Title: New distance-based exponential regression method and equations for estimating the chronology of linear enamel hypoplasia (LEH) defects on the anterior dentition.

Short Title: New regression method for estimating the chronology of linear enamel hypoplasia defects.

Alejandra Cares Henriquez

Marc F Oxenham

School of Archaeology and Anthropology

Australian National University, Canberra, ACT 2601, Australia

Corresponding Author

Marc F Oxenham

Phone +61 2 61254418

Marc.oxenham@anu.edu.au

Text pages

Bibliography pages 4

Tables 7

Figures 2

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ABSTRACT

Objectives: We present a new distance-based exponential regression approach based on published histological data to refine the objectivity, accuracy and precision of age estimates of LEH defect formation on the anterior dentition.

Methods:

Published histological data of anterior tooth crown growth for two samples (northern European and southern African) were fitted with exponential trendlines to construct exponential regression equations for each tooth type. A theoretical comparison of the age estimates produced by two commonly used methods, and those based on the exponential regression equations presented in this paper were undertaken. Paired-samples t-tests were used to determine whether the estimates obtained by these methods differed significantly.

Results: Exponential regression equations were able to accurately replicate age estimates produced by the decile-chart method. For defects that fell precisely on a decile, estimates differed by 1-24 days. Estimates based on the linear regression method were consistently younger by 5-14 months. For defects that fell within deciles, the exponential regression equation estimates, when different, were 1-4 months older than those yielded by the decile method.

Conclusions: By combining currently published histological data on anterior tooth crown growth with a regression approach, it is possible to produce more accurate age estimates than yielded by methods that do not rely on histological data. Furthermore, this approach also greatly improves the objectivity, precision and replicability of results, especially for defects that fall between deciles, when compared to the decile chart method.

Linear enamel hypoplasia (i.e., LEH) are developmental defects that result from episodic growth disruptions experienced during childhood. The identification and analysis of LEH is considered standard practice in bioarchaeological studies where they are regarded as an important tool for reconstructing aspects of health in the past (Goodman & Rose, 1990; Hillson & Bond, 1997).

Hypoplastic defects, which are characterised by a deficiency in enamel thickness, can manifest in a variety of forms, such as pitting, layers or patches of missing enamel, or horizontal grooves (LEH). LEH is the most common form and is associated with accentuated perikymata, where perikymata are the surface expression of the internal incremental growth layers of enamel known as striae of Retzius (Hillson & Bond, 1997; Skinner & Goodman, 1992). Because enamel does not naturally remodel, developmental defects of enamel remain as a permanent record and can provide evidence of the experience of systemic physiological stress.

The specific aetiology of the various types of enamel hypoplasia remains unclear and they are generally accepted as non-specific indicators of stress (Goodman & Rose, 1990). Although hypoplastic defects can result from inherited conditions as well as local trauma, the occurrence of inherited defects is quite rare (Hillson & Bond, 1997). The vast majority of defects are linked to factors of a systemic and episodic nature that disrupt the normal secretory activity of cells responsible for enamel production, such as dietary deficiencies, infectious disease, fevers, intoxication, metabolic disorders, parasite infestations, and environmental pollution (Goodman & Rose, 1990; Hillson, 1996; Hillson & Bond, 1997; Kierdorf, Kierdorf, Sedlacek, & Fejerskov, 1996; Pindborg, 1982; Psoter, Reid, & Katz, 2005; Skinner & Goodman, 1992; Suckling, Elliott, & Thurley, 1983; Suckling, Elliott, & Thurley, 1986; Wong, 2014).

The unique characteristics of enamel, the generally good preservation of teeth archaeologically, and the episodic nature of factors leading to LEH formation, means LEH can record the periodicity and duration of enamel growth disturbances associated with systemic stress events (Guatelli-Steinberg, 2008; Hillson & Bond, 1997). Therefore, at the most basic level, establishing the chronology, or estimating the approximate age of the individual at the time of defect formation, is one of the primary aims of research that incorporates the analysis of these defects. This information can then be utilised to undertake more comprehensive analyses enabling the reconstruction of individual life histories, which can be a valuable source of information for evaluating the social and environment context of past populations, in particular with relation to growth (Sandberg, Sponheimer, Lee-Thorp, & Van Gerven, 2014; Temple, 2016).

There is a clear association of LEH defects with the incremental growth layers of enamel that are deposited from the incisal edge toward the direction of the cemento-enamel junction (CEJ) (Hillson & Bond, 1997). This makes it possible to infer the approximate age of the individual at the time of defect formation based on the location of the defect on the tooth crown (Skinner & Goodman, 1992).

Current Methods for Estimating Chronology

There are two primary methods used for estimating the chronology (the age of the individual at the time of defect formation) of LEH that occurs on the anterior dentition. The first method is a distance-based method that relies on regression equations using a linear model of tooth growth to estimate the chronology of LEH defects based on their distance from the CEJ (Goodman & Rose, 1990). The second and more recent method is a decile-based chart introduced by Reid and Dean (2000), which has been constructed from histologically derived data and assumes a curvilinear model of enamel growth. Both are commonly used in bioarchaeological assessments of LEH (usually done on a macroscopic scale), as neither requires the presence of perikymata (incremental growth layers of enamel) to produce age estimates. In addition, the two methods are equally applicable in microscopic studies, particularly those dealing with worn archaeological samples where perikymata are not clearly visible or continuous (e.g. Cares Henriquez & Oxenham, 2017). However, there are some key differences between the two, the main one relating to the assumptions made regarding the rate of enamel growth. Furthermore, they also differ in their capacity for objectivity, precision, and accuracy.

