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Research Report

The characteristic time scale of cultural evolution

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Abstract

Numerous researchers from various disciplines have explored commonalities and divergences in the evolution of complex social formations. Here, we explore whether there is a "characteristic" time course for the evolution of social complexity in a handful of different geographic areas. Data from the Seshat: Global History Databank is shifted so that the overlapping time series can be fitted to a single logistic regression model for all 23 geographic areas under consideration. The resulting regression shows convincing out-of-sample predictions, and its period of extensive growth in social complexity can be identified via bootstrapping as a time interval of roughly 2,500 years. To analyze the endogenous growth of social complexity, each time series is restricted to a central time interval without major disruptions in cultural or institutional continuity, and both approaches result in a similar logistic regression curve. Our results suggest that these different areas have indeed experienced a similar course in the their evolution of social complexity, but that this is a lengthy process involving both internal developments and external influences.

Keywords: cliodynamics, cultural macroevolution, time scale, quantitative history

Significance Statement

Do human societies experience cultural evolution on similar time scales? Here, we analyze the Seshat: Global History Databank, which contains quantified historical and archaeological information from a global sample of societies around the world from the last 10,000 years. The first principle component SPC1 summarizes the variation in social complexity, and we show that a universal logistic growth model can be fitted to the SPC1 time series. This model implies the existence of a period of growing social complexity lasting about 2,500 years, with relatively minor changes before or after. These results provide new empirical support to ideas that there are common pathways in human social evolution across past cultures.

Introduction

Motivation to find characteristic time scales

Researchers from various disciplines have analyzed commonalities and divergences in the evolution of complex social systems (1–7). The recent emergence of cliodynamics as a discipline has started the analysis of the dynamics of human societies and states with data-driven scrutiny and modeling approaches from natural sciences (8, 9). Previous work established that a common set of factors associated with complex social formations typically moved in tandem across a wide variety of regions and time periods; factors such as social scale, the use of informational media, administrative hierarchies, monetary instruments, and others (5). These were interpreted as comprising the primary dimension of what could be called "social complexity" across cultures, though other dimensions can be adduced as well (3).

Various studies have already discussed or tried to identify the causal drivers of cultural evolution and evaluated the evidence for different theories of *why* cultures become more complex (7, 10–13). Beyond the *causal* similarities behind cultural evolution across cultures, researchers have also found evidence for *temporal* similarities and seemingly parallel time scales in the dynamics of various social structures. For example, models for societal collapse have been derived from demographic and fiscal data that show characteristic oscillation periods of a few centuries and a fine structure with a faster periodicity of approximately two human generations (4). Other theories suggest that cultural evolution leads to the emergence of similar political institutions and schools of thought at roughly identical time intervals across different geographic regions (14–16). Another recent study has evaluated the connection between the first emergence of complex societies in different world regions and the age of widespread reliance on agriculture in those areas (17), supporting the theory that agriculture is a necessary condition for the evolution of complex societies. While the time lag between the primary reliance on

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agriculture and the emergence of states was found to decrease over time, an average time lag of roughly 3,400 years for pristine states suggested the existence of a characteristic time scale, though this was not the explicit focus of that study. Similarly, the study on causal drivers in (7) also found that the time since the adoption of agriculture had a statistically significant effect as a linear predictor variable (called "AgriLag") for sociopolitical complexity, providing additional evidence for temporal regularities in the growth of complexity across different cultures and civilizations. A comparison between the rate of change in cultural and biological evolution concluded that the rapid cultural evolution helped humans to quickly adapt to changing environments and outcompete other species (18). Finally, using the same data as our article (cf. Seshat databank section), it was possible to identify periods of cultural macroevolution with either slow or rapid change in social complexity (6). While the interpretation of a characteristic time scale for cultural evolution may already be a worthwhile academic endeavor, using it as a baseline to identify and analyze differences in the rates of cultural evolution might also open up new directions for further research.

Nevertheless, as yet there is no consensus on whether there is a "typical" time scale for sociopolitical development cross-culturally, let alone what that time course might be. Such characteristic time scales of dynamic systems are, however, well documented in different areas of the natural sciences such as physics and chemistry (19, 20). Differentiating between fast and slow time scales in a dynamical system can lead to useful insights and can inform modeling assumptions for data analysis (21, 22). In particular, Haken's theory of the "enslaving principle" (23), according to which the dynamics of fast-relaxing modes are dominated (enslaved) by the behavior of slowly relaxing modes in a dynamical system, pioneered the research on how dynamics on different time scales influence each other in the same observed system. The existence of temporal regularities among societal dynamics would suggest that cultural evolution not only occurs in similar developmental stages across geographic regions and time periods but also in similar time intervals. This would add an important dimension to our understanding of *how* complex social formations evolve and raise a number of critical questions about what drives these cross-cultural patterns.

