



Focus

Applying event history analysis to explain the diffusion of innovations in archaeological networks

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ARTICLE INFO

Keywords:

Archaeological networks
 Cultural transmission
 Event history analysis
 Innovation diffusion

ABSTRACT

The simple dyadic structure of a network is the basis for studying a wide variety of entities and their relationships, as well as the outcomes of processes such as the diffusion of innovations. Here, we apply models from event history analysis and cultural evolutionary theory to investigate whether and by what means network ties facilitated the transmission of certain cultural traits in past complex societies. To illustrate the application of these models to archaeological data, we examine the spread of dynastic rituals by analyzing data collected from Classic Maya hieroglyphic inscriptions. In addition to providing a cautionary tale for the construction of archaeological networks, the results of this study highlight the compatibility of cultural evolutionary and social network approaches to investigate the spread of novel traits.

1. Introduction

The phrase “diffusion of innovation” refers to the process describing how an innovation (e.g., a new idea, information, disease, or technology) spreads over time among the entities in a population (Rogers, 1995). Starting from the seminal work of Ryan and Gross (1943), a large number of studies, in many contexts and disciplines, have investigated how individual, societal, cultural, economic and technological factors influenced the speed and character of diffusion. Most of these studies and corresponding theories of innovation diffusion (Ryan and Gross, 1943; Beal and Bohlen, 1955; Coleman et al., 1966; Valente, 1995) are based on the premise that social networks play a critical role in driving the diffusion of innovation in addition to other factors, such as geographical proximity and entity attributes. Within archaeology, innovation diffusion is considered to be one of the basic mechanisms of cultural transmission as it describes the way novel traits or practices spread between individuals in a population. While the archaeological record spans time periods of sufficient length to investigate diffusion processes, the incompleteness and lack of temporal precision of archaeological data present many challenges for understanding the specific mechanisms and factors responsible for innovation diffusion.

Some classic examples of diffusion of innovation in archaeology include studies on the spread of farming (Ammerman and Cavalli-Sforza, 1971), hunting technologies (Bettinger and Eerkens, 1999;

Jordan, 2014; Fort, 2015; Buchanan et al., 2017), pottery technology (Eerkens and Lipo, 2014), architectural technology (Östborn and Gerding, 2015, 2016), and the adoption of artifact styles (Dethlefsen and Deetz, 1966; Davis, 1983; Scholnick, 2012). These studies describe diffusion by analyzing the distributions of one or more traits in space and time using a variety of methods, such as seriation, typology, and agent-based and spatial modeling. They explain observed distribution patterns of cultural traits in the archaeological record by processes such as migration, exchange, contacts and geographical proximity and point out that the tendency to adopt a particular trait is dependent upon a range of complex and potentially interlaced factors and processes operating at multiple scales (Cavalli-Sforza and Feldman, 1981). The special issue on “Social Boundaries and Networks in the Diffusion of Innovations,” recently published in the Journal of Archaeological Method and Theory (Roux and Manzo, 2018), also emphasizes that diffusion mechanisms act at multiple levels and stresses the importance of network ties in explaining the spread of an innovation. Specifically, the papers in this special issue investigate and discuss whether social theories, network analysis methods and agent-based modeling could be applied to study the spread of innovations when partial information at different levels of analysis are available.

In the present study, we introduce event history analysis as a method to investigate the ways different factors facilitate the flow of cultural information in past societies when detailed historical records

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<https://doi.org/10.1016/j.jas.2019.01.006>

Received 22 August 2018; Received in revised form 13 January 2019; Accepted 27 January 2019

Available online 13 February 2019

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are available. Using royal rituals inscribed on Classic Maya monuments (Munson et al., 2016), we trace the diffusion of these cultural practices with event history models to investigate how the empirical network structure and other exogenous factors contributed to the spread of diverse dynastic traditions in Classic Maya society. Moreover, we point out that the goals of social network analysis complement the fundamental objectives of cultural evolutionary (CE) research developed in anthropology and archaeology over the last three decades (Shennan, 2011). A common goal of social network analysis is to use the network structure to *explain* certain outcomes such as the adoption of an innovation, the transmission of a certain practice or behavior, or the selection of a stylistic trait (Rogers, 1995; Valente, 1995; Borgatti et al., 2009; Rivera et al., 2010; Brandes et al., 2013). At its core, cultural evolutionary theory provides a framework to explain patterns of variation in the material record (Boyd and Richerson, 1985). Although it is surprising there has not been more crossover between these research domains, this paper demonstrates that there are significant parallels and important contributions to be made.

