Quantitative Historical Analyses Uncover a Single Dimension of Complexity that Structures Global Variation in Human Social Organization

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Supplementary Information

Supplementary Methods

Structure of Seshat: Global History Databank

***Background*:** Our collective knowledge about past societies is almost entirely in a form inaccessible to scientific analysis; stored in historians' brains or scattered over heterogeneous notes and publications. The huge potential of this knowledge for testing theories about political and economic development has been largely untapped. Founded in 2011, *Seshat: Global History Databank* brings together the most current and comprehensive body of knowledge about human history in one place (*1*). The Databank systematically collects what is currently known about the social and political organization of human societies and how they have evolved over time (*2*).
***Goal*:** The goal of *Seshat* is to enable researchers to conduct comparative analyses of human societies and rigorously test different hypotheses about the social and cultural evolution of societies across the globe and over long periods of human history.
***Time frame*:** Currently *Seshat* focuses on the time period between the Agricultural and Industrial Revolutions. The spatial reach is global, and eventually we plan to include in the Databank information on any past societies, up to the present, for which historical or archaeological data are available. However, reaching this goal will require many years and, as a first step, we analyze a sample of 30 locations across the globe, stratified by the world region and the antiquity of complex societies (see below). For each of the 30 global points we start at a period just before the Industrial Revolution (typically, 1800 or 1900 CE depending on the location) and go back in time to the Neolithic or equivalent period (subject to the limitation of data).
***Unit of analysis*:** Our unit of analysis is a *polity*, an independent political unit that ranges in scale from villages (local communities) through simple and complex chiefdoms to states and empires.
***Variables*:** In addition to the social complexity variables analyzed in this paper, we also code variables on warfare, religion and rituals, agriculture and resources, institutions, well-being, and the production of public goods. Overall, the current codebook includes 1500 variables. These variables are coded for any past polity that occupied one of our 30 world locations between the Neolithic and Industrial Revolutions. Currently there are 414 such polities in *Seshat*. As of September 2017, the Databank contains >200,000 coded values ("Seshat records", see below).

Systematic sampling of past societies

In order to assess whether different societies show commonalities in the way they have evolved we developed a geo-temporal, stratified sampling scheme to select the societies on which to collect data. We designed our sampling scheme with two goals in mind: 1) to include as much variation among the sampled societies as possible in terms of social organization, and 2) to ensure representation of different parts of the world. This issue is challenging as societies can expand or contract in geographical space, appear or disappear in the historical & archaeological records, and show varying degrees of continuity with earlier or later societies.
***Geographic sampling & Natural Geographic Areas (NGAs)*:** To overcome these issues and ensure that we collected data in a systematic manner we divided the world into ten major regions (see Figure SI1 and Table SI1). Within each region we selected three natural geographic areas (NGAs) to act as our basic geographical sampling unit. Each NGA is defined spatially by a boundary drawn on the world map that encloses an area delimited by naturally occurring geographical features (for example, river basins, coastal plains, valleys, and islands). The extent

of the NGAs does not change over time, and NGAs thus act as our fixed points which determine which societies we collected data for.

Stratification for maximizing variation in socio-political organization: Within each world region we looked for NGAs that would allow us to cover as wide a range of forms of social organization as possible. In effect we wanted to ensure that we captured information about the kinds of societies that researchers have previously discussed in relation to social complexity ("states", "chiefdoms", "stratified societies", "empires" etc.) without using typological definitions of such societies or employing a strong, limiting definition about what features such societies should have. We also wanted to make sure that we captured information about societies that are not traditionally thought of as complex ("small scale societies", "egalitarian tribes", "acephalous societies"). This approach enables us to assess whether the different features of these societies tend to co-occur and evolve in somewhat regular ways across time and space. Accordingly, within each world region one NGA was selected that saw some of the earliest developments of some kind of large-scale or centralized, stratified society that existing scholarship would refer to as a "complex society". We also chose another sampling point that was the opposite; ideally, it was free of such societies until the modern or colonial period. Finally, the third NGA was intermediate in terms of the time that political centralization emerged. Because different world regions acquired centralized societies at different times there can be substantial variation across 'early complexity' NGAs both in the time at which our measures of social complexity start increasing and the degree of social complexity that is eventually reached at the end of our sampling period. For example, Susiana, the early complexity NGA in Southwest Asia has much longer history of large societies than Hawaii, the early complexity NGA in the Pacific region.

Temporal sampling of polities: To populate the Databank, for each NGA we consulted the literature and chronologically listed all polities that were located in the NGA, or encompassed it. We chose a temporal sampling rate of one hundred years meaning that we only included polities that spanned a century mark (100AD, 200AD etc.) and omitted any polities of short duration that only inhabited an NGA between these points. This is short enough to capture meaningful changes in the social complexity of historical societies, but not too short to lead to *oversampled* data ("oversampling" results when the succeeding point in time contains the same information as the preceding one, thus not adding to the overall information content of the data set in terms of variability).

For those periods when the NGA is divided up among a multitude of small-scale polities (e.g., independent villages, or small chiefdoms) it is not feasible to code each individual polity. In such instances we use the concept of 'quasi-polity,' which is defined as a cultural area with some degree of cultural homogeneity that is distinct from surrounding areas and approximately corresponds to an ethnological "culture" (*3-5*) or an archaeological sub-tradition (*6*). We then collect data for each quasi-polity as a whole. This way we can integrate over (often patchy) data from different sites and different polities within the NGA to estimate what a 'generic' polity was like. This approach is especially useful for societies known only archaeologically, for which we usually don't know polity boundaries.

It is important to point out that our use of polities and quasi-polities is best understood as a means of sampling the vast literature on past human societies rather than trying to impose a rigid framework on the human past. Our data coding procedures enable us to capture changes in a particular variable within the lifetime of a polity and also allow us to capture variation within a

polity or quasi-polity where there is such evidence. We are also able to flexibly incorporate multiple lines of evidence and uncertainty as we outline below.
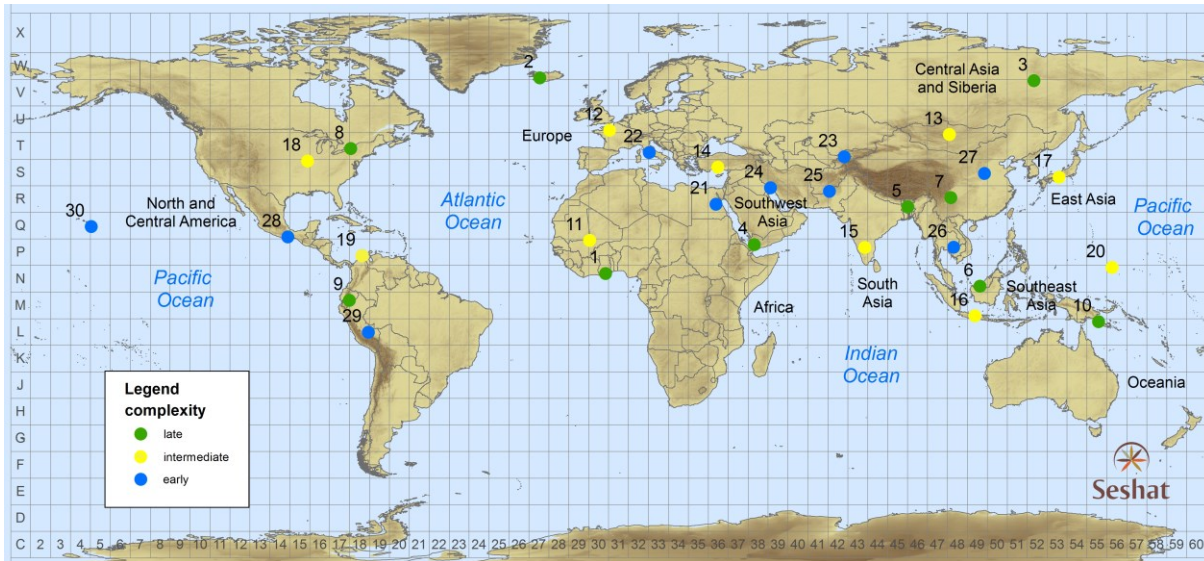

Figure SI1. *Locations of the 30 sampling points (Natural Geographic Areas) on the world map. For the key to the NGA numbers see Table SI1. Map adapted from (1).*

Table SI1. *The World Sample-30. The numbers of NGAs correspond to the numbers in Figures 1 and SI1.*

World Region	Late Complexity	Intermediate Complexity	Early Complexity
Africa	Ghanaian Coast (1)	Niger Inland Delta (11)	Upper Egypt (21)
Europe	Iceland (2)	Paris Basin (12)	Latium (22)
Central Eurasia	Lena River Valley (3)	Orkhon Valley (13)	Sogdiana (23)
Southwest Asia	Yemeni Coastal Plain (4)	Konya Plain (14)	Susiana (24)
South Asia	Garo Hills (5)	Deccan (15)	Kachi Plain (25)
Southeast Asia	Kapuasi Basin (6)	Central Java (16)	Cambodian Basin (26)
East Asia	Southern China Hills (7)	Kansai (17)	Middle Yellow River Valley (27)
North America	Finger Lakes (8)	Cahokia (18)	Valley of Oaxaca (28)
South America	Lowland Andes (9)	North Colombia (19)	Cuzco (29)
Oceania-Australia	Oro, PNG (10)	Chuuk Islands (20)	Big Island Hawaii (30)