Here, we adapt some of the methods employed in the natural sciences in an attempt to identify characteristic time scales in the evolution of complex societies. We utilize data collected by the *Seshat: Global History Databank* (24–26), a large repository of information about the dynamics of social complexity across world regions from the Neolithic to the early modern period (27). We find that, despite significant differences in the timing and intensity of major increases in social complexity reached by polities across the Seshat sample, there is a typical, quantitatively identifiable time course recognizable in the data. This result is robust to a variety of checks and covers polities from all major world regions and across thousands of years of history. Our findings offer a novel contribution to the study of cultural evolution, indicating the existence of a general, cross-cultural pattern in both the scale as well as the pace of social complexity development.

Seshat databank

The *Seshat: Global History Databank* includes systematically coded information on over 35 Natural Geographic Areas (NGAs) and over 200 variables across up to 10,000 years in time steps of 100 years ((25, 27); see also publicly available data at http://www.seshatdatabank.info/databrowser/). During the time interval captured by the Seshat databank, these NGAs are occupied by over 370 different identifiable polities, defined as an "independent political unit." This sample is constructed by identifying all known polities that occupied part or all of each NGA over time (24–26). The recorded variables are aggregated into nine complexity characteristics (CCs) and a principal component analysis shows that 77% of the variation in the data can be explained by the first principal component (SPC1), which has almost equal contributions from all nine CCs (5). In the case of missing data or expert disagreement in Turchin et al. (5), multiple imputation (28) was used to create several data sets with the differently imputed values which were aggregated into the principle component analysis. The NGAs in the Seshat data cover a wide geographical range and different levels of social complexity, though it is important to note that the Seshat sample is focused largely on relatively complex, sedentary societies (but not exclusively). Data on the CCs are sampled at century intervals, giving a time series of each polity's estimated social complexity measure throughout its duration.

Seshat data have allowed researchers to quantitatively test hypotheses on cultural evolution such as identifying drivers of social complexity and predictors of change in military technology, for example gauging the effect of moralizing religions on cultural evolution or predicting historical grain yields (7, 29–31). Further analysis of the Seshat data includes a discussion of ideas from biological evolutionary theory with respect to the *tempo* of cultural macroevolution, defined as "rates of change, including their acceleration and deceleration," concluding that "cultural macroevolution is characterized by periods of apparent stasis interspersed by rapid change" (6). These results strongly relate to the question of the present article, whether there is some generality in the time scale of cultural evolution in the Seshat data.

Data on culture/polity boundaries and duration

Each NGA's time series can contain data about very different polities that succeeded each other. Sometimes, a gradual and continuous change between the polities justifies treating predecessor and successor polities as closely related; for instance, in the Latium NGA (modern-day central Italy), Seshat records three separate polities for the Roman Republic, indicating the Early, Middle, and Late phases. These phases are culturally and (to a signfiicant degree) institutionally continuous, so can be treated as a single polity sequence. In other cases, there may have been an invasion or mass migration as a clear break point between the two polity's continuity; for instance, between the Ptolemaic Kingdom and Roman Principate polities in the Upper Egypt NGA. Data from Turchin et al. (27) and other information recorded in the Seshat sample, notably information on the relationship between polities, are here used to establish a list of continuous polities. The continuity is evaluated either as cultural continuity or as political–institutional continuity, and our cutout data for both approaches are published on (32).

Note that the Seshat data used in this article do not include information about modern polities. The latest datapoints in our sample are at 1900 CE and most data are from before 1850 CE (see the accompanying data file for details). This is because the focus of the Seshat project has been to study preindustrial social dynamics, and likewise our present study is concerned with historic, rather than modern, macrosocial evolution. Thus, the maximum values of SPC1 that we use in analyses represent the ceiling of premodern, preindustrial complexity.

Organization of this article

First, the used mathematical methods are briefly explained in *Methods and technical details*. *Approach: data transformation and exploratory analyses* explains how we transformed the time series data on each NGA in the Seshat sample to establish a common reference point to investigate the time course of changes in social complexity across NGAs. In short, we shift each NGA's time series with respect to a single anchor time such that the transformed time variable *RelTime* shows major overlap between the RelTime-vs.-SPC1-curves of all NGAs. Exploratory data analysis for the whole dataset reveals that there is a logistic relationship between *RelTime* and the SPC1 response variable. *Analysis of time scales* identifies the time scale of growth from the lower to the upper plateau of the logistic curve via bootstrapping. The logistic curve is compared to a regression using only either the culturally or institutionally continuous time series, and moreover, the duration of those continuous time series is compared to the estimated characteristic time scale. Finally, the results of the analyses are summarized and discussed in the last section. The SI Appendix gives additional details on the used data and the data preprocessing.