The distance-based linear regression approach was first introduced by Swärdstedt (1966), who drew on enamel developmental standards published by Massler, Schour, and Poncher (1941), specifically the ages at which enamel crown formation begins and ends, to estimate age at defect formation. By performing a linear interpolation within the range of these discrete minimum and maximum ages, Swärdstedt (1966) devised a chart that could be used to estimate the age of defect formation on the permanent dentition by determining the distance of the defect from the CEJ. Two decades later, Goodman and Rose (1990) refined the objectivity of these standards. They presented linear regression equations to assess chronology, based on the standards of Massler et al. (1941) and the mean crown heights of Swärdstedt (1966). These equations were later revised by Goodman and Song (1999), who acknowledged a number of inherent biases associated with the underlying standards used in the equations and, in particular, recommended applying a correction to account for hidden cuspal enamel as well as the naturally occurring population variation in crown height. The exclusion of cuspal enamel formation time is regarded as a major limitation of the Goodman and Rose (1990) regression equations by a number of researchers, as it is likely to significantly underestimate the chronology of early forming LEH (Goodman & Song, 1999; King, Hillson, & Humphrey, 2002; King, Humphrey, & Hillson, 2005; Skinner & Goodman, 1992).

The decile-based chart approach involves dividing the crown height of each tooth into deciles, where each decile represents 10% of the crown height. Each decile is then assigned a range of chronological ages based on the published standards. The chronology estimates of LEH defects are based on their location within deciles on the crown height of a tooth. As part of their histological study, Reid and Dean (2000) identified three key findings that affect the accuracy of previous standards for estimating the age of defect formation: 1) the rate of enamel growth is not constant but instead slows down over time, that is, it is not linear; 2) there is no observable relationship between tooth crown height and the time it takes for crown completion; and 3) visible surface enamel is unlikely to form prior to one year of age in all anterior tooth types. A second histological study by the same authors, confirmed that while variation in crown formation time can be expected amongst different populations, the range of variation within and between populations is smaller than reported in previous radiographic studies (Reid & Dean, 2006).

Studies by Martin, Guatelli-Steinberg, Sciulli, and Walker (2008), Ritzman, Baker, and Schwartz (2008), and more recently Lukasik and Krenz-Niedbala (2014), have sought to quantify the difference between the age estimates produced by the linear distance-based regression methods and the decile-based chart method. All three studies observed that the decile chart method yields much older ages than methods that rely on the original standards by Massler et al. (1941), including the distance-based regression method of Goodman and Rose (1990). Furthermore, they note that these differences are most apparent when analysing early forming LEH in the occlusal crown region, which relates to whether cuspal enamel formation times have been incorporated into the standard. In addition, the results obtained by

Lukasik and Krenz-Niedbala (2014) suggest that age estimates between the methods differed more for maxillary than mandibular teeth.

Ritzman et al. (2008) also investigated the extent to which the estimate for modal age of disruption was affected when using the Swärdstedt (1966) chart as opposed to the decile method (Reid & Dean, 2000, 2006), which was based on northern European and southern African samples. The Swärdstedt estimates were found to be some 18 months younger when using the African data and two years younger when using that of the European sample. Overall, Ritzman et al. (2008) concluded that the difference between the estimates of the two methods is sufficiently significant to potentially produce divergent interpretations of the biocultural factors underlying metabolic stress in both archaeological and living populations—a view supported by others (e.g. Hillson (2014)). This was especially evident when considering the peak age of LEH formation, an effect that was also observed by Krenz-Niedbała and Kozłowski (2013), and Lukasik and Krenz-Niedbala (2014). In contrast, Martin et al. (2008) argued that the differences are statistically (especially when teeth are scaled for wear), but not biologically, significant (a time difference from 1-4 months). This is particularly relevant when considering how these age estimates are used to reconstruct patterns of stress in archaeological populations.

Despite the different conclusions, all three studies agree that, at least from a theoretical perspective, the histologically derived decile-based method of Reid and Dean (2000, 2006) should produce more accurate age estimates. This is due to the erroneous assumption of a linear or constant rate of enamel development by the distance and regression-based methods, a problem that Hillson and Bond (1997) and other researchers also highlighted previously.

In contrast, the decile-based chart method not only takes into account the nonlinear growth of enamel, but also accounts for hidden cuspal enamel (considered to be the strongest factor in shifting the age of early forming LEH), and variation in crown initiation time by tooth type.

Even so, while the developmental growth data published by Reid and Dean (2000, 2006) are increasingly being utilised in studies to estimate the chronology of LEH defects (e.g. Berbesque & Hoover, 2018; Cares Henriquez & Oxenham, 2017; Gamble, Boldsen, & Hoppa, 2017; Miszkiewicz, 2015; Novak et al., 2018; Smith, Kurtenbach, & Vermaat, 2016; Temple, Nakatsukasa, & McGroarty, 2012; Tomczyk, Tomczyk-Gruca, & Zalewska, 2012; Trinkaus, Mednikova, & Dobrovolskaya, 2014), others continue to use the linear distance-based regression method (e.g. Krenz-Niedbala, 2014; Krenz-Niedbała & Kozłowski, 2013; Smith et al., 2016), or other iterations constructed from the original standards (e.g. D'Anastasio et al., 2013; Gawlikowska-Sroka, Dabrowski, Szczurowski, Dzieciolowska-Baran, & Staniowski, 2017).