Data Collection

Identifying social complexity variables and creating complexity characteristic measures:
Researchers from different disciplines have defined social complexity in different ways, each definition emphasizing different aspects, and with different measures being put forward to capture social complexity (*7-14*). As we stated in the Introduction, our approach is to be inclusive in that we make an attempt to code a variety of aspects of what different disciplines understand by social complexity, and attempted to be as "theory neutral" as possible in deciding on the list of variables to collect information on. In coming up with this list of variables we consulted a number of researchers who are historical and archaeological experts on societies from a variety of regions and time periods, and who represent a variety of theoretical persuasions. In total we identified c.70 variables relating to social complexity that could potentially be coded across different societies (see Codebook: http://seshatdatabank.info/methods/codebook/). Through our data collection process we found that some of these variables were easier to capture than others, or had information that was more widely recorded. For our final analyses we used information on the 51 variables that could reliably be identified and coded. The nature of the historical and archaeological records means that information can be patchy so we deliberately built some redundancy into our coding procedures meaning that different variables act as proxies for nine complexity characteristics. The first set of variables relates to the scale of societies: the total population of the polity, the extent of territory it controls, and the size of the largest urban center (Figure 1 of the main article). These variables were log-transformed prior to analysis.

Next come measures of hierarchical or vertical complexity ("levels of hierarchy" in Figure 1). These focus on the number of control/decision levels in the administrative, religious, and military hierarchies. Another measure of vertical complexity is the number of levels in the settlement hierarchy. The four hierarchical variables were averaged to yield the "levels of hierarchy" variable.

"Government" variables code for presence or absence of professional soldiers and officers, priests, bureaucrats, and judges. This class also includes characteristics of the bureaucracy and of the judicial system, and presence of specialized buildings (e.g., courts). Government variables were aggregated by adding the number of binary codes indicating "present" and dividing them by the total number of variables. The aggregated variable Government, thus is scaled between 0 and 1.

The variety of public goods and public works provided by the community is captured in "Infrastructure." Informational complexity is coded by the characteristics of the writing and record-keeping (more generally, informational) systems. We also record whether the society has developed specialized literature, including history, philosophy, and fiction. These binary codes were treated the same way as Government, yielding aggregated variables Infrastructure, Writing, and Texts (see Figure 1 of the main article).

Finally, the sophistication of the cash economy is reflected in Monetary System, which can take values between 0 and 6, reflecting the "most sophisticated" monetary instrument present in the coded society (Figure 1 in the main article). For example, if precious metals were used as money, while foreign and indigenous coins and paper currency were absent, Money would take the value of 3. If on the other hand, paper currency was present, the value of the aggregated variable is 6. Presence of "less sophisticated" instruments does not affect the value of Money.

It was not possible to code data for all variables for all polities (see below). For our final dataset we set a threshold that for a polity to be included 30% of the variables had to be coded (i.e., at least 16 of the 51 social complexity variables). This was to strike a balance between unnecessarily throwing away information by setting the threshold too high on the one hand, and including too many poorly covered polities that might create problems in the analysis stage on the other. We explored the effects of adjusting this threshold in confirmatory analyses below.

Data Coding Approach
Having identified the polities and quasi-polities, and defined our social complexity codebook data collection occurred in two phases. In Phase I research assistants searched published articles and books on a particular polity (often with advice from a regional or polity expert on what sources were likely to be most useful) in order to find information about each variable and enter it into the databank. In Phase II, where possible, experts on the polity, academic historians or archaeologists, went over the data to check coding decisions made by RAs and help us fill the gaps. Experts also indicate when the value should be coded as "unknown." When two or more experts disagree about the value or there is ongoing debate in the literature, all choices are entered as alternatives. For quantitative variables whose values are known only approximately, coders are instructed to enter a likely range [min, max] that roughly corresponds to a 90 percent confidence interval (i.e., omitting possible, but unlikely or unrepresentative values).

We refer to a coded value for a particular variable for a particular polity as a "Seshat record." Seshat records have complex internal structure. First, there is the value of the coded variable. For a numerical variable the value can be either a point estimate, or a range approximating the 90-percent confidence interval. Binary variables can take the following values: present, absent, inferred present, inferred absent, and unknown (a numerical variable can also be coded as unknown). "Inferred" presence or absence indicates some degree of uncertainty: when direct evidence of presence (for example) is lacking, but the expert can confidently infer it. For example, if iron smelting has been attested both for the period preceding the one that is coded, and for the subsequent period, we code it as "inferred present" even though there is no direct evidence for it (assuming there are no indications that this technology was lost and then regained). To incorporate this uncertainty into our analyses an inferred present codings is given a value of 0.9 (rather than 1), and and inferred absent is given a value of 0.1 (rather than 0). Binary variables can also have temporal uncertainty associated with them. For example, if we know that iron smelting appeared in the NGA at some point between 300 and 600 CE, we code period previous to 300 CE as absent, the period following 600 CE as present, and the period between 300 and 600 CE as effectively "either absent, or present".

As mentioned above, *Seshat* also reflects disagreements among the experts. When two or more experts propose different values for the same variable, all are entered. These values can also contain uncertainty. For example, a Seshat record may state that the population of a particular polity at 300 BCE was either between 30,000 and 40,000 people (according to Expert I) or between 60,000 and 120,000 (according to Expert II).

The second important part of a Seshat record is a narrative explaining why this particular variable was coded in this particular way. Typically, this narrative is first written by an RA, who may quote the relevant text from a reference (a book or an article). The narrative is then checked and edited by experts as needed. Subsequent experts can add to it and disagree with previously recorded estimates.

The third part of a Seshat record is the references to publications or other databases. As not all the knowledge that can be brought to bear on these issues is necessarily in the literature a

reference can also be attributed to an expert with knowledge of the polity. In such cases the expert makes a judgment on the coding themselves and provides a justification.

We expect that Seshat records will evolve as more experts are involved in checking them, and as new insights or evidence are produced by academic historians and archaeologists. As such changes occur, they do not simply overwrite the previous information; instead, the Databank stores these changes so that the evolution of any record can be examined at any later time. This feature of Seshat Databank ensures continuity and accumulation of knowledge. It also identifies gaps in our knowledge, where a lack of evidence prevents us from being certain about features of societies in the past.

Data Availability

We have created a website (http://seshatdatabank.info/) that illustrates the Seshat and shows how entries in the databank are supported by references, and explanations & justifications of the codes. The full set of NGAs with information on the social complexity variables is open access as an accompaniment to this publication. The databank is continually expanding and new variables are being added in order to address other research questions. All data in Seshat will eventually be made open access a certain period after data collection and analysis, creating a unique resource for building and sharing knowledge about the human past.

Data on complexity characteristics and principal components are available as online supplementary files (SI Datasets S1, S2). In future, researchers will also be able to download updated or expanded versions of the databank from the website above as text files suitable for analysis and reuse.

Supplementary Results

Cross-Validation

Predictability of variables: K-fold cross-validation was applied to the subset of data in which all rows lacked missing values ($n = 203$). For these cross-validation analyses where there was a range of estimates, we used the midpoint; similarly, we took an average of values where experts disagreed. Cross-validation results indicate that regression models can predict all variables much better than the mean (Table 1, Table SI2), with overall predictability (ρ^2) varying between 0.53 and 0.84. Overall ρ^2 in Table 1 and the values for all regions in bold in Table SI2 are calculated as an average of the ρ^2 values weighted by the number of polities from which they are drawn.

Predictability between regions: Overall different world regions are well predicted by the relationships between variables observed in other world regions (Table 1, Table SI2). However, there is some degree of variability between world regions in this respect. In several regions (Africa, Central Eurasia, East Asia, North America, and Southwest Asia) regression models predict all variables better than the mean (no negative prediction ρ^2). For Europe, only writing has a negative ρ^2. Other regions (Oceania-Australia, South America, and Southeast Asia) have between two and four negative ρ^2s (Table SI2). However, these are the same regions that have

very few complete observations ($n < 10$). Thus, it appears that the probability that variables are not well-predicted is a function of the sample size being predicted (Fig SI2), rather than some sort of difference between the predicted region and the "global norm". The fact that Europe, Central Eurasia, East Asia, Africa and Southwest Asia are generally well-predicted supports the hypothesis that these different aspects of complexity are functionally linked and co-evolve together. However, an alternative explanation is that the co-occurrence of traits may simply be due to the fact that these regions have been historically connected and traits have tended to spread between them. Going against this alternative explanation it should be noted that North America is also well predicted by models built on the data from those other regions, even though it developed largely in isolation from other world regions prior to 1500 CE.