Methods and technical details

Logistic regression curve

Logistic regression is used to model time series data which is mostly distributed at two plateaus with a transitory area between them (33). It is based on the characteristic sigmoid curve of the logistic growth model described in Verhulst (34), which models an exponential growth process constrained by a carrying capacity. The logistic curve has the functional form f with an asymptotic behavior

$$f(x) = \frac{a}{1+\exp(-c(x-d))} + b$$
$$f(-\infty) = b \quad \text{and} \quad f(\infty) = a + b. \tag{1}$$

Often, data are scaled such that $b = 0$ and $a = 1$, i.e. an asymptotic behavior between two binary plateaus at height 0 and 1.

Reversing the direction

Estimating the coefficients (a, b, c, d) can lead to numerical instabilities because it is possible to transform a logistic curve with $c > 0$ to an equivalent equation $\hat{f}$ with $c < 0$. Consider e.g. $a = 1$, $b = 0$, $c = 1$, and $d = 0$, then

$$f(x) = \frac{1}{1+\exp(-x)} = \frac{\exp(x)}{\exp(x)+1} = \frac{\exp(x)+1-1}{\exp(x)+1}$$
$$= 1 + \frac{-1}{1+\exp(x)}. \tag{2}$$

The last reformulation of f can now be parametrized via $\hat{a} = -1$, $\hat{b} = 1$, $\hat{c} = -1$, and $\hat{d} = 0$. This ambiguity can lead to the regression algorithm yielding positive and negative results for c during multiple runs. This can be prevented by setting an initial parameter guess with $c > 0$, which locks the algorithm into positive values for c.

Kernel density estimation

A kernel density estimation (KDE) tries to reconstruct a probability density function based on a sample $x_1, \ldots, x_n$ of measurement data by smoothing the histogram of the data (35, 36). The estimated density $\hat{\rho}(x)$ is modeled as a weighted sum of probability densities (kernels) centered around the measured x_i. In this article, the Gaussian density is used as the kernel via *scipy.stats.gaussian_kde* (37).

Residuals and root-mean-squared error

For an algorithm f which estimates values $\hat{y}$ from data X with true values y, there are several methods to evaluate the accuracy of f. One of them is the root-mean-squared error (RMSE). It is defined as

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} r_i^2} \tag{3}$$

via the residuals $r_i = \hat{y}_i - y_i$. An RMSE much smaller than the range of measured values y_i means that the model shows only little deviation from the data. A roughly symmetric distribution of the residuals around 0 indicates that the model does not have a bias toward particular values.

Coefficient of prediction

Another method to evaluate the quality of an estimated function f is the coefficient of prediction ρ^2 used in (5). It takes the value of $\rho^2 = 1$, if the prediction is always exactly true, and $\rho^2 = 0$, if the prediction is only as accurate as always using the mean $\bar{y}$. It is defined by

$$\rho^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (\bar{y} - y_i)^2}. \tag{4}$$

Bootstrapping

Bootstrapping is a flexible technique used to estimate standard deviations and confidence intervals. A sample $z_1, \ldots, z_n$ is resampled *with* replacement, i.e. a new sample $Z = z_{i_1}, \ldots, z_{i_n}$ is created that for some $j \neq k$ fulfills $i_j = i_k$. This procedure is repeated N times so that there are $Z_1, \ldots, Z_N$ bootstrapped samples. If N is large enough, then e.g. the mean $\mu(z)$ of the resampled data will converge to the true mean of the original sample, but the empirical distribution of the resampled means $\mu_1(z), \ldots, \mu_N(z)$ enables the calculation of the confidence interval of the empirical mean (38). This approach can be adapted to make inference on the standard deviation and CIs of any statistical property of the original sample.

Approach: data transformation and exploratory analyses

First, all raw SPC1 time series are rescaled via a min–max scaling, i.e.

$$\text{SPC1} = \frac{\text{SPC1}_{\text{raw}} - \min(\text{SPC1}_{\text{raw}})}{\max(\text{SPC1}_{\text{raw}}) - \min(\text{SPC1}_{\text{raw}})}. \tag{5}$$

This has the advantage of making the interpretation of high and low SPC1 values much easier as high/low correspond to close to 1 or close to 0, respectively. It also makes the parametrization of a logistic curve easier by restricting the observed data to a range between 0 and 1.

Anchor time

Considering that most NGAs have an SPC1 time series that starts at a low value barely above 0 and ends at a high value close to 1, a logistic regression model seems like a reasonable suggestion for the data. Although all NGAs experience a growth in SPC1 over time, they start at very different calendar years. Therefore, it is necessary to shift the time series via an anchor time so that in the new "relative" time, the growth phase in each NGA's time series coincide. Then, one logistic regression can be used for all shifted time series (cf. Fig. 1 and Logistic regression curve section). Hence, each NGA i needs an anchor time $T_a^{(i)}$ so that if all-time series are shifted by $-T_a^{(i)}$, they roughly overlap. The shifted time series of the NGAs and the logistic fit are shown in the main part of Fig. 1.