2. Diffusion of innovation: concepts and factors

Diffusion of innovation traditionally refers to the spread of new ideas, products as well as actual practices and behaviors within a defined social system (Rogers, 1995). Broadly, innovations, and the processes by which they spread and change, are studied across multiple scales—from cells to societies (Hochberg et al., 2017). Technically, the dynamics of this process can be described by an S-shaped cumulative frequency curve that represents the fraction of a population that has adopted an innovation at a certain point in time (Fig. 1). When several curves for the same trait are plotted together they can reveal the adoption rates or the time lag between the adoption of traits in different groups. While S-shaped diffusion curves have been observed in numerous studies (Rogers, 1995), one of the biggest challenges for CE research is identifying the factors that produce cultural innovation and understanding the transmission mechanisms. In archaeology, theoretical modeling has outstripped empirical investigation in this regard (Shennan, 2011, p. 239). For example, modeling has shown that biased transmission yields S-shaped curves, and when combined with

environmental learning these same patterns can emerge (Henrich, 2001). Similar curves may also result from populations with heterogeneous adoption thresholds, as with the decreasing adoption cost of new technology such as a black-and-white television (Bass, 1969; Kandler and Steele, 2009). Further, selectively neutral processes like drift can also generate an S-shaped curve characteristic of diffusion (Neiman, 1995; Lipo et al., 1997; Hahn and Bentley, 2003). These studies demonstrate that a wide variety of mechanisms may produce the S-shaped curves characteristic of diffusion.

Understanding cultural processes such as innovation diffusion has been a central topic in archaeology for well over a century (Lyman et al., 1997). While archaeology provides access to time periods of sufficient duration to track these processes, the empirical distributions of material culture variation we analyze are unknowably incomplete. Though we do not need to reconstruct each transmission event, the question is to what extent we can identify the interaction of these cultural evolutionary processes in the past based on the distributions of variation we observe in the present. Most computer simulations and mathematical models tend to focus on only certain aspects of the transmission process in isolation. Such research has been valuable in showing the potential effects of different variables yet there remains a major gap in understanding how these variables interact in real-world situations.

Given the complexity of cultural transmission processes and the unique challenges posed by the archaeological record, we identify several important factors that affect network-based studies of diffusion of innovation. Based on earlier reviews (Eerkens and Lipo, 2007; Wejnert, 2002), these factors include: (1) information content, (2) attributes of the individual entity, and (3) social and environmental contexts. Importantly, these factors are not independent but interact during transmission to produce the patterns observed in the archaeological record. The remainder of this section outlines a conceptual framework that briefly defines the nature of these factors. We then apply this framework to describe the variables incorporated into the current study. For more detailed discussion and case studies drawn from a wider range of disciplines, the sources cited above are recommended.

Information content refers to the actual information and/or objects

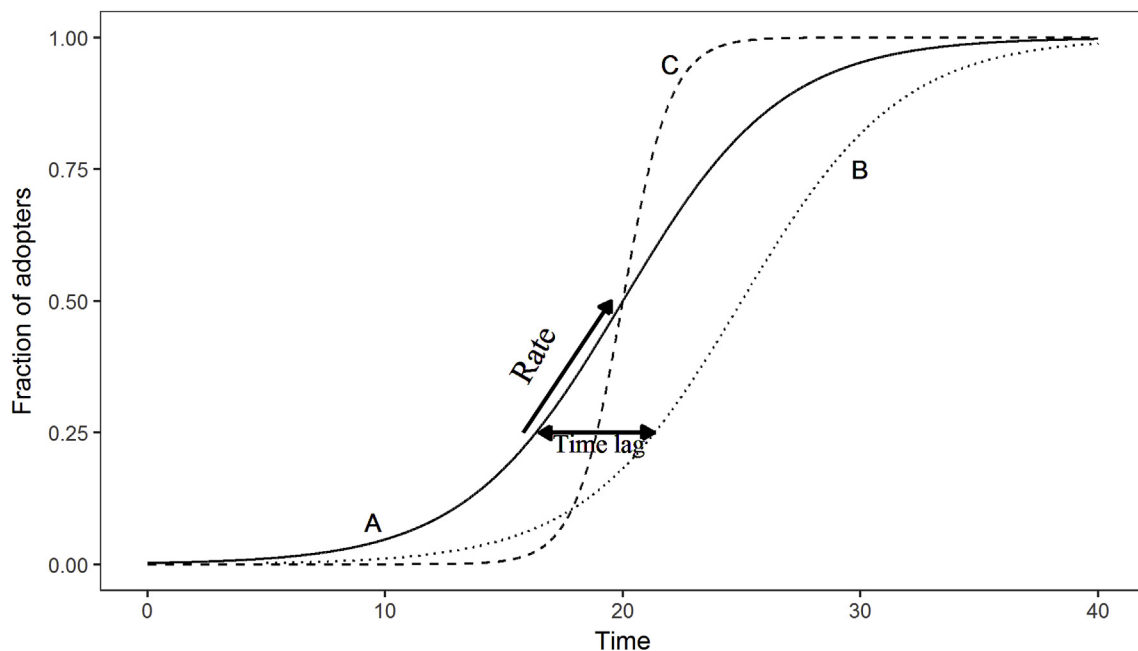


Fig. 1. Examples of S-shaped cumulative frequency curves for the diffusion of a trait in three groups A, B and C. There is a time lag between the diffusion in group A (solid line) and group B (dotted line) as suggested by the shift of the corresponding two curves. The adoption in group C (dashed line) took place at a faster rate as suggested by the steepest slope of the corresponding curve.