Table SI2. *Prediction ρ^2 as estimated by Cross-Validation. Italics mark world regions with n < 10 observations. "New World" refers to the combined results of predicting North American, South American, and Oceania-Australia polities by fitting regression models on "Old World" polities (see "confirmatory analyses").*

| Region	PolPop	PolTerr	CapPop	Levels	gov't	infra	writing	Texts	money	n
All Regions	**0.84**	**0.76**	**0.71**	**0.60**	**0.53**	**0.62**	**0.59**	**0.73**	**0.53**	**203**
Africa	0.90	0.89	0.72	0.68	0.63	0.57	0.73	0.83	0.37	41
Central Eurasia	0.64	0.34	0.63	0.29	0.42	0.76	-0.38	0.86	0.76	9
East Asia	0.84	0.70	0.77	0.30	0.65	0.70	0.73	0.93	0.37	34
Europe	0.84	0.68	0.69	0.57	0.40	0.53	-0.31	0.36	0.20	43
North America	0.92	0.92	0.80	0.97	0.91	0.84	0.79	0.96	0.89	11
Oceania–Australia	0.92	-0.46	0.97	0.74	-3.21	0.60	-2.60	0.14	-1.69	1
South America	0.97	0.95	0.78	0.59	-4.15	-24.57	0.89	0.48	0.74	5
South Asia	0.56	0.46	0.69	-0.05	0.62	0.69	0.40	0.46	0.46	12
Southeast Asia	-0.35	-4.27	0.30	0.60	0.08	-0.25	0.47	0.91	-1.15	8
Southwest Asia	0.79	0.75	0.72	0.57	0.35	0.78	0.19	0.71	0.58	39
"New World"	0.92	0.92	0.81	0.89	0.50	0.71	0.72	0.81	0.82	17
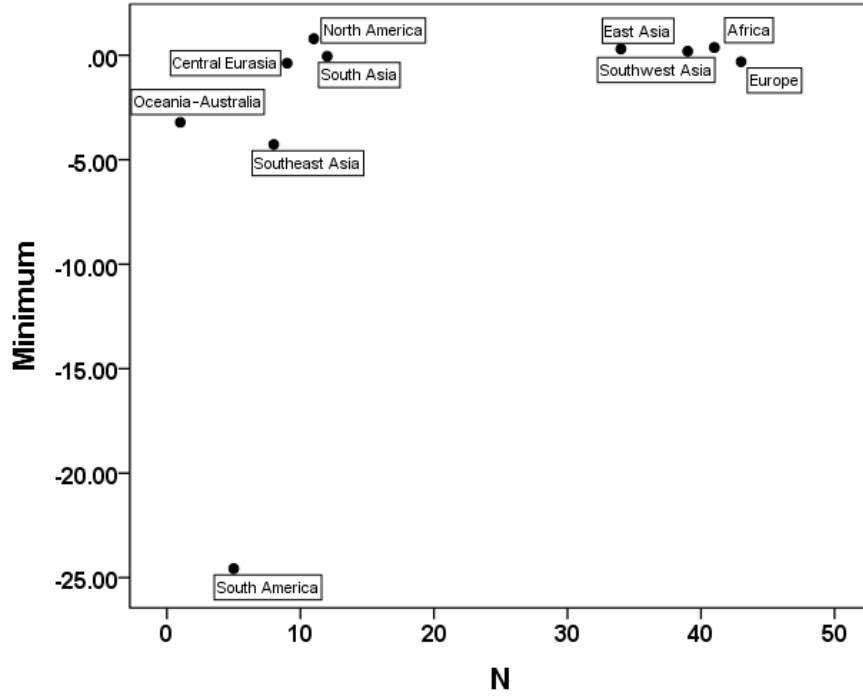
Fig SI2. *Minimum (Min) Prediction ρ^2 shows a positive relationship with number of polities (N) being predicted. This indicates that with fewer polities to predict the chances of obtaining low levels is greater, as general relationships have less opportunity to be observed.*

Table SI3. *Optimal number of predictor variables varies across response variables. Significant predictor variables in these minimum adequate models are indicated by asterisks.*

	Predictor Variables								
Response	*PolPop*	*PolTerr*	*CapPop*	*levels*	*gov't*	*infra*	*Writing*	*texts*	*money*
PolPop		*	*	*			*		
PolTerr	*								
CapPop	*			*					
levels	*		*			*	*		
gov't						*	*	*	
infra				*	*			*	*
writing	*			*	*			*	*
texts					*	*	*		
money						*	*		

Assessing optimal number of predictor variables: In earlier analyses we assessed the number of predictor variables required in the minimum adequate models. The optimal number of predictor variables needed to predict the response variable varied from one (PolTerr) to as many as five (writing, see Table SI3).

A general result of the cross-validation analysis is that it confirms that there is enough information within the dataset to allow internal prediction, which is the basis for the method of multiple imputation. We now turn to the results of multiple imputation for principal component analysis.

Principal components analysis based on multiple imputation

Principal Components Analyses were conducted on 20 imputed datasets. Below we report mean values from across these datasets and 95% confidence intervals.

All nine CCs were highly and significantly correlated with each other. Correlation coefficients varied between 0.49 (government and writing) and 0.88 (polity population and polity territory). Only a single principal component, PC1, has an eigenvalue greater than 1 (Table SI4, Fig SI3 – analyses conducted in SPSS). It explains 77.2 ± 0.4 percent of variance. The proportion of variance explained by other principal components drops rapidly towards zero (e.g. PC2 explains only 6.0 ± 0.4 percent). Furthermore, when we examine the "loadings" of the nine variables on PC1 (correlations between raw variables and PCs), we observe that all variables contribute about equally to PC1 (Figure SI5, Table SI5). Loadings on PC2 (Table SI5) seem to capture a slight residual but negative relationship between "social scale" variables (capital and polity population, hierarchical levels, and polity territory) and informational/economic complexity (writing, texts, and money). This could reflect cases where these features have diffused from large-scale societies where they were originally developed to smaller societies, or cases where large-societies have reduced in size but still retained these features. However, it should be emphasized that PC2 is not well-supported so we should be careful not to over-interpret this result. Overall, these results support the idea that different aspects of social organization have co-evolved in predictable ways, and that social complexity is a concept that can be well-represented by a measure such as PC1.

Table SI4. *Eigenvalues (means and standard deviations) for PCAs based on 20 imputed datasets. Only PC1 has an eigenvalue above the standard threshold of 1.*

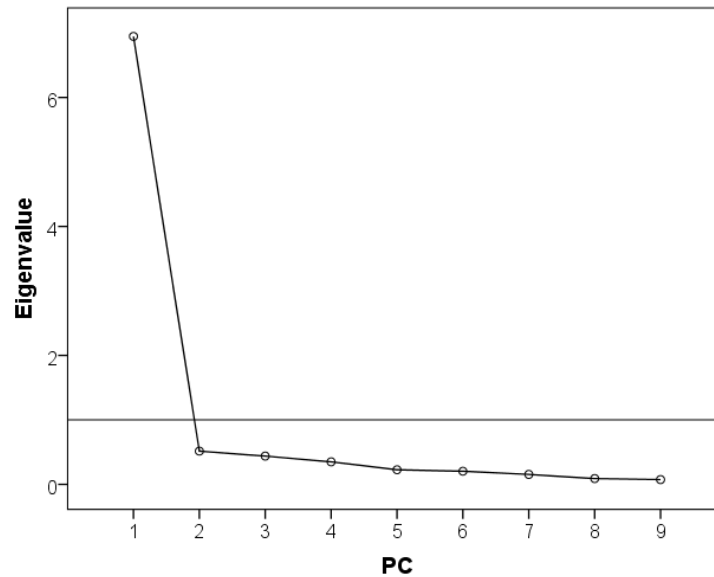| PC	Eigenvalue mean	Eigenvalue STD
1	6.95	0.02
2	0.54	0.02
3	0.42	0.01
4	0.35	0.01
5	0.22	0.01
6	0.20	0.00
7	0.15	0.01
8	0.09	0.00
9	0.07	0.00

Fig SI3. *Scree plot of mean eigenvalues for PCAs based on 20 imputed datasets. Only PC1 has an eigenvalue above the standard threshold of 1. The PCs also show a characteristic elbow after the first PC.*

Table SI5. *Pairwise correlations between the nine Complexity Components and the first two Principal Components (PC1 and PC2). Correlations between variables were calculated only for cases in which there was no missing data (n=203). Correlations between variables and PCs calculated using full dataset with imputed values (n=414).*

	PolPop	PolTerr	CapPop	levels	gvrnmt	infrastr	writing	texts	money
PolPop		0.88	0.85	0.78	0.66	0.75	0.66	0.77	0.66
PolTerr	0.88		0.74	0.70	0.59	0.63	0.61	0.69	0.54
CapPop	0.85	0.74		0.76	0.61	0.75	0.56	0.71	0.59
levels	0.78	0.70	0.76		0.68	0.72	0.51	0.69	0.63
gvrnmt	0.66	0.59	0.61	0.68		0.74	0.49	0.67	0.57
infrastr	0.75	0.63	0.75	0.72	0.74		0.57	0.76	0.71
writing	0.66	0.61	0.56	0.51	0.49	0.57		0.80	0.65
Texts	0.77	0.69	0.71	0.69	0.67	0.76	0.80		0.70
money	0.66	0.54	0.59	0.63	0.57	0.71	0.65	0.70	
PC1	0.95	0.87	0.91	0.89	0.88	0.88	0.86	0.92	0.79
PC2*	-0.23	-0.30	-0.27	-0.21	0.08	0.09	0.33	0.23	0.34