Both the linear distance-based regressions and the decile approach have advantages and disadvantages. What is most appealing about the distance-based linear regression method is that it provides an objective way of estimating the chronology of LEH defects. Moreover, it can generate precise age estimates based on the distance of the defect from the CEJ easily by inputting the observed measurement into a formula, all of which are characteristics that improve the replicability of the results. Its shortcoming lies in the flawed assumptions that underlie the standards on which it relies (i.e. constant rate of enamel deposition and no consideration of hidden cuspal enamel and crown initiation times), which reduces the accuracy of the age estimates.

On the other hand, the key strength of the decile-based approach is that the histologically derived data that underpins the estimates are more reliable and accurate. Not only do such estimates capture the nonlinearity of enamel growth, they also incorporate hidden cuspal enamel, crown initiation timing, and variation in crown height. However, a major drawback is the subjectivity that is introduced when the decile-based approach is used in its graphic form, which offsets the advantage it has over other existing methods. Although each of the deciles is clearly defined and associated with an age, the chart itself is not conducive to precise estimates when defects fall within one of the broad developmental phases, requiring at the very least some sort of visual interpolation. Because of this, most studies that employ the decile method tend to either report an age range (i.e. the ages of the two surrounding deciles), or the earliest age, which is the age of the most recently completed decile. Furthermore, because the age ranges associated with specific deciles differ depending on tooth type, without precise estimates for individual LEH defects, further subjectivity is introduced when trying to match these across multiple teeth of the same individual, as is common in bioarchaeological studies. These factors all contribute to a reduction in the replicability of the results.

In this study, we present a set of distance-based exponential regression equations derived from the more accurate, and increasingly used, developmental growth data published by Reid and Dean (2000, 2006), and Reid and Guatelli-Steinberg (2017). We suggest that by using regression equations to estimate the age of defect formation based on its distance from the CEJ, it is possible to refine the objectivity of the existing decile-chart approach, while offering more precise age estimates and improving the overall replicability of results. In addition, we undertake a theoretical comparison of the age estimates produced by the two primary methods currently used for estimating the chronology of LEH defects with those produced by the approach outlined in this paper.

METHODS

In our study, we use previously published histological data of surgically extracted anterior teeth consisting of a northern European sample (n=115) by Reid and Dean (2000) and a southern African sample (n=155) by Reid and Dean (2006); Reid and Guatelli-Steinberg (2017). The data for the northern European sample (Table 1) indicate the total amount of time required (in days/years) for each decile of crown height to form in each of the upper and lower anterior teeth. For the purposes of this study, the time represented between initial mineralisation of enamel and cuspal enamel completion is not essential and so has been omitted. The period of time represented at zero indicates the time when cuspal enamel is complete. The age at the first decile indicates the time taken for the first 10% of crown height to be completed, while the tenth decile indicates the time of full crown completion. In addition, we also reference linear regression equations by Goodman and Rose (1990) for a comparison of the age estimates produced by the three different methods (i.e. decile, linear regression, and exponential regression).

Curve Fitting and Model Selection

Linear and non-linear curve fitting of the data was undertaken to examine the relationship between time (chronology) and crown height (distance), to produce a model that best described the relationship (see Figure 1). In this case, because we are using growth data that place a limit on the ages at which cuspal enamel and full crown completion has occurred, we present age (y-axis) as a function of distance from CEJ or crown height (x-axis). For each model, the y-intercept was constrained to the maximum age of crown completion for each tooth as per data in Reid and Dean (2000, 2006); Reid and Guatelli-Steinberg (2017). Five models (R=5) were fitted to the data from each tooth type (upper central incisor, upper lateral incisor, upper canine, lower central incisor, lower lateral incisor, and lower canine). The fitted models included linear, exponential, quadratic and 3rd and 4th order polynomial functions. Table 2 lists the specific models fit on the upper central incisor (northern European sample), which we use to demonstrate our method.

Competing models in each set were compared and evaluated using the Akaike Information Criterion (AIC) method, which measures the relative quality of a set of competing statistical models for a given dataset in an attempt to identify the (likely) best model, in order to evaluate and inform our decision on model selection (Akaike, 1973, 1981; Burnham & Anderson, 2002). The AIC, which is based on information theory, estimates the relative information lost if a certain model were to be employed when compared to another model. It balances the trade-offs between any given model's goodness of fit as assessed by sum-of-squares, and the complexity of the model as assessed by the number of parameters (k) to be fit.

The AIC works on the notion that although continually adding parameters to a model makes it possible to better approximate a dataset, this becomes a trade-off against over-fitting and losing information about the real underlying pattern. Thus, the 'best' model is that which is the most parsimonious and has the lowest relative AIC value in a set of competing models (Burnham & Anderson, 2002; Motulsky & Christopoulos 2004):

$$AIC = -2\ln(L) + 2k$$

where L is the value of the likelihood function evaluated at the parameter estimates, and k is the number of estimated parameters (degrees of freedom). In our study, we use a second-order corrected AIC (AIC_c), which is recommended when sample size n is small compared to the number of parameters k (i.e. $n/k < 40$), calculated as:

$$AIC_c = AIC + \frac{2k(k+1)}{n-k-1}$$

where n is the number of observations, k, and AIC are defined above (Burnham & Anderson, 2002; Hurvich & Tsai, 1989; Motulsky & Christopoulos 2004).