transmitted between individuals. Concretely, content describes characteristics of the innovation itself—the complexity of that information, the form in which it comes, its repetitiveness as well as how it is structured (Eerkens and Lipo, 2007, pp. 247–249). While archaeologists do not have direct access to the ideas or knowledge of ancient people, the content and characteristics of what is transmitted has direct implications on the resulting material culture variation observed in the archaeological record. Because of this, some archaeological applications of cultural transmission theory have treated information content, in particular the analysis of “stylistic” variability, as selectively neutral (Neiman, 1995; Lipo et al., 1997). However, innovations can be evaluated by the potential adopter and chosen based on observed outcomes, which have entered into models of guided variation and direct bias (Boyd and Richerson, 1985). Archaeologists have also recognized that some degree of experimentation and practice is involved in learning a new technology or determining whether to adopt an innovation (see Schiffer and Skibo, 1987). In cases where the innovation is a religious idea or behavior the emphasis on information content may be less applicable since it is difficult to evaluate the perceived benefits and success of one ritual over another (c.f. Collar, 2013); however, in other cases, it is possible to evaluate the different types of messages encoded by the ritual (Rappaport, 1999, pp. 52–54).

The second factor influencing diffusion of innovation are individual-level attributes of the senders and receivers of cultural information. These variables can be easily represented as entity attributes and measured by network position using centrality indices or role equivalences (Scott, 1991; Wasserman and Faust, 1994), and/or by network closure (Coleman, 1988, 1990) and brokerage (Burt, 2001; Peeples and Haas, 2013) as measured by the position of individuals in particular patterns of ties. The simplest assumption is that the likelihood that an entity adopts an innovation increases with the proportion of adopters in his/her social networks. This idea is the fulcrum of contagion models (Menzel and Katz, 1955; Goffman and Newill, 1964), and analogous to conformist or frequency-dependent biased transmission (Boyd and Richerson, 1985). In the cultural transmission literature, researchers have also explored the degree to which prestige and high-status can bias the adoption dynamics of certain traits (Henrich and Gil-White, 2001). From the adopter perspective, Kandler and Steele (2009) demonstrate that S-shaped diffusion curves can also be generated by heterogeneous populations of adopters with differential thresholds for adoption. Although a key factor explored in agent-based models, there has been little empirical work in archaeology to investigate this variable.

The third factor focuses on the environmental and social contexts that modulate diffusion. A basic assumption of diffusion research is the recognition that innovations are not independent of their environmental and cultural context. In particular, Wejnert (2002, pp. 310–315) highlights three components that are crucial: geographic settings, societal culture, and political conditions. Geographic proximity is a determinant factor in innovation diffusion because it affects the frequency of communication and the personal nature of interactions between actors (Hägerstrand, 1967). Although spatial effects alone are insufficient for modeling community network structure (Daraganova et al., 2012), they are important variables that can be easily incorporated into archaeological network analysis of cultural transmission. Additional population-level factors that should be incorporated into diffusion models include trait frequency and population size. For archaeological network analysis, it is important to consider the structural and historical constraints of network ties as more than just a proxy outcome of past social interaction (Munson, 2019).

The goal of recent cultural transmission research is to tease apart these different forces in order to elucidate the pathways and factors responsible for empirical patterns of cultural diffusion in the archaeological record. As McLean (2017, p. 56) notes, “a cardinal assumption of much diffusion research is that we can better understand what is going on if we understand the topology—the shape and patterns—of the social network in which that diffusion occurs, and if we know more

about the positions of particular persons or organizations within that network.”

Over the last decade, archaeologists have employed social network analysis to various ends (Knappett, 2011; Brughmans, 2013; Collar et al., 2015), however many studies presuppose that artifact similarity or co-presence are indicative of past social interaction (Östborn and Gerding, 2014; Golitko and Feinman, 2015; Mills et al., 2015; Mol et al., 2015; Habiba et al., 2018). Archaeological network representations based on these proxy criteria are convenient and common, but also potentially oversimplify the social processes that archaeologists ultimately seek to understand. In particular, such representations can problematize the explanatory goals of network analysis if the process is used to interpret the outcome (Borgatti et al., 2013, p. 7). To avoid this trap of circular reasoning, we argue that archaeological network analysis needs to consider models and methods that better address the specific processes that produce the patterns we observe (Munson, 2019). Considering the geographic location and extant network ties between Maya sites, we can trace the diffusion pathways of dynastic rituals without recourse to a value judgment about the nature of the ritual innovation itself or debating the relative status of one site or ruler over another. Instead, we focus on structural circumstances to evaluate how these network variables and environmental contexts facilitate and constrain the spread of diverse ritual practices within Classic Maya society.