The anchor time can be chosen as the year during which the NGA i's is SPC1 value crosses a threshold value. It has already been shown that there is a clear threshold $SPC1_0$ between high and low values of SPC1 in the data, which was used to define the *RelTime* variable in Turchin et al. (31). A similar methodology was also used in Whitehouse et al. (39), but there, the authors used the emergence of a moralizing religious belief as the "year zero" to shift each NGA's time series. Copying the procedure from Ref. (31) to get the *RelTime* variable, $SPC1_0$ is chosen as the minimum between the two maxima in the KDE (explained in Kernel density estimation section) of the SPC1 values (Fig. 1A). The anchor time $T_a^{(i)}$ is then selected as the first recorded data point when the NGA i exceeds $SPC1_0$. An illustration of the anchor time shift is provided in the SI Appendix. Thus, the 12 NGAs that never exceed $SPC1_0$ are discarded from this analysis. On the one hand, this is not too problematic because their limited growth in SPC1 means that they would have only contributed little information to the estimation of SPC1's characteristic growth time, but on the other hand, this discards all NGAs from the world region Oceania–Australia in the Seshat sample, meaning that it might introduce a bias. We discuss this and other possible limitations of the approach further in Summary and discussion section.

Logistic regression

The RelTime-vs.-SPC1 data are fitted to a logistic regression curve (cf. Logistic regression curve section) via the optimization algorithm *scipy.optimize.curve_fit* from Virtanen et al. (37). The quality of the regression curve is evaluated with the methods from the Residuals and root mean squared error section. With the exception of a few outlier observations occurring in several of the NGAs, all-time series qualitatively agree with the regression curve fairly well. Also, the majority of the residuals shown in Fig. 1B are distributed roughly symmetrically in a neighborhood of zero. The distribution of the residuals and the rather low value of RMSE ≈ 0.11 both indicate that the logistic regression is a suitable model for the shifted SPC1 data.

To further increase our trust in the quality of the regression, it is evaluated via the coefficient of determination ρ^2 in an out-of-sample prediction. The data are split randomly into equally sized training and testing data sets and a logistic regression curve f_i is estimated by only using the training data. Then, f_i is used to predict the values for the test data and the prediction is evaluated via the ρ^2 metric in subsection Coefficient of prediction. The random training-test-split is repeated $i = 1, \ldots, 100$ times, each time using the estimated parameters from the full time series as initial values, and the resulting ρ^2 values have an average of $\rho^2 = 0.81 \pm 0.01$ far above 0 and therefore further strengthens our trust in the logistic model.

Additionally, we train a model on data of the past to predict the future values in an out-of-sample prediction. We only use time series of NGAs with at least 30 recorded values for this and add the last 10 values (roughly 1 millennium) to the test data while the remaining earlier observations are added to the training data. Time series with <30 observations would have added little information to the training data and were thus discarded. Nevertheless, the time series of 18 NGAs remained in our sample for this prediction test. The resulting model achieved an $\rho^2 \approx 0.30$ far above 0 on the unknown future data and therefore increased our confidence in the logistic model.

Analysis of time scales

Finding a characteristic time scale

Having established that the data can be accurately captured by a logistic curve, we can investigate our research question; namely, how many years did it typically take in these different regions to transition from a polity with low SPC1 to one with high SPC1? Or to reformulate the question: when does the curve leave the low plateau and when does it reach the high plateau? We attempt to answer these questions by estimating the heights of the plateaus and their respective uncertainties and by checking when the regression curve crosses these thresholds.

We performed 1,000 steps of bootstrapping by sampling from the list of NGAs and by estimating the regression parameters $(a_i, b_i, c_i, d_i)_{i=1,\ldots,1,000}$ for each sample (cf. Bootstrapping section). According to the asymptotic behavior in Eq. [1], the plateaus are given by b_i and $a_i + b_i$. In order to make conservative estimates instead of being influenced by noise, an upper boundary for the lower plateau's value Th_1 and a lower boundary for the upper plateau's value Th_2 are used as the thresholds. Th_1 is chosen as $Th_1 = \mu(b) + 3\sigma(b)$ of the bootstrapped distribution of b, Th_2 as $Th_2 = \mu(a+b) - 3\sigma(a+b)$. For each bootstrapped logistic curve $f_i(t)$, it is then determined at which *RelTime* values $t_1^{(i)}$ and $t_2^{(i)}$ it crosses the lower and upper thresholds Th_1 and Th_2. We can then understand the mean value

$$\mu\left(t_2^{(i)} - t_1^{(i)}\right) = \mu\left(t_2^{(i)}\right) - \mu\left(t_1^{(i)}\right) \approx 2{,}500 \text{ years.} \tag{6}$$

as the characteristic time scale for the period of rapid cultural evolution between low and high plateaus of sociopolitical complexity, across geography and not in reference to any specific time period. Note that one can also choose less restrictive thresholds via $Th_1 = \mu(b) + \sigma(b)$ and $Th_2 = \mu(a+b) - \sigma(a+b)$. With these thresholds, the regression curve leaves the vicinity of the lower plateau rather quickly but needs much longer until it is close enough to the upper plateau to be considered as having reached the upper plateau. These 1σ thresholds would result in a longer time scale of roughly

$$\mu\left(t_2^{(i)} - t_1^{(i)} \,\middle|\, 1\sigma\right) \approx 4{,}000 \text{ years.} \tag{7}$$

Bootstrapping enables a flexible selection of the uncertainty range and therefore allows to confirm these results for various uncertainty levels.