* PC2 did not produce an eigenvalue greater than 1 in the PCA analysis and its importance should not be over-interpreted
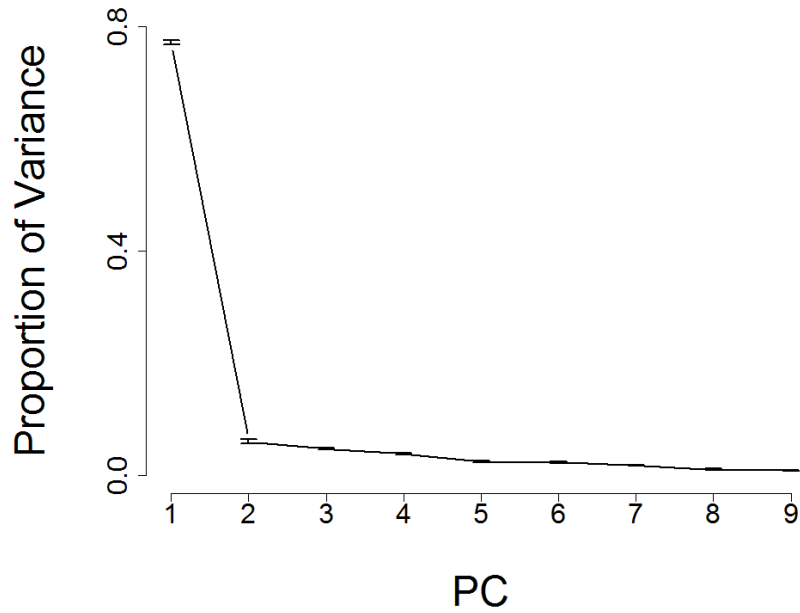
Figure SI4. *Proportion of variance explained by each principal component from the PCA. Error bars indicate 95% confidence intervals.*
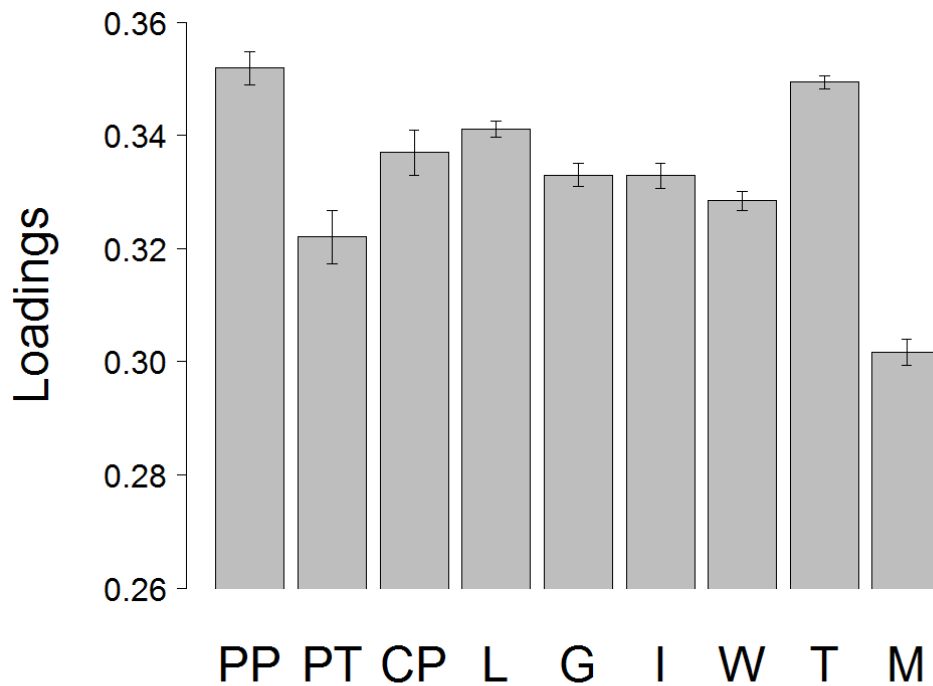

Figure SI5. *CC loadings on PC1. Error bars indicate 95% confidence intervals (note the restricted range on the Y axis, indicating that any differences in loadings between CCs are relatively small).*

Social Complexity Trajectories

Below we present the values for PC1 plotted through time for each NGA (Figure SI6). We have grouped NGAs into their world regions to aid comparisons. The values for PC1 have been rescaled here so that they go from 0 ("low complexity") to 10 ("high complexity"), to assist in interpretation. The broken thin lines indicate 95% confidence intervals. The more missing values, which have to be imputed, and the more uncertainty and disagreement, the wider the confidence interval is. These trajectories are mapped geographically and shown simultaneously in a video (Movie S1).

In line with previous analyses of social evolution, trajectories of the polities in each of our world regions show an overall increase in social complexity (*6, 13*), but also show episodic declines (*15-17*). Additionally, many other interesting features are revealed by these trajectories. For example, the trajectory for Latium (modern day Rome in the "Europe" world region) shows a fairly straightforward pattern and reflects a significant increase of complexity in the early Iron Age (tenth-ninth century BC), an apex during the early-middle Imperial Period (first-third century AD) and a dramatic decrease after the fall of the Roman Empire (476 AD). In the Konya Plain in Southwest Asia there are several of these increases and decreases, but still with an overall upward trend. The trajectory of social complexity dramatically increases at the beginning of the Early Bronze Age (3000 BC), and reaches the peak during the Hittite (1600-1200 BC), the Achaemenid (500-330 BC), the Roman (1-330 AD), the Byzantine (330-1000 AD), and The Ottoman Empire (1453-1922 AD). This also illustrates how the polities that inhabit and control our NGAs (and are thus included in our dataset) may actually originate from outside the NGA. In Susiana, also in Southwest Asia, social complexity significantly increases at the beginning of Susa II period (3800 BCE), and reaches the highest point during the Achaemenid (559-330 BC), the Seleucid (312-63 BC), and the Sasanian Empire (224-651 AD), and with several other fluctuations. The sometimes dramatic increase in social complexity seen at various points in these trajectories could be evidence for the idea that social organization evolves in punctuated bursts, as societies restructure and new forms of organization emerge over relatively short periods (*18-20*). However, in our data, some of these observed changes may actually be due to more complex societies from other regions conquering the NGA, as the Konya case illustrates. This idea will be formally tested in future work, using statistical techniques to test between competing hypotheses about the mode and tempo of social evolution (*19, 20*).

Figure SI6 *Evolutionary trajectories of our PC1 variable for each NGA within each of our 10 world regions*
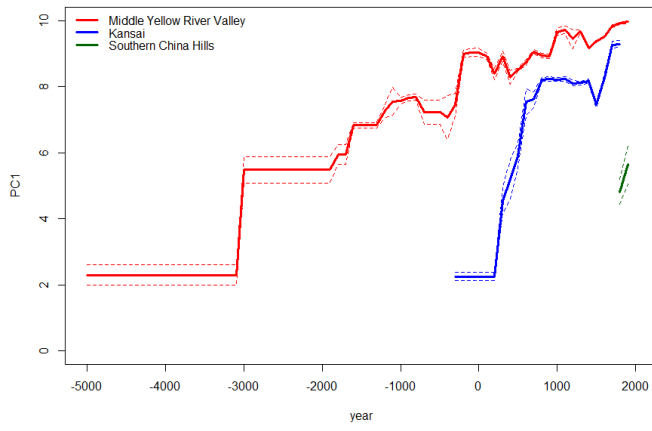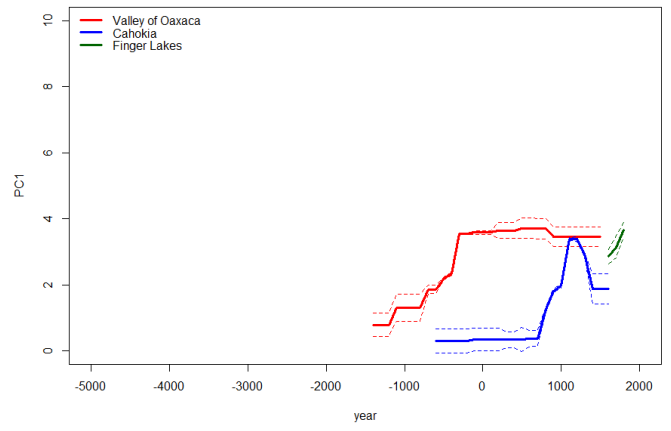