3. Event history analysis

In the social sciences, the term “event history analysis” denotes a set of statistical methods that seeks to explain and predict the occurrence of an event for the entities within a population. An event refers to a transition from one discrete state to another. Examples of such events may include marriages, migration, employment status, death, healing, as well as failure of a mechanical or electronic component. These examples indicate that event history analysis can be applied to a wide variety of problems in disciplines as diverse as demography, sociology, epidemiology, economics, and industrial engineering. In various application fields, this method is also referred to as survival analysis, failure analysis, life-time analysis or duration analysis (see Aalen et al., 2008 for a more technical description; see Allison, 2014 for a concise introduction). For diffusion of innovation, the event is the adoption of a new trait and represents a transition from the state of non-adoption to the state of adoption. In this context, the application of event history models allows distinguishing among the various determinants of diffusion described above (Valente, 2005).

Event history data are typically collected by observing a set of entities over time, usually during an observation interval, and by recording the time at which the event occurred. For some of the entities, the observation might be incomplete since the time at which an event took place cannot be observed as is commonly the case with archaeological data. This happens when the event occurred (1) after the end of the observation period; (2) after the entity dropped out of the study for reasons that are not related to the event; or (3) before the entity entered the observation period. In the first two cases, we say that the observation is right censored while, in the latter case, we say that the observation is left truncated. Due to this particular feature of the data, common statistical methods (e.g. linear or logistic regression models) cannot be used. Event history analysis, however, provides specific techniques to deal with these sorts of incomplete data, thus lending particular salience to archaeological applications.

There are two main classes of event history models that can be applied to analyze the diffusion of innovations. The first class comprises discrete-time techniques for analyzing data collected at discrete time points and consisting of a series of binary outcomes denoting whether the adoption occurred at each observation point. The second class encompasses continuous-time methods, which are applied when the data are collected over variable lengths of time and time is treated as a

continuum rather than a sequence of discrete time points. In this case, the outcome variable is the time to the adoption. In the following, we focus on continuous-time methods and we refer to Allison (2014) and Box-Steffensmeier and Jones (2014) for a description of discrete-time models.

In continuous-time models, the dependent variable is the hazard (or transition) rate, which is defined as the risk that an entity adopts a new trait within the short time interval $[t, t + \Delta t]$, conditional on the fact that the entity has not adopted the trait yet. A variety of models have been developed to investigate the dependence of the hazard rate on the explanatory variables. In the following, we consider proportional hazard models (see Appendix A for more details) defined as

$$h_i(t|x, z, y) = h_0(t) \cdot \exp\left(\sum_j \beta_j x_{ij} + \sum_k \gamma_k z_{ik} + y_i(\varphi, \sigma)\right). \quad (1)$$

In the formula, the hazard rate $h_i(t|x, z, y)$ is expressed as the product of two quantities. The first quantity is the baseline rate function $h_0(t)$, a nonnegative function describing the baseline tendency of entities to adopt a novel trait solely as a function of time. This term can be thought of as the intercept in a linear regression model. The second quantity describes the association between the hazard rate and the site attributes (x_1, \dots, x_j) , the network variables (z_1, \dots, z_k) , and the geographic proximity (y) of the entities. More details and examples about those variables are provided in Table 1 and Appendix B. The parameters β_j and γ_k quantify the strength and the direction of the association between the hazard rate and each single covariate. Positive (or negative) values of these parameters indicate that higher values of the corresponding covariates lead to an increase (or decrease) of the risk of an event to occur (see Table 1). For those familiar with logistic regression, parameters of an event history model are interpreted in a similar way to parameters of a logistic regression model with the difference being that in the former's case the parameters are interpreted as hazard whereas in the latter's case as odds ratios. The function y_i is a gaussian process depending on two parameters φ and σ controlling for the spatial variation and autocorrelation of the trait, respectively.

The estimation of event history models is based on the maximum likelihood approach a description of which can be found in Aalen et al. (2008).

4. Application

We now illustrate how event history models can be applied to archaeological data using a case study drawn from Classic Maya (ca. 250–900 CE) hieroglyphic inscriptions. The objective of this analysis is to test what factors may have contributed to the spread of specific royal rituals inscribed on hieroglyphic monuments. Data used in this study are derived from the Maya Hieroglyphic Database (Looper and Macri, 1991–2018). It was previously used to analyze ritual diversity across multiple scales; a full description of the dataset can be found in Munson et al. (2016). Although the results from this earlier study found high degrees of ritual similarity among large lowland Maya centers and significant variation between large and medium-sized sites, it failed to adequately explain the factors behind these patterns (Munson et al., 2016). Since these inscriptions are associated with calendrical dates and known locations, we can incorporate this spatiotemporal information to analyze the diffusion of innovation using event history analysis. Additional relational data encoded in the inscriptions permit examination of multiple network configurations that may have contributed to the spread of these ritual practices.

4.1. Data

Following the conceptual framework outlined in Section 2, we describe the dataset and variables used in the event history analysis. In this analysis, we utilize a subset of the Maya Hieroglyphic Database

(Looper and Macri, 1991–2018). The extant dataset is comprised of 1581 ritual inscriptions from hieroglyphic monuments found at 198 distinct sites that covers a period of 800 years, from 8.6.0.0.0 to 10.8.10.0.0 based on the Maya Long Count calendar system (159–998 CE). These monuments record various information about the dynastic histories and sociopolitical relationships between polities and named rulers. Importantly, these monuments also include calendrical dates that allow us to identify the first recorded instance of specific glyphs necessary to track diffusion of innovation. For each site, the geographical coordinates and the number of glyph blocks is also available. The classification and tabulation of royal rituals included in the current study can be found in Munson et al. (2016).

