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# Does deposition depth control the OSL bleaching of fluvial sediment?

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# Abstract

The Optically Stimulated Luminescence (OSL) signal from fluvial sediment often contains a remnant from the previous deposition cycle, leading to a partially bleached equivalent-dose distribution. Although identification of the burial dose is of primary concern, the degree of bleaching could potentially provide insights into geomorphic processes. However, comparison of bleaching between samples is complicated by sample-to-sample variation in aliquot size and luminescence sensitivity. Here we develop an age model to account for these effects. With measurement data from multigrain aliquots, we use Bayesian computational statistics to estimate the burial dose and bleaching parameters of the single-grain dose distribution. We apply the model to 46 samples taken from fluvial sediment of Rhine branches in the Netherlands, and compare the results with environmental predictor variables (depositional energy and environment, sample depth, depth relative to mean water level, dose rate). We find no significant correlations between any predictor variable and the bleaching parame-

ters, although large uncertainties may be obscuring relationships. However, the best bleached samples are found close to the mean water level. Based on these results, we hypothesize that bleaching occurs mainly during fluvial transport rather than upon deposition, with extra bleaching possible for sediments near the transition of channel to overbank deposits due to local reworking after deposition either by wind or water.

#### 20 **1** Introduction

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The use of Optically Stimulated Luminescence (OSL) for dating Holocene fluvial deposits is widespread. However, fluvial sediments are not ideal for OSL dating because the energy of sunlight under water may not be sufficient to reset the OSL signal in some grains prior to their deposition. The remnant OSL signal can then cause the burial dose to be overestimated, leading to an overestimate of the age. This phenomenon is referred to as poor, partial, or heterogeneous bleaching (e.g. Wallinga, 2002a).



While the burial age is usually the primary consideration, there are good reasons to quantify the degree of bleaching too. Firstly, it may provide information on the robustness of an OSL age. Secondly, the degree of bleaching might yield information on the sediment source or sediment-transport processes. For instance, if a tsunami deposit appears well-bleached, it could indicate that shallow shore-face or intertidal deposits provided the primary sediment source (Murari et al., 2007). For fluvial deposits, poor bleaching might for instance reflect short transport distances, or an old deposit acting as primary source.

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To compare the bleaching between samples, it is first necessary to distinguish the <sup>10</sup> part of the equivalent dose (*D*<sub>e</sub>) built up since the time of deposition, from the poorly bleached remnant dose. Previous studies have avoided this issue by deliberately sampling modern or known-age sediment. Such studies have indicated that bleaching is better in coarse sand-sized grains compared to finer grains (Olley et al., 1998; Truelsen and Wallinga, 2003), and may be dependent on depositional context (Murray et al., <sup>15</sup> 1995; Schielein and Lomax, 2013) and transport distance (Stokes et al., 2001; Jain et al., 2004 and references therein).

Nevertheless, the inherent variability from sample to sample makes definitive conclusions hard to come by. The main problem arises in distinguishing signal from noise: how much of the sample-to-sample variation in bleaching is due to physical processes,

- as opposed to random statistical fluctuations? Studies focusing on modern or knownage deposits seldom have enough samples for confident conclusions to be drawn, and no study has attempted to account for natural variation between identical samples. Moreover, Jain et al.'s (2004) review showed a discrepancy in residual doses of modern fluvial samples compared to young known-age samples, with modern samples yielding
- <sup>25</sup> larger residual doses. They argued that modern deposits may yet be re-mobilised, so their transport history is not representative of deposits preserved in the stratigraphic record.

Here we focus not on modern samples, but samples of various ages that have already been used for age estimation. This approach allows for more samples to be



included, and avoids the bad-modern-analogue issue, but presents the additional problem of separating out the burial dose from the remnant dose. For this purpose we have designed a new, Bayesian age model for partially bleached  $D_{\rm e}$  distributions. We define the degree of bleaching by the proportion of grains that were well-bleached upon deposition, rather than by the remnant dose. We apply the model to a suite of 46 samples from embanked floodplains of the lower Rhine, and correlate the outcome with geomorphic data for each sample.

# 2 Methods

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# 2.1 Samples and measurements

- We use a dataset of OSL measurements on a suite of 46 samples from embanked floodplain deposits formed during the past 700 years. Different parts of the dataset have been presented by Hobo et al. (2010), Wallinga et al. (2010) and Hobo et al. (2014). Samples come from four different sites, all located in the Rhine delta in the Netherlands (Fig. 1). At each of the sites, several cores (diameter 14–19 cm) were taken in a cross-
- section perpendicular to the river course (see Hobo et al., 2010 for examples). Samples were extracted from the cores in subdued orange light and prepared using methods described by Wallinga et al. (2010). For each of the sample sites, cross-sections were constructed based on the borehole database of Utrecht University (Berendsen and Stouthamer, 2001), and additional hand corings. The cross sections were interpreted to identify morphogenetic units (see also Hobo et al., 2014).

For all samples, radionuclide concentrations were determined with high-resolution gamma-ray spectroscopy, from which dose rates were estimated using standard conversion factors. Sand-sized quartz grains were extracted for SAR OSL measurements (Murray and Wintle, 2003) for equivalent dose measurements. Details of the procedure are described by Hobo et al. (2010) and Wallinga et al. (2010). The grainsize fractions varied between samples (180–212, 180–250, or 90–180 µm). The measurement



protocols were similar for all samples. The dose response was defined using a single regenerative dose (Wallinga et al., 2010); net OSL signals defined using the early background subtraction (Cunningham and Wallinga, 2010); and low preheat temperatures were selected to avoid thermal transfer (e.g. Truelsen and Wallinga, 2003).