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EUROPE

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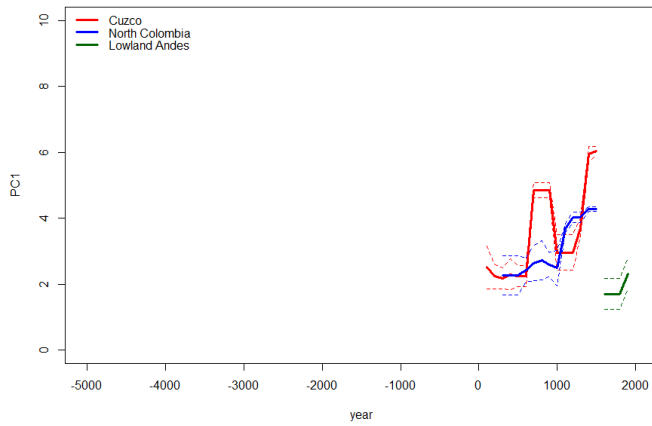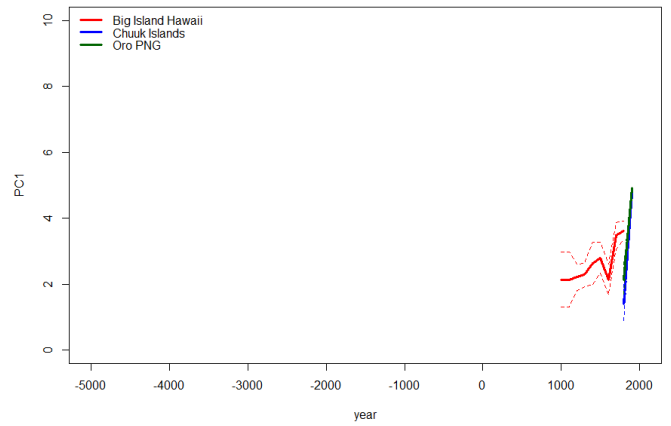
SOUTHWEST ASIA
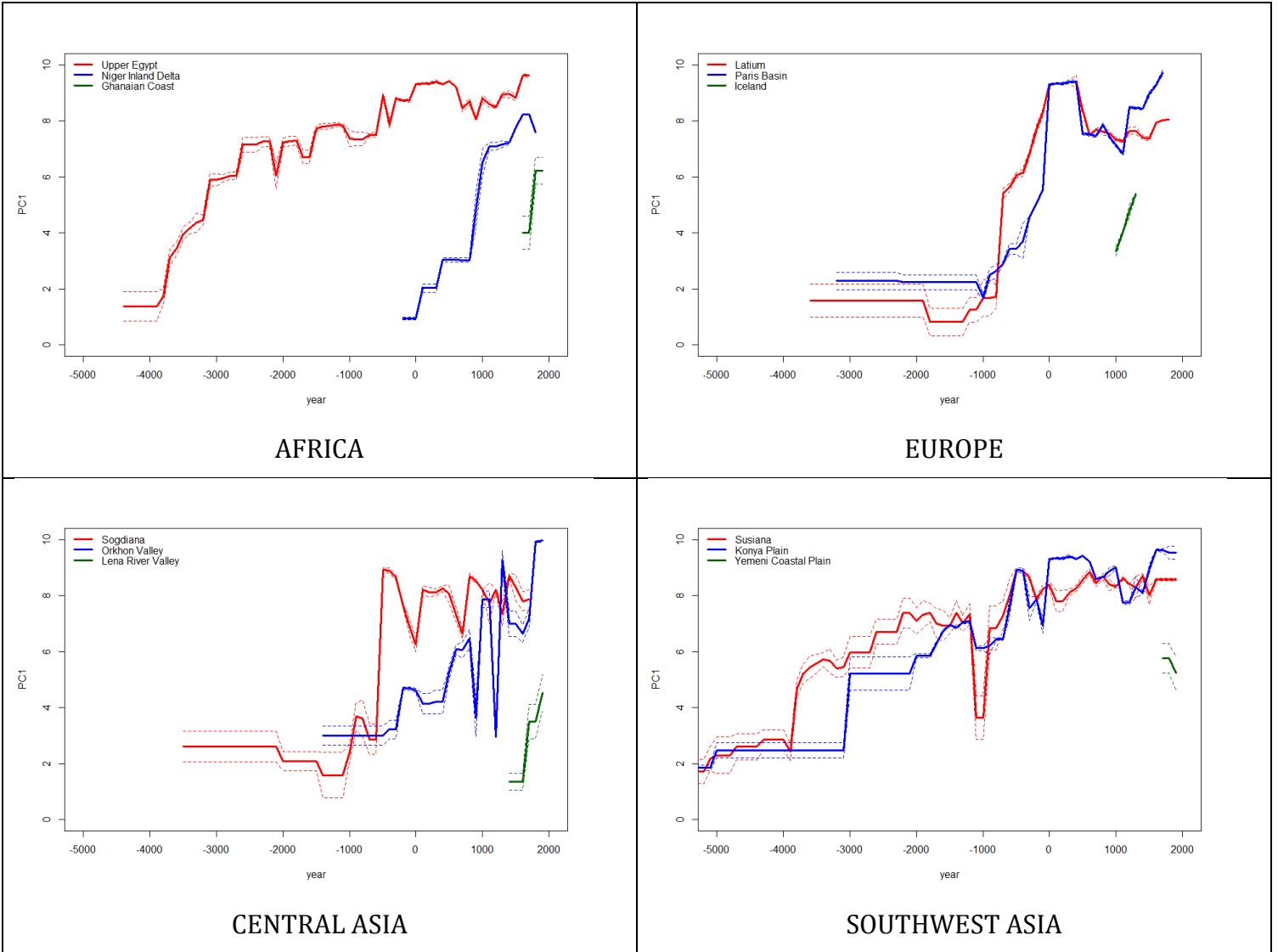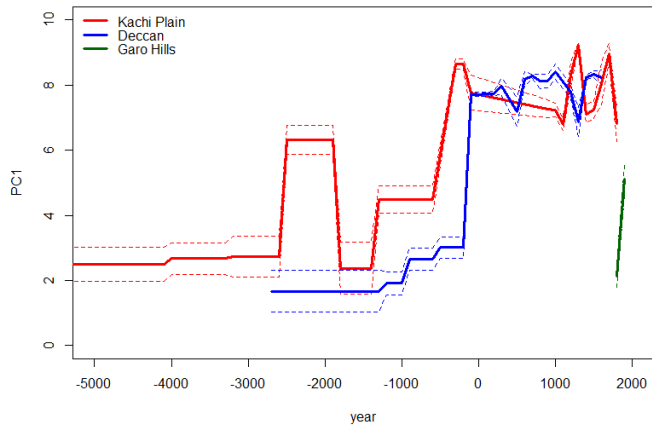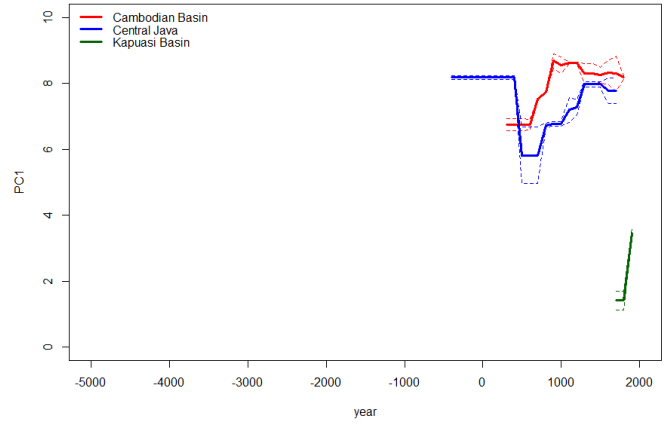
SOUTH ASIA

SOUTHEAST ASIA

EAST ASIA

NORTH AMERICA

SOUTH AMERICA

OCEANIA

Confirmatory analyses

In order to produce our main results we had to make a number of decisions and assumptions about how to conduct our statistical analyses. We have performed a number of confirmatory analyses to check the robustness of these results and show the effects of making different assumptions or decisions.

Adjusting the inclusion threshold

In earlier analyses we tested the effects of using different inclusion thresholds (our chosen default value being 30%). We tested the effects of performing PCA on datasets using 10%, 50% , and 100% (i.e. only cases with complete codings) coverage thresholds (in the latter case multiple imputation was not required to impute missing values). Adjusting the inclusion threshold had little effect on the proportion of variance explained by PC1: 10% cutoff – n=409, r^2=0.76; 50% cutoff - n=409, r^2=0.77; 100% - n=205, r^2=70.6). Our results are therefore not an artefact of either our inclusion threshold, or the multiple imputation procedure.

Accounting for sampling biases

In our main dataset some NGAs have a greater coverage than others due to differences in the timing of the beginnings of agriculture in different regions, and the level of research effort that has previously gone in to studying different regions of the world. Although we have attempted to offset some of these biases through our stratified sampling approach, there remains the possibility that parameter estimates from our results may be biased due to uneven coverage. We therefore used bootstrap resampling to create random sub-samples that lead to more balanced datasets. We did this in two ways: 1) Our analysis treats individual polities that span multiple centuries into separate polities for each century. Therefore, for any given polity that produced identical entries across centuries we resampled to produce only one entry per polity. 2) To ensure even geographic coverage, we resampled 10 polities per world NGA. If our main results are due to an overrepresentation of certain NGAs we would expect to see a large drop in the percentage of variance explained by PC1 in these confirmatory analyses. Sampling of one entry per polity had almost no effect on the proportion of variance explained by PC1 (n=285, r^2=0.79), and resampling of 10 polities per NGA only resulted in a relatively small drop in the proportion of variance explained by PC1 (n=300, r^2=0.69).

