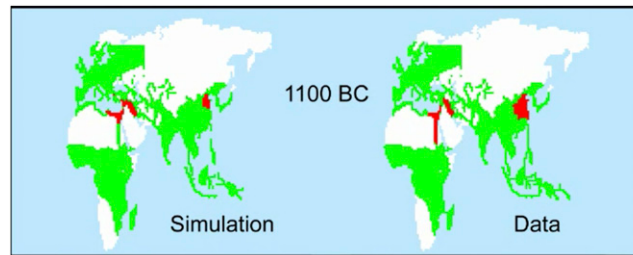


**Movie S1.** Comparison between the distributions of large-scale polities in the historical data (right-hand side) and the data generated by the simulation model (left-hand side) for each time slice over the period 1,500 BCE to 1,500 CE.

[Movie S1](#)

## Other Supporting Information Files

[*SI Appendix* (PDF)](#)