We can check the general validity of these results by explicitly identifying for each NGA i the first time $\tau_1^{(i)}$ that their SPC1 value exceeds Th_1 and the first time $\tau_2^{(i)}$ they exceed Th_2. With the exception of the Ghanaian Coast, all NGAs cross Th_2 and therefore, this procedure yields 22 time durations $d^{(i)} = \tau_2^{(i)} - \tau_1^{(i)}$. Only for the two NGAs Kachi Plain and Middle Yellow River Valley (two "pristine" states, cf. Discussion section) does the duration $d^{(i)}$ exceed the 4,000 years estimated as an upper boundary in Eq. (7). Both the mean (2,200 years) and median (2,100 years) are in line with the main estimation in Eq. (6).

Continuous polities

There are two reasons why it makes sense to restrict the logistic regression only to a central part of each NGA's time series, during

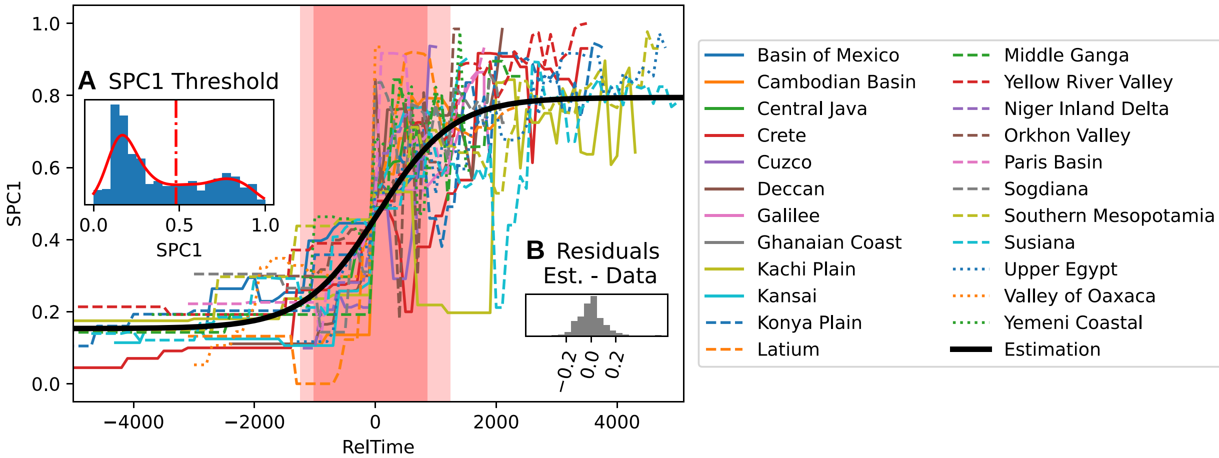

Fig. 1. Time series of RelTime vs. SPC1 for all 23 NGAs that cross $SPC1_0$ and the logistic regression. Marked in red is the area of growth between the two plateaus of the curve as identified in *Analysis of time scales*. The various time series are shown in the SI Appendix in multiple plots to make the identification easier. A) distribution of SPC1 for all 35 NGAs, the associated KDE (red) and the threshold $SPC1_0$ (vertical); B) residuals of the logistic regression.

which the polities in that NGA are not disrupted by external influence or major dislocations in sociopolitical structures. First, the logistic regression starts at a plateau of low values of SPC1 close to 0 and ends at a plateau of high values close to 1. Therefore, even a bad interpolation for the central part can achieve a good RMSE, if the plateaus of the high and low tails are sufficiently accurate. However, this would not be a reliable estimation to make an inference on the growth phase in the center of the curve. Second, if the NGA's polity is, e.g. annexed by another, more developed polity, then it inherits the invading polity's high SPC1 value and may make a sudden jump in the SPC1 curve. However, the logistic regression here is intended to model steady, uninterrupted growth like in Verhulst (34) and not major transitions driven by developments experienced elsewhere, as through annexations by an external invader. Therefore, it makes sense to divide each NGA's time series into intervals which are separated by sharp, discontinuous changes within each NGA and to restrict the analysis of the NGA to its central interval, i.e. to the time series from the polities that cross the $SPC1_0$ threshold.