As a broader check on whether our findings have been driven by a bias to data availability in Africa and Eurasia (the "Old World") we fit models on data from the Old World and predict the remaining three regions (North America, South America, and Oceania-Australia, or the "New World"). Even though the New World polities developed without contacts with the Old World polities, they are highly predictable, with coefficients of prediction ranging between 0.5 and 0.92 (Table SI2). Prediction in the opposite direction is more problematic due to the smaller number of societies and the smaller range of variation. Scale variables are predictable at 0.29-0.77, but all other variables (except money) produced negative values. Rather than being indicative of

different co-evolutionary processes occurring in the Old and New World the lower predictability based on the New World is likely to be due to the smaller amount of variance in our complexity characteristics found in this part of the world. This difference in degree of variance in complexity characteristics between the Old and New world itself could result from differences in the rate at which innovations in the non-scale complexity characteristics that could support large scale societies were developed. It is well known that centres of the emergence of large-scale societies were more isolated from one another in the New World, and large-scale societies there did not spread as much as in the Old World until after European contact (*21*). In the New World the rate of adoption of depended on societies developing them independently. However, in the Old World the rate of adoption was elevated through being able to borrow such innovations from neighbouring societies (*22*). The fact that we can predict the values for complexity characteristics for the New World based on the values and relationships from the Old World suggests that similar co-evolutionary processes were indeed at play in both regions even if societies within these regions had their own unique evolutionary trajectories and specific histories.

Effects of variable choice

To assess whether our results are dependent on the particular variables combination of variables included in the analyses we ran two further sets of analyses: 1) we included only one population variable (polity population) and all the other non-population complexity characteristics, 2) we included only one population variable and removed one of the non-scale complexity characteristics (CC8:"texts"). The first analysis helps us assess whether the results are biased by the inclusion of several population variables, potentially leading to an overestimate of the importance of PC1 and an underestimate of any other dimensions of complexity. The second analysis helped us assess whether the inclusion of a particular non-scale variable, which could be argued to be more relevant to certain cultural traditions, was biasing our results. These additional analyses again had remarkably little impact on our findings: including only one population variable returns a single principal component that explains 78.7% (±0.4%) of the variance, while also removing "texts" returns a single principal component that explains 77.7% (±0.4%) of the variance (see tables SI6&SI7). These results are not that surprising as examining the loadings of the original PCA indicates that all variables load approximately equally onto PC1. Interestingly, the cross-validation analysis shows a slight reduction in the predictability of polity population when the other population variables are not included (table SI8). Again this is perfectly understandable from the previous results - the population variables have some of the strongest correlations with each other (which is, after all, why we are examining the effect of removing them) so removing two of them means the ability to predict polity population relies on the slightly weaker correlations with the other variables.

Overall, these confirmatory analyses suggest that our main findings are robust to the specific choices we have adopted for our analysis.

Table SI6. *Principal Component Analysis including only Polity Population as a direct population variable (analyses conducted in SPSS, variables included: PolPop, Levels, Government, Infrastructure, Information System, Texts, Money)*

Principal component	Eigenvalue mean	Eigenvalue STD	% of Variance mean	% of Variance STD
1	5.51	0.01	78.74	0.19
2	0.42	0.01	6.04	0.08
3	0.36	0.01	5.20	0.09
4	0.27	0.00	3.91	0.06
5	0.19	0.01	2.71	0.08
6	0.16	0.01	2.27	0.10
7	0.08	0.00	1.13	0.04

TableSI 7. *Principal Component Analysis removing the non-scale variable "texts" (analyses conducted in SPSS, variables included: PolPop, Levels, Government, Infrastructure, Information System, Money)*

Principal component	Eigenvalue mean	Eigenvalue STD	% of Variance mean	% of Variance STD
1	4.66	0.01	77.66	0.22
2	0.42	0.00	7.00	0.07
3	0.31	0.01	5.13	0.13
4	0.27	0.00	4.48	0.07
5	0.19	0.01	3.14	0.09
6	0.16	0.01	2.58	0.11

Table SI8. *Comparison of cross-validation (ρ^2) prediction scores from analyses with all variables and analyses that only include Polity Population as population variable.*

CV Analysis	PolPop	PolTerr	CapPop	Levels	gov't	infra	writing	Texts	money
All population variables	0.84	0.76	0.71	0.60	0.53	0.62	0.59	0.73	0.53
Only Polity Population	0.66	-	-	0.63	0.53	0.58	0.59	0.75	0.53

Testing the Multiple Imputation Method

We have also assessed whether the multiple imputation method used in this study could have introduced bias into our results. The results above indicate that running analyses on cases that are fully coded does not substantially change parameter estimates or overall findings. At an earlier phase in our investigations to further examine this issue we created 100 artificial data sets that randomly introduced missing values into our "complete data set", reproducing the pattern of missing values in the "overall data set" at that time. We then applied the MI procedure to each of them. Each artificial data set was constructed as follows. We started with the first row of the complete data set. The program then chose a random row in the overall data set and determined if there were any missing values in the row. If yes, then missing values were added to the first row of the complete dataset for any variables that had missing data in the row from the overall data set. This procedure was repeated for the second row of the complete data set, and so on. The result was that the artificially constructed data set had the same pattern of missing values as the overall data set. The artificial data set was then subjected to the multiple imputation procedure in exactly the same way as the overall data were analyzed, except the results were based on 10 imputations, to speed up the calculations.

By comparing the PCA results based on the artificial dataset with results from the complete dataset, we see that the Multiple Imputation procedure accurately captures the overall patterns in the data both in terms of the number and pattern of PCs produced (Figure SI7), and the loadings of the different variables on to PC1 (Figure SI8). We repeated this analysis for 100 artificial data sets and compared the distribution of the proportion of variance explained by PC for both the estimated PC1s and the true PC1. The true value of PC1 is 0.706, while the mean and the mode of the estimated PC1, based on 100 artificial data sets with missing values, is 0.685 and 0.695, respectively (Figure SI9). The distribution is asymmetric, suggesting that the estimates based on MI procedure are biased—they tend to under-predict the true PC1. However, the degree of this bias is tiny (0.01 between the true value and the most likely estimate, the mode). Furthermore, the bias is conservative in that replacement of missing values by MI results in slightly under-predicting the true PC1). Taking these considerations together, we conclude that our overall MI procedure works very well for the goals of our study and has not created a bias that is driving our results and conclusions.
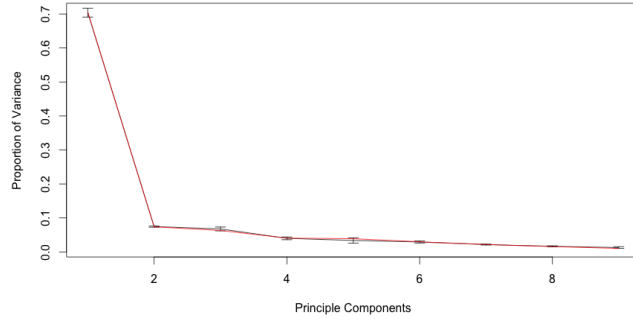
Figure SI7. Comparison of factors extracted from the real dataset (red line), and the 10 artificial datasets, which had missing values added and then replaced via the multiple imputation procedure. Multiple imputation does not introduce a bias in the artificial datasets in comparison to the real dataset.
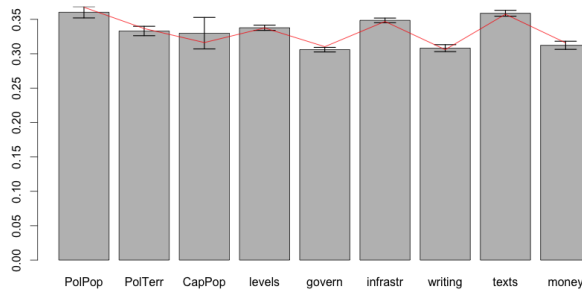
Figure SI8. Comparison of variable loadings onto PC1 from the real dataset (red line), and the 10 artificial datasets, which had missing values added and then replaced via the multiple imputation procedure. Multiple imputation does not introduce a bias in the artificial datasets in comparison to the real dataset.
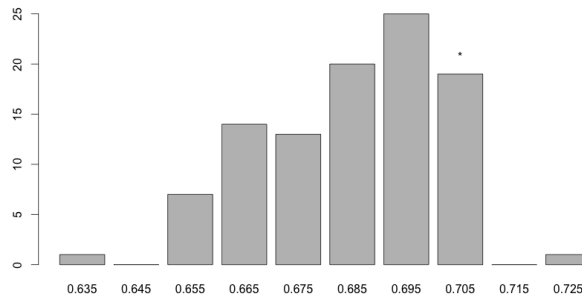
Figure SI9. Distribution of proportion of variation explained by PC1 in 100 artificial datasets, which had missing values added and then replaced via the multiple imputation procedure. The true value for PC1 (indicated by an asterisk) is well within the range of estimates in the artificial datasets, and is only slightly higher than the modal value for the artificial datasets. Artificial datasets tend to lead to a slight underestimate of the true value for PC1.