Model selection using AIC involves calculating relative AIC scores of each model in a set to determine which of the competing models is more likely to be correct, and to quantify this probability. Other additional measures are usually calculated to assess the strength of evidence for each candidate model. These include the AIC differences (Δi), Akaike weights (w_i), and evidence ratio (ER). The computed relative Akaike scores (AIC_c) were first used to rank the candidate models against each other from best to worst and then used to calculate the AIC_c differences, calculated as:

$$\text{Delta } AIC_i = \Delta i = AIC_i - \text{AIC}_{\text{min}}$$

where AIC_i is the AIC_c score for the ith model and AIC_{min} is the AIC_c score of the 'best' model (the model with the lowest score) to determine the probability of each model as being the best model. As a general rule of thumb, $\Delta_i < 2$ indicates the candidate model has substantial support, and is almost as good as the best model (Burnham & Anderson, 2002). Burnham, Anderson, and Huyvaert (2011) note that while earlier literature has suggested that models with $\Delta_i > 2$ were poor in relation to the best model, and could be dismissed, this arbitrary cut-off is now known to be poor. Instead, they recommend considering models with Δ_i 0 – 7 as plausible; Δ_i 7 – 14 as equivocal, and $\Delta_i > 14$ as implausible.

Next, Akaike weights (w_i), which represent the ratio of the Δ_i of a specific model i relative to the entire set of competing models (R), and can be used as another measure of the strength of evidence, were calculated as:

$$w_i = \frac{\exp\left(-\frac{1}{2}\Delta_i\right)}{\sum_{r=1}^{R}\exp\left(-\frac{1}{2}\Delta_r\right)}$$

where Δ_i is the ΔAIC_c, and *R* is the number of candidate models used in the analysis.

Finally, the model probabilities of the best second-best models were used to compute an evidence ratio (ER), to quantify how much more likely the best model is to be correct versus the other model in question, which are calculated as

$$\mathrm{ER} = \mathrm{w}_{best}/\mathrm{w}_i$$

where w_i is the competing, or in our case, the second-best model. The results of the above-mentioned calculated measures are presented in Table 3.

Exponential Regression Fitting and Construction of Equations

In Figure 2 we present the pattern of growth for upper lateral incisors from Reid and Dean (2000) as a continuous black line to demonstrate our method. These data were fitted with exponential trendlines (black dashed line), which were used to produce individual exponential regression equations for each tooth type as listed in Table 4.

In these exponential regression equations, the *y* intercept for each regression is set as the maximum age for crown completion, that is the age at the tenth decile, *e* is the mathematical constant, and *x* is the distance of the defect from the CEJ as a proportion of crown height available. The *x* is calculated as the distance from CEJ (*d*) divided by the length of the tooth available in mm (*l*), which itself is divided by the percentage of tooth that is missing (1 - *m*). The formula for calculating *x* can be expressed as:

$$x = {}^{d}\Big/\frac{l}{1-m}$$

The linear regression equations of Goodman and Rose (1990), which are used when applying the current distance-based method for estimating the chronology of LEH defects, were shown as a dotted black line in Figure 2 and plotted alongside the decile and exponential distance data. Following the above method, a set of equations for the data from southern African sample by Reid and Dean (2006) were also constructed, and can be seen in Table 5. For these, updated crown initiation times and crown completion ages published by Reid and Guatelli-Steinberg (2017) were used.

We estimated the age of defect formation for two sets of 10 hypothetical LEH defects on a upper lateral incisor assuming no crown height wear, in a manner analogous to that employed by Ritzman et al. (2008), in an effort to undertake a theoretical comparison of the age estimates produced by the two commonly used methods and those of the exponential regression equations presented in this paper. The first set is comprised of 10 defects, each of which represents one of the 10 deciles of crown height, as defined by the Reid and Dean (2000) decile chart. Three age estimates were calculated for each of the 10 defects in set 1. The first estimate was produced using the Reid and Dean (2000) chart, and reports the age as the age of the last completed decile. The second age estimate was calculated using the distance-based exponential regression equations presented in this paper, while the final estimate was calculated using the distance-based linear regressions of Goodman and Rose (1990). The second set is made up of 10 randomly generated numbers (distances) which fall between each of the decile intervals. Two age estimates were calculated for each of the 10 defects to quantify the difference between estimates produced using the decile chart and the exponential regression equations. Paired-samples t-tests were used to compare the difference between the age estimates produced by the different methods used in each set.

RESULTS

Curve Fitting and Model Selection

Figure 1 offers a visual depiction of the curve fitting results as undertaken on data from northern European upper central incisor (set 1), which we use here to demonstrate our method (for fitted models see Table 2). Charting of the data along with visual inspection confirmed that which has been previously published: Enamel growth is not linear, but rather curvilinear, with crown formation gradually slowing down over time. In other words, there is an exponential increase in the time represented by each percentage of crown height.

Both the exponential and quadratic growth models, which are similar in form, performed better than all other competing models in all six sets. These two models consistently had the lowest AIC_c scores and were found to be the most parsimonious models for the given data (see Table 3). Therefore, the exponential and quadratic models were identified as being the two best candidate models. In some instances, the exponential performed better, such as in sets one and three, while in the others the quadratic model performed slightly better. In all cases, when comparing the best and second-best model, the $\Delta_i < 14$. The only exception to this was in set one, where $\Delta_i = 14.56$, and the exponential model was 1455 times more likely to be the best model. However, at its maximum, the difference between the predictions produced by two models is in the order of 16 days, which occurs on set 6 (Exponential S = 0.106, Quadratic S = 0.061). In fact, in most cases, both models had a higher than 99.99% probability of being correct. Consequently, we regard both the exponential and quadratic models to be equivalently supported by the data and equally good for estimating the chronology of LEH.