As mentioned earlier, there are two ways of identifying such discontinuous changes: either via cultural changes of via major institutional changes of the polity's governance. Both approaches are analyzed separately. The central time series for both methods and their resulting logistic regressions are shown in Fig. 2.

Cultural continuity

One set of sequences was determined by the absence of a major cultural dislocation; namely, the introduction of a new ideological and linguistic system, major population displacement, or major technological advance (the adoption of iron metallurgy, for instance). This is a very broad and lenient definition of continuity, as it allows for very different social formations to be part of a single sequence and can include significant developments. In Egypt, for instance, we treat nearly the entire Pharaonic period (from the Naqada period to the Achaemenid conquest) of over 3,000 years, including the so-called Intermediate periods when central rule was fragmented (though many cultural and social features were retained), as a culturally continuous time period.

For the 23 NGAs under consideration, the mean value of data points for the culturally continuous central interval is 11.7, i.e. there is on average a bit more than 1 millennium of data. While this is much shorter than the characteristic time scale of roughly 2,500 years, the longest continuous time series of the NGAs show a similar length to that of the characteristic time scale (cf. the left half of Table 1). Hence, the logistic regression for these cutouts is rather close to the regression of the full data (cf. main part of Fig. 2) and in particular, the regression curves' steepness (i.e. their time of growth) is quite similar.

Institutional continuity

For institutionally continuous time periods, we follow a similar procedure as above, though with different criteria for continuity leading to shorter sequences. Namely, we break each sequence at any significant political/institutional change, even if there was much continuity in sociocultural forms. In Egypt, for instance, the institutional sequence starts at the First Dynasty period and ends a the end of the Old Kingdom period and the First Intermediate Period, which we call the "Period of the Regions." The mean value of data points for institutionally continuous central time series is only 5.9 and represents 500 years of data. Even the longest continuous sequences now do not last as long as the characteristic growth time of 2,500 years (cf. right half of Table 1). Moreover, the logistic regression has only very little data for the parameter estimation (cf. Fig. 2B) and hence, the logistic regression has a much lower SPC1 level for the upper plateau than the regression to the full data (main part of Fig. 2), because the cutout time series are too short to reach the high-SPC1 levels.

Summary and discussion

Summary

Exploratory data analysis shows in Fig. 1 that the logistic regression is a suitable model for the RelTime-vs.-SPC1 time series. Bootstrapping allows us to narrow down the time interval of rapid SPC1 growth to 2,500 years, as highlighted in Fig. 1. Together, these results illustrate that there is a uniform behavior in the macrolevel growth of social complexity represented by the time evolution of SPC1. While the data and so the findings are at a fairly coarse temporal resolution, this is an important finding regarding the cross-cultural similarity, and hence comparability, in what might be called sociopolitical macroevolution.

If the data are restricted to the central part of each NGA's time series without any discontinuous cultural or institutional transitions, the logistic regression is still a reasonable model and shows

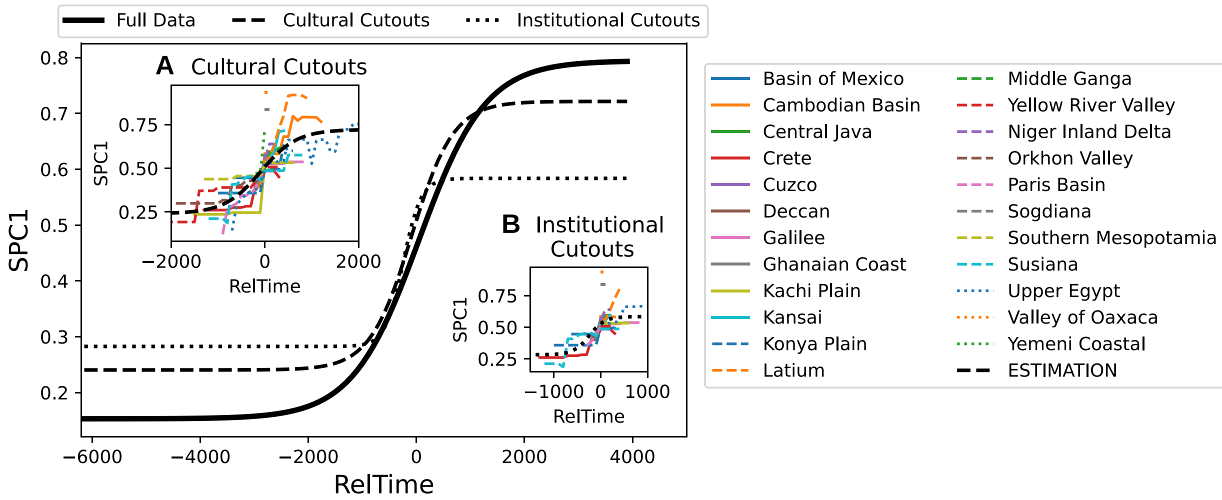

Fig. 2. Estimated logistic curves for the full data and the two cutout methods. A) Each NGA's central time series and resulting logistic curve for the culturally continuous time series. B) The same as a) for the institutionally continuous time series.