Relations among the sites were derived from references to foreign sites or rulers recorded on the monuments (Munson and Macri, 2009). The inscriptions document different types of sociopolitical relations providing evidence of contacts among the sites and information on the possible conduits of diffusion. Every relation is dated so that it is possible to trace the time at which pairs of sites were related. For simplicity, we do not distinguish among the different relational types and we do not account for multiplicity or directionality (a relation from the site in which the inscription was recorded to the other site mentioned in the inscription). We also assume that two sites were in contact since the date of the earliest inscribed relation and thus we do not consider the duration of relations since we only know their beginning time.

The resulting network (Fig. 2) consists of 406 unique relations recorded among the 198 sites listed in the Maya Hieroglyphic Database. Since 119 out of the 198 sites were isolates, we based our analysis on the 70 sites (red nodes in Figs. 2) and 138 links forming the largest connected component (Wasserman and Faust, 1994) of the network. The largest connected component is a subgraph in which there is a path between every pair of nodes (i.e. it is a subset of the nodes and links whereby any node can be reached by any other node).

In this study, we trace the diffusion of the two most frequently recorded royal rituals to illustrate the application of event history analysis. Royal accession rituals are by far the most frequent ($n = 283$) and were documented at 30 of the 70 sites (42.9%) in the largest connected component of the network. The accession rituals mark the installation of a Maya ruler as *k'uhul ajaw* (divine or holy lord), but may be celebrated in a number of ways. Based on the extant hieroglyphic inscriptions, we have identified six different verb root variants that converge on shared meanings of royal accession: *ajaw*, *ch'am k'awil*, *chum*, *joy*, *k'al hun*, and *(y)okte'* (Munson et al., 2016 see supplemental Table 1). The scatter ritual is the second most frequent ritual ($n = 167$), recorded at 37 of the 70 sites (52.9%). This ritual, denoted by the verb roots *chok* and *puk*, involves the scattering of precious substances that have been interpreted previously as incense, fire, seeds, blood, or water. A recent study found these rituals are closely connected to agricultural cycles and may therefore represent symbolic acts of sowing or planting (Jobbová et al., 2018). Other royal rituals were recorded on monuments less frequently and at fewer sites within the largest connected component and are therefore excluded from the current study. Each instance of the selected rituals is associated with an inscribed calendar date which provides the necessary temporal information for investigating diffusion.

Although this dataset includes high-resolution temporal information, the model specification required several assumptions. We estimated the existence of a site based on the earliest and latest monument dedication dates at each site. Furthermore, we supposed that sites were “at risk” of adopting a ritual only after the first date that particular ritual was performed (8.6.0.0.0 or 159 CE for the accede and 9.0.4.0.0 or 439 CE for the scatter ritual). Therefore, we computed the beginning of the time at risk for each site as the maximum of the earliest recorded monument date and the first recorded date of the ritual. The end of the time at risk is the time of the occurrence of an event, for the sites which adopted the ritual, and the last inscribed date for a site which did not adopt the ritual (right censored observations).

Table 1
List of covariates used to specify the model in Equation (1) for analyzing the diffusion of innovation. The network configurations represented below the name of each covariate. Dots represent sites and their color indicates if a site has already adopted a ritual (black dot) or not (grey dot). A tie denotes the presence of a social/political relation between two sites. The last column of the table indicates the nested model(s) in which each variable is included.