What we can rule out is the linear model, which is clearly a poor representation of the data. The linear model consistently had the highest AIC_c score (ranked worst), with a standard error of regression of 0.362 (132 days) at its worst, and 0.212 (77 days) at its best. Similarly, higher order polynomials are also less parsimonious and run the risk of overfitting.

The choice of the quadratic or exponential model is left to the analyst, depending on the computational tools they have available. They will deliver largely the same result, and there is little evidence to suggest that predictions would change in a meaningful way between the two. In this paper, we use the exponential equation as the representative function, which fits the data well and is less complex from a computational perspective.

Exponential Regression Fitting and Equation Construction

The exponential regression equations for each tooth type of the northern European and southern African samples are presented in Tables 4 and 5. The equation for estimating the age of a defect found on the upper lateral incisor in the northern European sample, which we also used in our theoretical comparison of age estimates, is 5.1 multiplied by *e* to the power of -0.106*x*. The reported R-squared values for all equations, which measure how close the data are to the fitted regression line, were above 0.99. The standard error of the regressions, which is a measure of the accuracy of estimates or predictions, ranged between 0.03 and 0.11 for the northern European set, and 0.04 to 0.08 for the southern African set.

The results of the theoretical analyses comparing the age estimates produced by the decile, linear regression and exponential regression method outlined in this paper are presented in Tables 6 and 7. For set 1, where defects fell precisely on each decile (see Table 6), the maximum difference between all the age estimates produced by the exponential regression equations when compared to those produced by the decile chart was 0.8 months, or 24 days. The differences ranged from 0.02-0.8 months, or 1-24 days, while the average deviation was 0.4 months, or 12 days. The standard error of the estimate for the exponential method was 0.04, which is the equivalent of 15 days.

The maximum difference between all the age estimates produced by the linear regression equations when compared to the decile chart was 14 months or 1.2 years. The largest differences were observed toward the incisal edge of the tooth, that is, for the early forming LEH. Differences ranged from 5-14 months, while the average deviation was eight months. The standard error of the estimate for the linear regression equation was 0.82, which is the equivalent of 297 days. The differences observed at the distance of 10mm (the cuspal tip of the tooth) were excluded since, in practice, defects would not be identified at that location when assessing LEH. All the age estimates produced by the linear regression equations were younger than those produced by the decile chart.

Two paired-samples t-tests were conducted to compare the difference between the age estimates produced by the decile method and the two regression methods (exponential, linear). There was no statistically significant difference between the age estimates produced using the decile method ($M = 3.16$, $SD = 1.10$) when compared to those produced using the exponential regression method ($M = 3.17$, $SD = 1.10$); $t(10) = 0.9571$, $p = .36$. On the other hand, there was a statistically significant difference between the age estimates produced using the decile method ($M = 3.16$, $SD = 1.1$) when compared to those produced using the linear regression method ($M = 2.49$, $SD = 1.33$); $t(10) = 7.08$, $p = .0001$. The results suggest that when estimating the age of the defects that fall precisely on a decile, the exponential regression method produces age estimates that are more comparable to those produced using the decile method than those produced by the linear regression method.

For set 2, where defects fell within deciles (see Table 7), the maximum difference between all the age estimates produced by the exponential regression equations when compared to those produced by the decile chart was four months. The differences ranged from 1-4 months, while the average deviation was two months. The age estimates produced by the exponential regression equations, when different, were older than those yielded by the decile chart. However, this is because the decile chart estimates report the age of the last completed decile.

Two paired-samples t-tests were conducted to compare the difference between the age estimates produced by the decile and exponential regression method. There was a statistically significant difference in the age estimates produced using the decile method (M = 2.97, SD = 0.94) when compared to those produced using the exponential regression method (M = 3.11, SD = 1.00); $t(9) = 4.03$, $p = .003$. These results suggest that when estimating the age of defects that fall between deciles, the estimates produced by the decile chart significantly underestimate the defect's age of occurrence.

DISCUSSION

Although the decile chart method by Reid and Dean (2000) was not intended to be regarded as a set of new standards from which to estimate the chronology of LEH defects, it has become increasingly used in this way by many bioarchaeological studies. The main reason given by researchers for choosing the decile approach when considering which method to use, is that it accounts for components of enamel growth ignored by the linear method. However, in its current chart form, as it is most widely used, a major limitation is introduced by the lack of objectivity and precision that comes from relying on a chart to produce the estimate. In most cases, studies are forced to report either an age range, or the age of the most recently completed decile. This introduces an additional layer of subjectivity when matching individual defects across multiple teeth of the same individual in order to discount defects that may not be related to systemic physiological stress. It is no surprise then, that contemporary studies continue to employ the older distance-based linear regression equations, despite the flawed assumptions that underpin the standards on which they are based.

In this study, we present a set of distance-based exponential equations that have been constructed from the published histologically derived data of enamel growth from northern European and southern African samples by Reid and Dean (2000, 2006) and by Reid and Guatelli-Steinberg (2017). We suggest that by combining this data with a distance-based exponential regression approach, it is possible to remove the subjectivity that comes from using the decile chart method to estimate the age of LEH defect formation, especially for defects that fall between deciles. In addition, a regression approach is conducive to producing more precise and replicable age estimates than using a chart. More importantly, the exponential regression improves the accuracy of age estimates without compromising on those features that currently make less accurate methods seem more attractive.