Table 1. For both methods of identifying continuous time sequences, the four longest continuous central time series and the amount of data points they contain (given as their length) are summarized.

NGA	Cultural continuity length	NGA	Institutional continuity length
Yellow River	38	Susiana	17
Upper Egypt	33	Crete	17
Kachi Plain	22	Konya Plain	15
Susiana	21	Upper Egypt	10

The data points are sampled at intervals of one century. The culturally continuous time series are much longer than the longest institutionally continuous sequences.

a similar shape to the full data as depicted in Fig. 2. In particular, the regression based on the culturally continuous time series show a very similar steepness (i.e. growth period) to the full regression curve.

Discussion of the time scale and continuous sequences

First and foremost, despite the high effort put into the Seshat Databank project, one has to note that our result for the characteristic time scale should not be regarded as a perfectly exact value. New research leads to constant updates of the Seshat data and the uncertainty associated with ancient archaeological data also must be kept in mind. Thus, the estimated time interval of rapid SPC1 growth of 2,500 years should be interpreted with caution as a guideline and order of magnitude, but not as an exact measurement.

Figure 2 shows that the culturally continuous and institutionally continuous time series result in a similar logistic regression to the full data. Notably, Table 1 shows that the culturally continuous time series have a much longer duration than the institutionally continuous ones. In particular, in the Yellow River Valley, Upper Egypt, Kachi Plain, and Susiana, the culturally continuous time series is approximately as long (or even longer) as the characteristic time scale of SPC1 growth. This is expected for regions that saw the emergence of large, complex states relatively early in history and without any precedent from neighboring societies—the so-called "pristine" or "primary" states (40, 41)—which these regions all experienced. However, this is not the case for most other NGAs, indicating that in those NGAs, the growth from the lower to the higher SPC1 plateau did not take place over the course of just one culturally continuous era, but rather included developments across cultural spheres and, in most cases, including developments being "brought in from the outside" in the form of direct conquest or more indirect influence. The institutionally continuous time series are all significantly shorter than the characteristic growth time, as expected from the criteria used to generate those sequences. This is notable, as it suggests that in order to transition from low to high social complexity, major shifts in the NGA's governing institutions are necessary to facilitate the increase in social complexity. In other words, our findings suggest that major transitions in social complexity are not feasible for a single polity to accomplish but require multiple social formations or "phases" of rule building successively (but not monotonically, as the above figures illustrate) on prior developments. Such major, iterative transformations, naturally, tend to occur over very long time-scales, longer than the typical duration of any sociopolitical formation. Indeed, no region in our sample witnessed a single continuous cultural or institutional phase that persisted long enough to oversee this full course of macroevolution, while only a few managed this process over the course of a few "internally grown" phases; other regions' evolution was disrupted or at least strongly influenced by developments across multiple phases and through interaction with external polities. Nevertheless, the general similarity of the three regression curves in Fig. 2 shows that our analysis is stable with respect to the exact selection of time periods and different cutout criteria used.

It is interesting to compare those NGAs that crossed the threshold $SPC1_0$ to those that failed to do so and stayed at lower complexity values. The latter group had a mean of only 6.4 recorded data points, i.e. there were only complex social formations coded as part of the Seshat sample for a period of roughly six centuries. On the other hand, the NGAs that did reach a high complexity and exceeded the threshold $SPC1_0$ had a mean of 57.3 recorded data points, corresponding to almost 6 millennia of observed data. Partly this is explained by different availability of historical and archaeological evidence in different regions, but it suggests also that cultural developments in the low complexity NGAs could have followed the same trajectory of logistic growth, if they had been given enough time.

Unfortunately, the necessity to identify an anchor time for this analysis means that all NGAs from the Seshat world region Oceania–Australia had to be discarded for this research. The bias introduced by this has to be kept in mind while interpreting our results.

Note also that, as explained above, the Seshat data utilized in this study represent premodern polities, predominantly from before 1850 CE. These timescales, then, are characteristic of developments before the advent and spread of industrial technologies. Future work may seek to extend the measurement of sociopolitical complexity used here, perhaps adding new categories or thresholds to accommodate modern developments. For instance, the measure of monetary complexity which forms a part of the SPC1 measure (following Turchin et al. (5)) include variables about the presence of paper currency and debt structures but are currently unable to capture for instance developments in digital financial records or cryptocurrency, critical components of many modern monetary systems.