Variables and model term	Description	Parameter interpretation	Model
<p>Baseline hazard</p> <p>Baseline hazard: $h_0(t; \alpha, \lambda) = \alpha \lambda t^{(\alpha-1)}$, $\alpha > 0$, $\lambda > 0$, $t \geq 0$.</p>	<p>Baseline tendency of sites to adopt a ritual as a function of the time elapsed from the first occurrence of that ritual. This term is equivalent to the intercept in linear regression model.</p>	<p>α: dependence of rate on time (trend)</p> <ul style="list-style-type: none"> - $\alpha < 1$: negative dependence on time (the hazard rate decreases over time) - $\alpha = 1$: independence on time (the hazard rate is constant over time) - $\alpha > 1$: positive dependence on time (the hazard rate increases over time) <p>λ: variation in the hazard rate over time (speed) the higher λ, the higher the variation over time</p>	0 to 3
<p>Site attribute</p> <p>Number of glyph blocks: $\beta_{\text{glyr}} x_{\text{glyr}}$</p>	<p>Number of glyph blocks recorded on the monuments of a site. This variable controls for sample size.</p>	<p>$\beta_{\text{glyr}} > 0$: the greater number of glyph blocks, the more likely the ritual was adopted</p>	0 to 3
<p>Contextual factor:</p> <p>Geographic proximity</p> <p>Geographical proximity: γ_i is assumed to be a gaussian process with marginal variance equal to σ^2 and covariance between any two sites of distance d apart to be $\sigma^2 \exp(-d^{\psi})$</p>	<p>Spatial variation of ritual adoption controlling for the effect of the geographical setting of the sites on adoption.</p>	<p>σ is a parameter measuring the spatial variability of ritual adoption</p> <p>$\sigma > 0$: ritual adoption is not uniform over the region</p> <p>φ is the spatial decay parameter measuring the strength and the direction of the autocorrelation between sites</p> <p>$\varphi > 0$: the likelihood that a site adopts a ritual increases if there are close by sites that have already adopted a ritual</p>	1 to 3
<p>Network variables</p> <p>Proportion of adopters: $\gamma_{\text{adopt}} z_{\text{adopt}}$</p> <p>Number of triangles: $\gamma_{\text{tr}} z_{\text{tr}}$</p> <p>Number of two-paths: $\gamma_{\text{tp}} z_{\text{tp}}$</p>	<p>Proportion of adopters within the neighborhood (i.e. among the direct contacts) of a site. This variable controls for the exposure of sites to the ritual and models the idea that sites connected to sites that have already adopted a ritual are more likely to adopt the ritual as well. This idea is the fulcrum of contagion models (Menzel and Katz, 1955; Goffman and Newill, 1964) and is equivalent to a special case of frequency-dependent (conformist) bias for social networks.</p> <p>Number of triangles with at least one adopter in which a site is embedded. This variable models network closure: Being embedded in a network structure where every site is connected to any other sites facilitate communication among sites and foster diffusion.</p> <p>Number of two-paths with at least one adopter in which a site is embedded. This variable models the effect of indirect contacts on adoption.</p>	<p>$\gamma_{\text{adopt}} > 0$: the higher the proportion, the more likely the adoption of the ritual</p> <p>$\gamma_{\text{tr}} > 0$: the higher the number of triangles with at least one adopter, the more likely the adoption of the ritual</p> <p>$\gamma_{\text{tp}} > 0$: the higher the number of two-paths with at least one adopter, the more likely the ritual adoption</p>	2 to 3

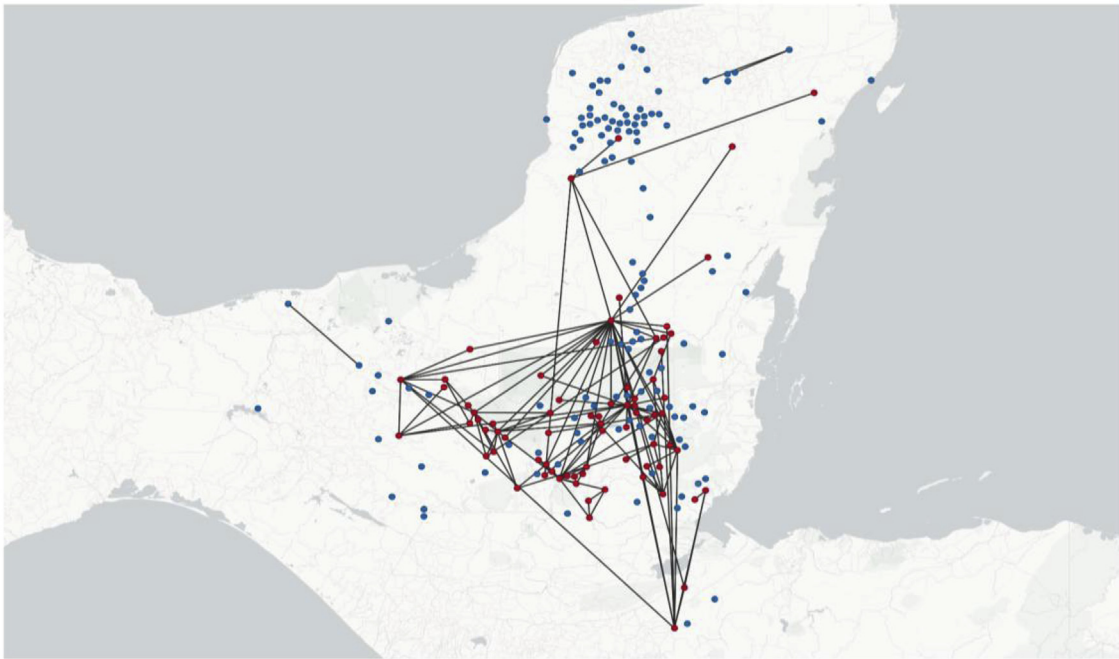


Fig. 2. Network of relations among the 198 sites present in the Maya Hieroglyphic Database. Red nodes are sites belonging to the strongest component of the network. Ties in the network do not account for the different type of the relations and for multiplicity, i.e. there is a link between two sites if at least one dynastic relation was inscribed.

4.2. Model specification and estimation

Based on the factors outlined in Section 2 and the available data, we specified a set of covariates representing the possible determinants of diffusion. Table 1 lists the covariates along with the corresponding descriptions, diffusion factors, and parameter interpretations. Appendix A provides a comprehensive description.