Like the decile-based chart approach, the exponential equations presented in this paper are based on proportions of total crown height and can therefore accommodate naturally occurring individual and population variations in crown height. Unlike the existing linear regression equations, these will not produce negative age estimates near the incisal edge when examining larger teeth. Another noteworthy feature of these equations is that they incorporate estimates of tooth crown wear, thus ensuring that this is taken into account when dealing with worn archaeological dental assemblages. However, it should be noted that wear estimates can themselves potentially introduce another source of error.

Our theoretical comparison shows that the exponential regression equations perform exceptionally well when compared to age estimates produced by the decile chart, with an average of only 12 days difference for defects that fell precisely on a designated decile on the upper lateral incisor (northern European). On the other hand, estimates produced by the linear regression equations, were consistently younger by up to 1.2 years, with an average difference of seven months. Additionally, the results suggest that the exponential regression equations offer an improvement especially for estimating the chronology of defects that fall within deciles, which is where most defects are located. This is because age estimates produced using the decile chart method must be reported as either the age of the last completed decile, making the age estimate younger than it should be (by an average of four months, and as much as 6.2 months in deciles that represent a larger interval of time), or as a broad age range, which can then be problematic when matching defects across multiple teeth on the same individual.

In the absence of more population specific standards being available, others have used the decile chart method extensively and applied it to all sorts of populations other than those from which these data are derived (i.e. northern European and southern African) (Reid & Dean, 2000, 2006). Still, it needs to be recognised that the developmental projections may vary between different populations (Reid & Dean, 2006). Therefore, the overall accuracy of any method employed, including the exponential regression method presented here, will also inevitably be tied to how well the standards being applied reflect the developmental pattern of the group being studied.

CONCLUSION

Curve fitting of histologically derived data of enamel growth has confirmed that the relationship between time (chronology) and crown height (distance) is not linear, but rather curvilinear. Furthermore, when considering different models to describe the underlying pattern of growth, it is evident that a linear model is a poor representation of the data. Both the quadratic and exponential models were equivalently supported by the data and are equally suitable for estimating the chronology of LEH defects. In this paper, we choose the exponential model, which is simpler from a computational perspective.

The approach we propose has several advantages over existing methods. It removes the subjective element that is introduced into age estimates when using the decile chart, which requires the observer to visually judge where the defects falls in relation to the defined intervals. It provides more accurate age estimates than methods that do not rely on histological data, (i.e. the linear regression method). In addition, it produces precise age estimates for all LEH defects, including those that fall between the defined intervals of the decile method, which is crucial for objectively matching defects across multiple teeth on the same individual. Furthermore, not only are estimates easy to generate using a formula, but they can also take into account observed estimates of crown height wear and can accommodate teeth of varying sizes.

Although the methods discussed in this paper are most commonly used in macroscopic assessments of LEH, the approach and/or equations presented here will be equally useful for microscopic studies that require a method for estimating the chronology of LEH defects when perikymata are not clearly visible or continuous (e.g. Cares Henriquez & Oxenham, 2017). They may also prove useful in studies of living populations, such as reported on by Ungar, Crittenden, and Rose (2017), which rely on photographs to assess LEH defects.

As new histological data become available, either population specific or of larger samples, the approach outlined in this paper can be used to easily update or construct new equations that capture these differences.

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FIGURE CAPTIONS

Figure 1. Curve fitting of enamel growth data of upper central incisor (northern European). Data for Decile method taken from Reid and Dean (2000)

Figure 2. x-axis is distance from CEJ in mm; with corresponding decile given in parentheses. Data for Decile method taken from Reid and Dean (2000); Data for Linear Regression taken from Goodman and Rose (1990).

Table 1. Timing of anterior tooth growth stages along complete crown height in days for northern European sample (years in parentheses) – extracted from Reid and Dean (2000)

Decile	Distance from CEJ (mm)	Upper Central Incisor		Upper Lateral Incisor		Upper Canine		Lower Central Incisor		Lower Lateral Incisor		Lower Canine	
10	0.0	1836	(5.0)	1861	(5.1)	1946	(5.3)	1399	(3.8)	1522	(4.2)	2266	(6.2)
9	1.0	1612	(4.4)	1691	(4.6)	1768	(4.8)	1257	(3.4)	1361	(3.7)	2048	(5.6)
8	2.0	1421	(3.9)	1502	(4.1)	1571	(4.3)	1101	(3.0)	1202	(3.3)	1781	(4.9)
7	3.0	1223	(3.4)	1339	(3.7)	1383	(3.8)	953	(2.6)	1033	(2.8)	1533	(4.2)
6	4.0	1041	(2.9)	1199	(3.3)	1236	(3.4)	825	(2.3)	873	(2.4)	1319	(3.6)
5	5.0	875	(2.4)	1073	(2.9)	1099	(3.0)	710	(2.0)	749	(2.1)	1125	(3.1)
4	6.0	749	(2.0)	966	(2.7)	983	(2.7)	618	(1.7)	642	(1.8)	971	(2.7)
3	7.0	652	(1.8)	878	(2.4)	879	(2.4)	543	(1.5)	558	(1.5)	839	(2.3)
2	8.0	569	(1.6)	802	(2.2)	789	(2.2)	475	(1.3)	481	(1.3)	724	(2.0)
1	9.0	489	(1.3)	727	(2.0)	706	(1.9)	406	(1.1)	414	(1.1)	627	(1.7)
0	10.0	417	(1.1)	657	(1.8)	629	(1.7)	346	(1.1)	358	(1.0)	548	(1.5)