Interpretation and comparison to previous work

With the shifted time index RelTime, the logistic regression model of the SPC1 time series achieves a high accuracy in capturing the evolution of sociopolitical complexity measured by SPC1. Previous work has already demonstrated a significant amount of cross-cultural generality in the factors contributing to the evolution of sociopolitical complexity ((5), supplemented by findings in Refs. (3, 42)). While the comparison between biological and cultural evolutionary rates in Perreault (18) also explores and supports the idea of a characteristic speed of cultural evolution, its data on cultural evolution was limited to physical artifacts and their material properties (such as ceramic vessel thicknesses and dagger blade lengths) because it was published before the Seshat data. Therefore, our research greatly expands on the results of Perreault (18) by also taking sociopolitical changes into account. Notably, a previous study on the Seshat data has already identified a characteristic growth pattern of SPC1 and the second principal component SPC2 and found that a rapid period of scale is first followed by a growth of information processing and economic complexity and then by further growth in scale (3).

Here, we expand on this prior work by identifying that the time scales involved in these developments also exhibit a general, characteristic shape. Nevertheless, the macrolevel evolution of social complexity is a lengthy and nonmonotonous process; this emerges clearly from our analyses distinguishing the full regional time-series involved in the transition from low to high thresholds of SPC1 from sequences of cultural or institutional continuity. We see no examples of this evolution accomplished during a single institutionally continuous sequence. Further, in all NGAs, there are not only noisy periods during which SPC1 grows but also crises during which sociopolitical complexity sharply declines, only to recover later and continue increasing. These findings highlight that different parts of the world experienced similar processes of social complexity growth and also that this process involved multiple phases of cultural and sociopolitical structures building off of (and occasionally recovering from) prior developments in each region.

While the sample of past societies explored in this article is certainly not exhaustive, they comprise a fairly representative sample of regions from different parts of the world and include societies from different periods, cultures and different developmental experiences. Our results thus lend novel empirical support to the idea (6, 16) that sociocultural evolution does indeed occur in similar time scales across different cultures and geographies. Future research can expand these insights by including additional societies and exploring alternate thresholds of complexity to identify anchor times to include more NGAs from the original sample, because the current thresholding procedure in particular excluded some NGAs from modern-day Oceania–Australia from our analysis. A further potentially fruitful avenue for future research will be to extend the time-series treated here into the present day, making adjustments to the coding scheme to allow the SPC1 ceiling to capture the developments in complexity that have occurred since the industrial revolution as noted above. We would expect that recreating the analyses we preform in this article on a dataset extending into the present would alter the characteristic time-scales identified here only slightly and that a model like the ReLU curve $f(x) = \max(0, x)$ might then be a better fit than the logistic regression. Note, however, that unlike the logistic curve in the section on Exploratory analyses of the Seshat data, the ReLU function could not achieve a positive ρ^2 for the prediction of future Seshat data because it tended to overshoot above the recorded maximum SPC1 levels. We argue that it would be more valuable to assess characteristic timescales in different eras or technological regimes to assess whether the pace of evolution differs. We hypothesize, for instance, that sociopolitical complexity evolution has both sped up and become more uniform globally since the industrial revolution than in previous periods.

In terms of the underlying approach, our study tries to single out the autocatalytic effect of social complexity growth. To this end, it not only focused on one NGA at a time but also compares our regression results to the culturally and institutionally continuous periods for the respective NGA. Thus, we uncover an empirical pattern in the temporal evolution of SPC1 that has not yet been fully discussed by previous work, e.g. in causal analyses of the drivers of social complexity like in Turchin et al. (7). Our methodology differs from, e.g. the regression model in Turchin et al. (7) by deliberately choosing a very simple model to single out the temporal evolution whilst disregarding possible drivers of the observed dynamics. We believe this approach can be utilized to answer other questions about long-run cultural evolution, for instance the processes by which key technologies (e.g. metallurgy, military technology, communications media, etc.) are invented in certain locations and then adopted in others.

While the autocatalytic growth model provides an elegant interpretation of our findings (the current level of complexity facilitates further growth until the presence of an upper boundary of complexity is approached), it has to be regarded with caution: We sought as far as possible to disentangle culturally and institutionally endogenous developments from those driven by interactions with other polities, though even the internal developments are not free from external influence. Previous work, for instance, shows the strong effect of military conflicts with other states on the growth of sociopolitical complexity (7, 30). Hence, the autocatalytic model might be a useful low-dimensional description of the data, but not an exhaustive explanation. In short, our findings exposes a cross-cultural temporal pattern whose causes need to be fleshed out in future work.

Finally, the findings of the present article can be used as a benchmark for future additions to the Seshat data: if a new NGA is added to the databank and shows a clear divergence from the logistic curve, it may be prudent to either check, if there are any mistakes in the data generation and interpolation, or if the divergences can be explained by historical developments. Such a benchmark may thus be useful for further expansion of the Seshat databank.

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Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

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Author Contributions

T.W. performed all analyses and drafted the manuscript. D.H. assisted in conceptual development and drafting the manuscript.

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Data Availability

The data underlying this article are available in zenodo in Wand and Hoyer (32) and can be accessed via https://doi.org/10.5281/zenodo.8120128.

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