We estimated four nested models for each of the considered rituals (see Appendix B for the model specifications and their estimates). Model 0 is the baseline model and controls for sample size using the number of glyph blocks recorded in each site. In addition to these variables, Model 1 controls for the geographical location of the sites. Model 2 and Model 3 add network variables to evaluate what kinds of ties facilitate innovation diffusion. The former includes the proportion of adopters within the neighborhood of a site, which represents a special case of frequency-dependent biased transmission specific to social networks. The latter additionally considers the triangles and the two-path covariates which are indicative of network-based diffusion (Franz and Nunn, 2009). In the following, we refer to Model 0 and Model 3 as the null and the full model, respectively. The deviance information criterion (DIC) was used to determine the model with the best fit for each ritual. Lower values of the DIC indicated a better fit.

4.3. Results

Table 2 shows the parameter estimates of the best fitting model for each ritual. The models were estimated using the software R (R Core Team, 2018) and the package spatsurv (Taylor and Rowlingson, 2017). The best fitting model for the accession ritual is the full model. All the variables are significant at the 0.05 level. The positive coefficients for the baseline hazard suggest that the probability of adoption increases over time. The very small value of the parameter α is due to the considerable duration of the time period we analyzed. The full model indicates that the likelihood of adopting an accession ritual depends on the network variables. In particular, the positive coefficients of the network variables suggest that the risk of adoption increases with the proportion of adopters in the neighborhood of a site, the number of

Table 2

Parameter estimates of the best fitting model for each ritual. An asterisk indicates that a parameter is significant at a 95% level. The models were estimated using the R package spatsurv (Taylor and Rowlingson, 2017).

	Accession	Scatter
<i>Baseline hazard</i>		
α	3.5978*	3.7119*
λ	< 0.0001*	< 0.0001*
<i>Site attribute</i>		
Number of glyph blocks	1.0015*	1.0015*
<i>Contextual factor: geographic proximity</i>		
σ	1.3185*	0.6852*
φ	0.1605*	0.1425*
<i>Network site factors</i>		
Proportion of adopters	0.1075*	
Number of triangles	1.3872*	
Number of two-paths	0.9467*	

adopters that are indirectly connected to a site, and the embeddedness of a site in groups of well-connected sites with at least one adopter. Jointly interpreted, these results indicate that the network structure plays a significant role in the diffusion of the accession ritual. More specifically, both network closure, and direct and indirect contacts with sites that have already adopted the accession ritual foster the diffusion of this ritual. This model also controlled for the number of glyph blocks and the geographic setting. The positive parameter for the number of glyph blocks indicates that the more glyph blocks recorded at a site, the higher the likelihood of adoption. The parameters related to geographic proximity are also positive and significant. The two parameters σ and φ suggest that the adoption of the accession ritual is characterized by a positive spatial autocorrelation, i.e., sites close to other sites adopting the accession ritual are more likely to adopt that ritual as well. While consistent with previous findings (Scholnick et al., 2013; Munson et al., 2014, 2016), these results provide a more explicit test of specific network configurations by accounting for the timing and spread of this dynastic ritual.

In contrast, the best fitting model for the scatter ritual suggests that the network factors are not determinants for the diffusion of this ritual. Instead, the spread of the scatter ritual is best explained by time, space, and sample size. In particular, the risk of adopting a scatter ritual increases over time and is fostered by geographical proximity as well as the total number of glyph blocks present at a site. This result is surprising because it challenges findings from previous studies that showed a strong association between overall ritual similarity and network ties between sites (Munson et al., 2016). These findings have important implications for the ways that archaeological networks are constructed and analyzed, which are discussed in greater detail below.

5. Discussion

Diffusion of innovation aims to explain how attitudes, ideas, and novel traits spread in a population. As demonstrated by many studies in the social sciences literature, a multitude of factors might be responsible for the spread of new traits. Those factors are often intertwined, and thus, their effect cannot be studied separately. In this paper, we argue that the development of methods for analyzing the diffusion of cultural traits in archaeology is often limited to testing single determinants due to the simplifying assumptions made in them and/or the availability of data. Thus, new methods need to be developed or adopted from other disciplines in order to explore a wider range of factors contributing to the spread of ancient technologies, artifact styles, or past practices. Recent developments in network analysis and event history models provide us with sophisticated tools to analyze innovation diffusion in a more nuanced way. As a multivariate technique, these models allow investigating and distinguishing the effects of various determinants of diffusion. We demonstrate the applicability of these models by examining the effects of sample size, spatial proximity, and network variables on the diffusion of specific Classic Maya rituals.