Table 2. Curve fitting of five models on enamel growth data of upper central incisor (northern European)

Model (Set 1)	
Linear	$y = -0.4422x + 5.03$
Exponential	$y = 5.03e^{-0.147x}$
Poly 2	$y = 0.026x^2 - 0.6461x + 5.03$
Poly 3	$y = 0.0002x^3 + 0.0234x^2 - 0.638x + 5.03$
Poly 4	$y = -0.0004x^4 + 0.0074x^3 - 0.0193x^2 - 0.5642x + 5.03$

Table 3. Summary of AIC results for models relating to enamel growth data of six anterior tooth types (northern European)

SET 1 - 11 UCI													
Model	**R^2**	**S**	**SS**	**N**	**K**	**AIC$_c$**	**Rank**	**Δ_i**	**RL**	**w_i**	**ΔB_1-B_2**	**ER**	**P (%)**
Linear	0.9054	0.31	0.0971	11	1	-46.53	5	47	0.000	0.000			
Exponential	0.9980	0.04	0.0014	11	1	-93.22	1	0	1.000	0.999	0.00	1455.8	>99.99%
Quadratic	0.9991	0.06	0.0037	11	2	-78.65	2	15	0.001	0.001	14.56		0.07
Poly 3	0.9992	0.20	0.0417	11	3	-46.66	4	47	0.000	0.000			
Poly 4	0.9997	0.14	0.0184	11	4	-48.35	3	45	0.000	0.000			
SET 2 - 12 ULI													
Model	**R^2**	**S**	**SS**	**N**	**K**	**AIC$_c$**	**Rank**	**Δ_i**	**RL**	**w_i**	**ΔB_1-B_2**	**ER**	**P (%)**
Linear	0.9179	0.255	0.0653	11	1	-50.87	5	41	0.000	0.000			
Exponential	0.9978	0.040	0.0016	11	1	-91.70	2	0	0.798	0.438	0.45		>99.99%
Quadratic	0.9992	0.033	0.0011	11	2	-92.15	1	0	1.000	0.549	0.00	1.3	>99.99%
Poly 3	0.9994	0.036	0.0013	11	3	-84.74	3	7	0.025	0.013			
Poly 4	0.9999	0.051	0.0026	11	4	-69.88	4	22	0.000	0.000			
SET 3 - 13 UC													
Model	**R^2**	**S**	**SS**	**N**	**K**	**AIC$_c$**	**Rank**	**Δ_i**	**RL**	**w_i**	**ΔB_1-B_2**	**ER**	**P (%)**
Linear	0.9324	0.257	0.0661	11	1	-50.75	5	46	0.000	0.000			
Exponential	0.9995	0.032	0.0010	11	1	-96.43	1	0	1.000	0.596	0.00	1.64	>99.99%
Quadratic	0.9993	0.028	0.0008	11	2	-95.45	2	1	0.612	0.365	0.98		>99.99%
Poly 3	0.9993	0.032	0.0010	11	3	-87.69	4	9	0.013	0.008			
Poly 4	0.9997	0.020	0.0004	11	4	-90.58	3	6	0.054	0.032			
SET 4 - 31 LCI													
Model	**R^2**	**S**	**SS**	**N**	**K**	**AIC$_c$**	**Rank**	**Δ_i**	**RL**	**w_i**	**ΔB_1-B_2**	**ER**	**P (%)**
Linear	0.9285	0.212	0.0450	11	1	-54.98	4	41	0.000	0.000			
Exponential	0.9973	0.052	0.0027	11	1	-85.92	2	10	0.006	0.006	10.14		0.62
Quadratic	0.9989	0.027	0.0008	11	2	-96.06	1	0	1.000	0.994	0.00	159.49	>99.99%
Poly 3	0.9989	0.049	0.0024	11	3	-78.23	3	18	0.000	0.000			
Poly 4	0.9999	0.209	0.0435	11	4	-38.85	5	57	0.000	0.000			
SET 5 - 32 LLI													
Model	**R^2**	**S**	**SS**	**N**	**K**	**AIC$_c$**	**Rank**	**Δ_i**	**RL**	**w_i**	**ΔB_1-B_2**	**ER**	**P (%)**
Linear	0.9240	0.246	0.0603	11	1	-51.77	4	38	0.000	0.000			
Exponential	0.9967	0.065	0.0043	11	1	-80.94	2	8	0.015	0.014	8.44		>99.99%
Quadratic	0.9984	0.037	0.0014	11	2	-89.38	1	0	1.000	0.980	0.00	67.91	>99.99%
Poly 3	0.9989	0.541	0.2925	11	3	-25.23	5	64	0.000	0.000			
Poly 4	0.9998	0.033	0.0011	11	4	-79.19	3	10	0.006	0.006			
SET 6 - 33 LC													
Model	**R^2**	**S**	**SS**	**N**	**K**	**AIC$_c$**	**Rank**	**Δ_i**	**RL**	**w_i**	**ΔB_1-B_2**	**ER**	**P (%)**
Linear	0.9250	0.362	0.1310	11	1	-43.24	3	35	0.000	0.000			
Exponential	0.9970	0.106	0.0112	11	1	-70.32	2	8	0.017	0.017	8.13		>99.99%
Quadratic	0.9985	0.061	0.0037	11	2	-78.45	1	0	1.000	0.983	0.00	58.25	>99.99%
Poly 3	0.9989	0.532	0.2834	11	3	-25.58	5	53	0.000	0.000			
Poly 4	0.9998	0.202	0.0409	11	4	-39.54	4	39	0.000	0.000			