Supplementary Discussion

Sampling of NGAs and generality of findings

Currently our database contains 30 NGAs from which we have sampled the polities that controlled these areas over long periods of human history. Our decision to stratify our sampling efforts by broader world regions and onset of large-scale societies means we have extensive coverage of the diversity of human social and political organization. Limiting our sample to 30 NGAs was a necessary practical step in making headway in building a comparative historical database on this scale. Examining the maps (Fig 1, and SI1) it appears that at first glance there are large areas that do not have NGAs from which we have sampled polities. However, large parts of these areas (particularly in North America, South America, and Australia) were not inhabited by agriculturalists at the time of contact with Europeans and therefore are not our focus for constructing our database (which focuses primarily on post-paleolithic, agricultural polities). Other areas, particularly in more northern latitudes or desert areas, were sparsely populated and would therefore not add many extra polities. The choices made about which particular NGAs to choose was also partly based on practical concerns about having sufficient information and having the interest and availability of regional experts who were able to guide the process of data collection. In future it would be good to add further NGAs to regions such as sub-Saharan Africa that are currently relatively sparsely sampled. Collecting data for these areas faces important challenges due to the fact that traditionally such areas have received less academic attention than some other parts of the world, and in some cases there are substantial issues around preservation of archaeological remains (e.g. tropical rainforest soils are often not conducive to preservation).

We currently have no strong reason to suspect that the addition of agricultural polities from other areas would substantially alter our findings (however this remains an open possibility that can be addressed in future). For example, if we examine polities in a region such as North America, where social complexity emerged relatively late, we do not see a substantial difference in the relationships and trajectories we have been able to identify in other places (Fig SI6, Fig SI10,Table SI2). As we increase our coverage of polities in future we will be able to further examine the similarities and differences both within and between regions. Currently there are two areas where we have begun to intensify the coverage of NGAs: Meso-America (where we have begun coding polities in the Basin of Mexico and the Petén Basin [Mexico/Guatemala]), and Europe (where we have identified NGAs relating to the spread of the Neolithic). An interesting point of comparison in future studies may be to include more pastoral or hunter-gatherer societies to assess whether different modes of subsistence affects the patterns we have identified here. Differences in resource type can affect the way individuals are distributed in space, which may have consequences for the types of institutions that are effective for joining individuals and groups together. More generally, the fact that we have been able to detect consistent patterns in the evolution of social complexity indicates that, even though our coverage is not comprehensive, we are still able to uncover important principles that are applicable to wide variety of societies from differing cultural, historical, and ecological contexts.
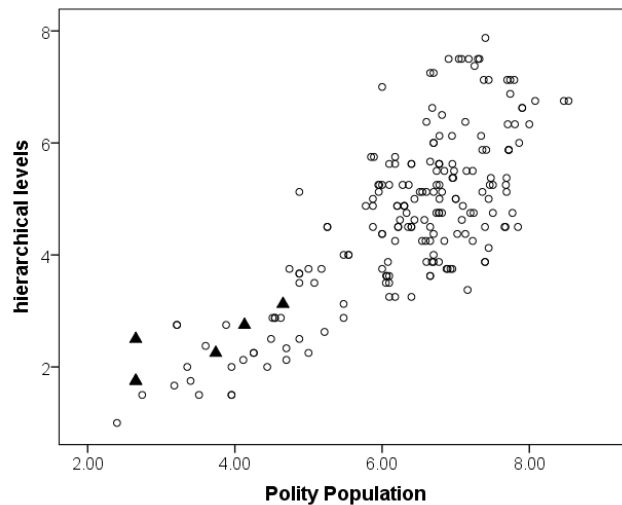
Figure SI10. *Relationship between Hierarchy and Polity Population for medium and late complexity polities in the North America region (Cahokia and Finger Lakes NGAs, but not Oaxaca)(black triangles), and all other NGAs. The distribution of North American polities sits within the distribution of the other polities, and there are similar correlation coefficients between these variables for both sets of polities (North America: r=0.83, All other NGAs: r=0.76). This indicates that the North American polities did not evolve in a substantially different way from polities in other regions.*

Testing Evolutionary Trend Mechanisms

Our approach is also well-suited to go beyond identifying patterns in socio-political evolution and investigate why social complexity has shown a tendency to increase over time. One idea that we can address by examining the temporal changes in our data is what kind of mechanism lies behind the trend towards increasing complexity. Evolutionary biologists distinguish between two types of general trend mechanisms: *passive* and *driven (23-25).* This concept has also been applied in previous work to examine related issues around the evolution of socio-political complexity in human societies (*20, 26*). A passive trend relates to the fact that our starting point might be close to the lowest possible value (a "wall"), which means that there is more scope for change in one direction rather than another. Once away from the "wall" increases and decreases are equally likely. Over time the maximum level of complexity is expected to increase as this area of "trait space" can be expanded into, but there is nothing that particularly favours more complex organisms or societies. In a driven trend there is a force that actively favours larger values of the feature in question (i.e. more complex organisms/societies are at a selective advantage and a more likely to produce ancestors). The idea that larger, more complex societies have an advantage in competition between groups has a long history in anthropology, archaeology and related disciplines (*13, 27-32*). Diagnostic features of driven trends are that increases are more common than decreases, which is the case for almost all regions in our data

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set (the average extent of increases is also generally greater - both in absolute terms and as a proportion of prior complexity)(Table SI9). Another way of distinguishing between trends is to examine how the distribution of the trait in question changes over time. In a passive trend the mean of the distribution increases due to the tail of the distribution increasing. In a driven trend, however, the mode of the distribution also increases, which seems to match what we see in our data (Figure SI11). Overall, the present results are consistent with the idea that competition between groups, particularly in the form of warfare, has been an important driving force in the emergence of large, complex societies. Future work will test competing ideas about the cause of this driven trend towards increased complexity.

Table SI9. *Number and extent of increases and decreases in complexity across regions. Values were calculated from differences between values in PC1 from one polity to the next.*

| REGION	Inc	Dec	Net Change in PC1			Proportional Change in PC1		
			Min	Max	Mean	Min	Max	Mean
AFRICA	31	19	-1.67	2.59	0.28	-0.24	3.81	0.18
CENTRAL ASIA	19	21	-3.51	4.49	0.17	-0.46	1.17	0.10
EAST ASIA	38	12	-1.14	3.01	0.25	-0.15	1.88	0.08
EUROPE	36	18	-1.67	2.27	0.22	-0.68	1.23	0.08
NORTH AMERICA	17	7	-2.13	2.33	0.17	-1.00	6.67	0.37
OCEANIA	8	1	-0.84	2.60	0.43	-0.30	1.32	0.29
SOUTH AMERICA	11	7	-2.79	3.24	0.27	-0.46	1.13	0.12
SOUTH ASIA	27	11	-3.19	4.78	0.28	-0.56	1.45	0.14
SOUTHEAST ASIA	11	6	-0.64	2.35	0.33	-0.09	1.51	0.14
SOUTHWEST ASIA	50	34	-3.81	5.78	0.16	-0.58	2.07	0.08
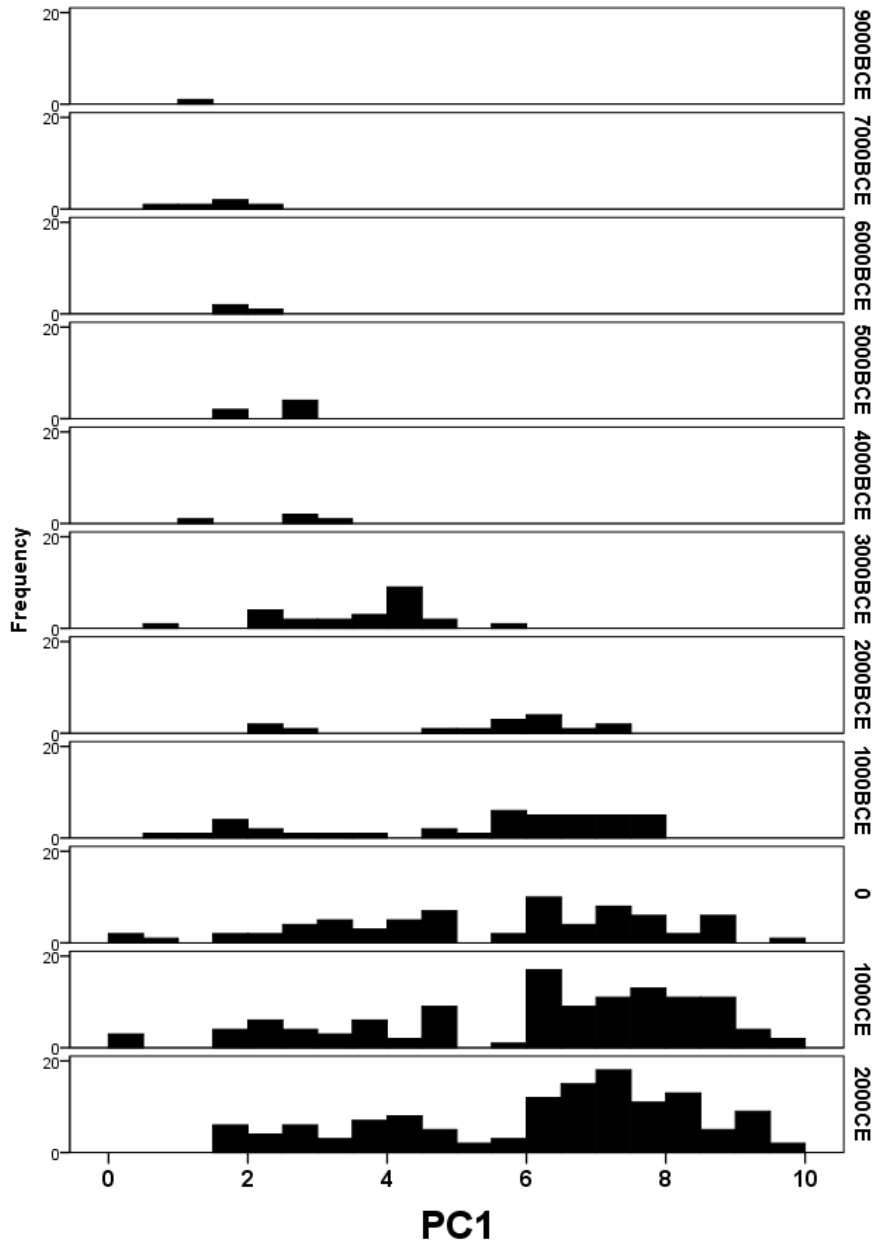
Figure SI11. *Changing distribution of Social Complexity over time. The mode of the distribution takes increasingly greater values over time, which is consistent with a driven evolutionary trend. Rows are 1000-year time slices, dates reflect upper date boundary (e.g. 7000BCE refers to 7999BCE to 7000BCE)*