Based on previous findings, we hypothesize that network ties were important conduits for the spread of Classic Maya royal rituals. The model estimates indicate that this hypothesis is supported by the data for the accession rituals, but not for the scatter ritual. Instead, more parsimonious factors such as geographical proximity and sample size better account for its diffusion. To explain these different mechanisms of diffusion, we return to the idea of information content and consider the messages encoded by these particular rituals. Recognizing that, in general, human ritual practice is a form of communication, Rappaport (1999, pp. 50–54) identifies two broad categories of information transmitted through rituals. Self-referential messages include information about an individual's status or current state and are statements that represent “the immediate, the particular, and the vital aspects of events,” whereas canonical messages represent “the general, enduring, or even eternal aspects of universal orders” that transcend the present (Rappaport, 1999, p. 53). Although all rituals are, by definition, “more or less” invariant, self-referential messages tend toward greater degrees of variation than more standardized canonical messages (Rappaport, 1999, pp. 36, 54). Framed in this way, accession rituals align more closely with self-referential statements about a newly appointed ruler's status or power, while scatter rituals follow more canonical acts associated with agricultural ceremonies. The six different verb roots denoting royal accession further underscore the self-referential and variable nature of these dynastic rites. Such distinctions in information content have important implications for understanding the way in which these rituals spread. The diffusion of self-referential messages about an individual's status, power, and authority may represent an inherently social process that involves competition, lineage or some other kind of interaction as defined by the network variables. On the other hand, the spread of canonical messages may be facilitated by participation in much broader traditions surrounding monument dedication, period ending ceremonies, and agricultural cycles as suggested by the scatter ritual. These findings underscore the importance of considering the specific information content alongside individual-level

attributes and network properties for the diffusion of innovations.

These findings also have important implications for archaeological network science more generally. Although many studies employ measures of artifact similarity to reconstruct network ties and infer past social interactions, it is equally important to consider how traditional geographic and phylogenetic factors affect the transmission of cultural traits. Failure to incorporate these variables into network models may produce results that under-specify neutral processes or misrepresent the mechanisms responsible for the empirical patterns archaeologists observe.

Our example demonstrates that models and mechanisms derived from the cultural evolutionary (CE) literature complement the application of social network methods to investigate factors contributing to the diffusion of innovations. We used event history analysis to examine the effects of sample size, spatial proximity, and various network variables for conformist-bias transmission. Although we used the number of glyph blocks recorded at each site to control for sample size biases, some might argue that the quantity of inscriptions could also serve as a proxy for prestige (i.e., the more monuments commissioned by a ruler, the higher his/her status). While this approach would have allowed us to evaluate the role of prestige-bias transmission, we would have to assume a complete dataset. As in most archaeological cases, our observations are limited due to the fragmentary nature of the material record. In this case, we know that some sites have poor monument preservation which yield illegible inscriptions. Therefore, we exhibited caution in the use of proxy measures to estimate prestige, but future studies could investigate alternative measures such as plaza area or construction volume that are independent of sample size.

Although we examined a number of factors in this study, there are some limitations that remain to be addressed. Despite the precision of the Maya calendrical system, sources of incomplete information might lead to i) left truncation and right censoring; ii) measurement errors in the dependent variable—the earliest inscribed date of a ritual might not correspond to the time to adoption—and independent variables—particularly the number of glyph blocks and the network covariates. Even though event history models are able to deal with right censoring and left truncation, they cannot control for measurement errors as other statistical models. Previous analysis of this data investigated the different types of sociopolitical relationships that constitute this network (Munson and Macri, 2009; Scholnick et al., 2013). Although we believe that different types of ties might foster the diffusion of rituals in various ways, the data on specific ritual categories are too sparse to test this with sufficient power. Another potential limitation of applying event history models to archaeological data relates to temporal resolution. If the trait being analyzed is observed over a long period of time (e.g., several centuries), it may be unrealistic to assume that the diffusion process occurred over such a long stretch of time. In our application, rituals were recorded over a period of more than 800 years. If the time period can be truncated, using calibrated radiocarbon dates for example, this might improve the results. Additional important information that could support the idea of a diffusion is the repetition of the ritual events over time. Repetition can boost diffusion and could be modeled by using event history models for repeated events. These models, however, are still under development and will be applied in future studies.

Despite the limitations deriving from data resolution and missing information, we argue that event history models provide a valuable and flexible method to simultaneously analyze and test different processes responsible for the diffusion of cultural traits. They can be applied in a variety of contexts with entities ranging from individuals to households or, more generally, aggregated units, such as sites. They can also deal with diverse time resolution. We focused only on continuous-time models due to the nature of the data in this illustrative example; however, discrete-time event history models can be applied to archaeological case studies where the temporal information is derived from ordered stratigraphic deposits and other relative dating methods.

Therefore, we believe that further investigations and archaeological applications of event history models would be desirable to properly evaluate the potential of these methods in archaeology.

Conflicts of interest

The authors declare that they have no conflict of interest.

Funding

This research was supported by the project NEXUS1492, which has received funding from the European Research Council under the European Union's Seventh Framework Programme (FP7/2007–2013)/ERC grant agreement no 319209, and by a grant from the National Science Foundation (Award No. 1328928).

Acknowledgements

Special thanks to Martha Macri, Matthew Looper, and Yuriy Polyukhovych for their work on the Maya Hieroglyphic Database.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jas.2019.01.006>.

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