S = Standard Error of the Regression - Measure the precision of the model's predictions; SS= Sum of Squares of Residuals; N= sample size K= Number of Parameters to be fit; AICc- Akaike Information Criterion (corrected); Rank= based on AICc score (lowest value being best) Δi = Difference between model with lowest score (best model) and other model; RL= Relative likelihood; wi= Akaike weight; ΔB1-B2 = Difference in AICc score between best and second-best model; ER=Evidence Ratio; P=Probability of model being correct as %

Table 4. Exponential regression equations constructed using histological data for northern European sample from Reid and Dean (2000)

Tooth		Age Estimate Equation	R^2	S
Upper Central	I^1	Age[a] = $5e^{-0.146x}$	0.9975	0.09
Upper Lateral	I^2	Age = $5.1e^{-0.106x}$	0.9978	0.04
Upper Canine	C^1	Age = $5.3e^{-0.112x}$	0.9992	0.03
Lower Central	I_1	Age = $3.8e^{-0.135x}$	0.9964	0.07
Lower Lateral	I_2	Age = $4.2e^{-0.144x}$	0.9975	0.06
Lower Canine	C_1	Age = $6.2e^{-0.141x}$	0.9969	0.11

[a] Age in years (multiply by 365 for age in days).
e is the mathematical constant.
x is the distance of the defect from the CEJ in mm as a proportion of crown height available
S is Standard Error of the Regression

Table 5. Exponential regression equations constructed using histological data of southern African sample from Reid and Dean (2006) and Reid and Guatelli-Steinberg (2017)

Tooth		Age Estimate Equation	R^2	S
Upper Central	I^1	Age[a] = $4.2e^{-0.124x}$	0.9958	0.07
Upper Lateral	I^2	Age = $4.9e^{-0.107x}$	0.9915	0.08
Upper Canine	C^1	Age = $4.4e^{-0.127x}$	0.9988	0.05
Lower Central	I_1	Age = $3.4e^{-0.146x}$	0.9987	0.04
Lower Lateral	I_2	Age = $3.6e^{-0.139x}$	0.9980	0.04
Lower Canine	C_1	Age = $5.2e^{-0.128x}$	0.9976	0.08

[a] Age in years (multiply by 365 for age in days).
e is the mathematical constant.
x is the distance of the defect from the CEJ in mm as a proportion of crown height available
S is Standard Error of the Regression
Both crown initiation times as well as crown completion times are taken from updated data in Reid and Guatelli-Steinberg (2017). Decile formation times are taken from Reid and Dean (2006).

Table 6. Set 1- Theoretical Comparison of Age estimates of LEH defects that fall precisely on a decile by three methods on unworn upper lateral incisor (northern European)

	Age Estimates (years)			**Difference (months)**	
Distance (mm)	Decile*	Exp Reg	Lin Reg	ER-D	LR-D
0.0	5.10	5.10	4.50	0.02	-7.28
1.0	4.63	4.59	4.10	-0.56	-6.51
2.0	4.12	4.13	3.70	0.13	-5.10
3.0	3.67	3.71	3.29	0.51	-4.56
4.0	3.28	3.34	2.89	0.64	-4.78
5.0	2.94	3.00	2.49	0.76	-5.47
6.0	2.65	2.70	2.09	0.65	-6.80
7.0	2.41	2.43	1.69	0.28	-8.75
8.0	2.20	2.18	1.28	-0.16	-11.11
9.0	1.99	1.96	0.88	-0.33	-13.50
10.0	1.80	1.77	0.48	-0.40	-16.06
Formula		$5.1e^{-0.106x}$	$-0.402 \times H_t + 4.5$		
			Max	0.8	-14
			Range	0.02-0.8	5-14
			Average Deviation	0.4	8.2
			Standard Error of Estimate (years)	0.040	0.82
			Standard Error of Estimate (days)	15	297

*Earliest age; Distance = distance in mm from CEJ; ED-R= Exponential Regression minus Decile; LR-D=Linear Regression minus Decile. Age estimates have been rounded up to 2 decimal points. Maximum difference, range and average deviation rounded up to 1 decimal point when less than 1 month, otherwise rounded up to the nearest integer.

Table 7. Set 2 - Theoretical Comparison of Age estimates of LEH defects that fall between deciles by two methods on unworn upper lateral incisor (northern European)

	Age Estimates (years)		**Difference (months)**
Distance (mm)	Decile*	Exp Reg.	ER-D
0.30	4.63	4.94	3.74
1.95	4.12	4.15	0.40
2.60	3.67	3.87	2.47
3.20	3.28	3.63	4.23
4.99	2.94	3.01	0.80
5.97	2.65	2.71	0.75
6.37	2.41	2.60	2.32
7.69	2.20	2.26	0.73
8.49	1.99	2.07	1.00
9.36	1.80	1.89	1.11
Formula		$5.1e^{-0.106x}$	
		Max	4
		Range	1-14
		Average Deviation	2

*Earliest age; Distance = distance in mm from CEJ; ED-R= Exponential Regression age minus Decile age. Age estimates have been rounded up to 2 decimal points. Maximum difference, range and average deviation rounded up to the nearest integer.