Co-evolution, punctuated change, and "types" of socio-political organization

Our analyses indicate that are strong co-evolutionary relationships between different features of human societies. If correlated change in these features is relatively rapid, then certain "types" of socio-political organization may become apparent based on recurring associations between certain combinations of traits (*18-20*). Examining the evolutionary trajectories of the different NGAs (Fig 3, SI6) the data appear to show long periods of stasis or gradual, slow change, interspersed with sudden large increases in the measure of social complexity over a relatively short time span. This pattern is consistent with a punctuational model of social evolution, in which the evolution of larger polities requires a relatively rapid change in socio-political organization including the development of new governing institutions and social roles in order to be to stable (*18-20*). The assessment of these evolutionary rates will require more formal testing in future investigations and will need to take into account the fact that some periods of stasis indicate periods when the data from our polities show no change. This may reflect an absence of evidence and could potentially lead to errors in the assessment of rates of change. There do appear to be many instances of limited amounts of change prior, and many horizontal lines are of relatively short duration which would not substantially affect rate estimations. It therefore seems unlikely that these patterns are completely an artefact of the way our data are organized as a time series. Another consideration is the possibility that large changes in PC1 could indicate a new polity taking control of an NGA rather than the kind of change within a society that is envisioned under the punctuational change hypothesis.

To provide an initial assessment of the idea that societies may fall into certain types we conducted a Hierarchical Cluster analysis of PC1. The dendrogram in Figure SI12 shows some initial support for the idea of distinct "types", with a relatively large distance between two main clusters. This indicates a clear distinction between societies with large populations that exhibit many of the non-scale features of complexity, and smaller societies that often lack most of these features (see Fig SI12 (left)). Other potential groupings within these clusters may also indicate important stable combinations of traits that will be investigated in future research (Figure SI13). In line with previous empirical investigations of this question (*11, 19, 20, 33*), the clusters identified in these analyses may indicate that certain combinations of traits are indeed evolutionary stable. Typological schemes of human societies (e.g. band, tribe, chiefdom, state) have been common in studies of socio-political evolution (*13, 34-36*). These schemes have often been criticized, partly because the categories are seen as rigid and do not focus enough on how and why changes occur (see (*20*)). The clusters identified in the present analyses should not be thought of as strict categories as there remains substantial variation within each of the clusters. However, the present study further indicates how we can test hypotheses about the degree to which human groups exhibit the kind of patterned variation that traditional typological schemes are attempting to capture, or indeed test hypotheses about other kinds of patterned variation (*37-39*). Our historical, comparative approach illustrates how this can be done in a manner that enables us to empirically assess the degree of variation within and between categories, and can help in understanding how and why changes between categories can occur.

Fig SI12. *Hierarchical cluster analysis of PC1 from each polity, based on average linkage between groups (x-axis)(analysis conducted using SPSS)(right). Two main clusters are discernible due to the large average distances between them. Within each of these clusters two sub-clusters are identified (A&B and C&D). Values of Polity population and government (below) showed peaked distributions within each of the main clusters in line with the idea that these clusters represent distinct "types" of socio-political organization.*
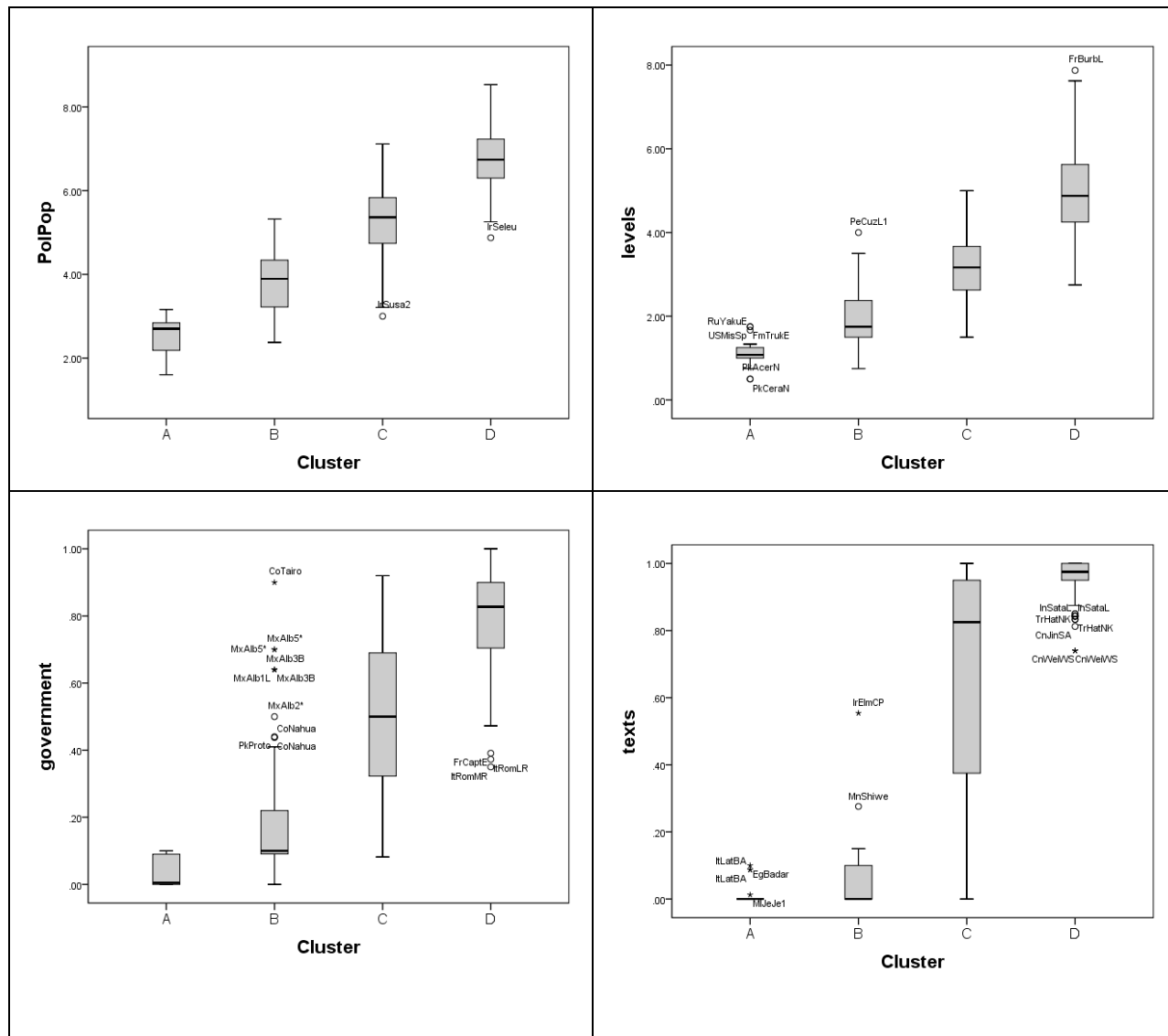
Fig SI13. *Distributions of different CCs by the four main clusters identified above. Variation in characteristics such as polity population, hierarchical levels, and government seem to be well-summarized by the four clusters, where as a characteristic such as "texts" seems to be better summarized by just two clusters (main clusters 1(A&B) and 2(C&D)).*

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