- <sup>5</sup> We identified nine variables that could influence the bleaching of the sample. The choice of variables is based on our judgement of possible relevance and data availability. With regard to sample position, we considered the average river water level at the site (recorded in 2001), the height of the present surface at the sample location, the depth of the sample below the present surface, and the depth of the sample relative to the 2001 average water level. With regards to the sample nature, we considered the
- <sup>10</sup> the 2001 average water level. With regards to the sample nature, we considered the depositional environment, the sample grain size, the dose rate,  $D_e$ , and the OSL age (although the  $D_e$  and OSL age are derived from the model, they could also be considered as predictor variables). Table S1 (in the Supplement) provides an overview of all variables that are considered.

#### 15 2.2 Statistical rationale

We seek to define a poor-bleaching score based on the measured  $D_{\rm e}$  distribution, which can then be used to compare bleaching between samples. Previous attempts have applied a statistical model directly to the  $D_{\rm e}$  distribution to define a summary statistic (e.g. the f-statistic, Spencer et al., 2003, skewness and kurtosis applied to

- <sup>20</sup> single-grain SG distributions, Bailey and Arnold, 2006). This type of approach may be valid if the observed  $D_e$  distribution is a function of the burial dose and remnant dose. For multi-grain (MG) aliquots, the OSL signal comes from many grains; the  $D_e$  for an aliquot is the average of those grains, weighted by their OSL sensitivity (e.g. Wallinga, 2002b; Duller, 2008; Cunningham et al., 2011). So for MG datasets, the  $D_e$  distribution
- <sup>25</sup> is a function of the burial and remnant doses, and also the aliquot size and the singlegrain sensitivity distribution.

Aliquot size and SG sensitivity may vary between samples, so for a statistic to be useful, it must be independent of these factors for the range of samples considered.



A model defined directly on the  $D_e$  distribution of young samples is also likely to be sensitive to the burial dose, as the measurement precision decreases with  $D_e$ . Our dataset contains many samples, measured over several years on different OSL readers. While the SG sensitivity distributions are likely to be similar, the aliquot size varies both between and within samples: measurements used either 2 mm or 3 mm mask size, with grain sizes of 180–212, 180–250 or 90–180 µm.

- A statistic defined from the MG aliquot  $D_e$  distribution (such as the burial dose, overdispersion, degree-of-bleaching) may not have any real-world meaning, because the data is affected by the confounding variables of aliquot size and SG sensitivity. The
- <sup>10</sup> meaningful parameters operate at the single-grain level, so the approach we take here is to estimate what combination of single-grain parameters would lead to the measured MG  $D_{\rm e}$  distribution. There are two parts to the procedure. First, we define the parameters operating at the single-grain level, and how the MG distribution can be derived from them. Second, we use Bayesian computational statistics to estimate the value <sup>15</sup> each parameter must take to reproduce an observed MG  $D_{\rm e}$  distribution.

# 2.3 From single-grain parameters to the multigrain-aliquot distribution

# 2.3.1 The single-grain sensitivity distribution

The size of the OSL signal induced from a given radiation dose varies from grain to grain. The sensitivity distribution also varies between samples (Duller et al., 2000).
Quantifying the SG sensitivity is important for dating partially bleached samples, because it governs the extent of averaging across multi-grain aliquots (Cunningham et al., 2011). We therefore need to define the SG sensitivity distribution in order to simulate an MG *D*<sub>e</sub> distribution. While this can be done using a single-grain measurement system, there are practical difficulties: some grain holes may be empty, some may contain more than one grain; and with many sensitivity values clustered around zero, it is difficult to distinguish signal from noise.



Here we use computational Bayesian statistics to estimate the SG sensitivity distribution from the MG sensitivity data. The first step is to parameterise the SG sensitivity, for which we use the gamma distribution. The gamma distribution can be formatted with two parameters: a shape parameter *a*, and a scale parameter *b*. By altering these parameters, the gamma distribution can comfortably fit a range of measured SG sensitivity distributions (Fig. 2a). Moreover, when a MG aliquot is simulated from SG sensitivity data, the MG distribution can also be fitted with a gamma distribution (Fig. 2b). For measured data, we already know the MG sensitivity distribution (from the regenerative-dose signal), and the number of grains in the aliquot (from the grain size and mask size); we can therefore estimate the parameters *a* and *b* of the SG sensitivity distribution using a computational Bayesian procedure similar to that described below.

# 2.3.2 Modelling the *D*<sub>e</sub> distribution

The single-grain parameters are as follows:

- SG sensitivity, drawn from the gamma distribution with parameters:
  - a Shape parameter
    - b Scale parameter
- The burial dose, drawn from a normal distribution with parameters:
  - γ Mean

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- $\sigma_{\rm b}^{\rm SG}$  Standard deviation
- The remnant dose, drawn from the positive part of a normal distribution with mean of 0 and:
  - $\sigma$  Standard deviation
  - p Proportion of well-bleached grains



- Additional parameters:
  - $n_{q}$  Number of grains in each aliquot
  - n<sub>a</sub> Number of aliquots

The simulated natural OSL signal from  $n_a$  aliquots is the sum of the signal from  $n_g$ grains, with Poisson noise added. Each grain is assigned a sensitivity value (per gray) drawn from the gamma distribution with parameters *a* and *b*, and an indicative dose. The indicative dose combines the burial dose, drawn from a normal distribution, and a remnant dose, drawn from a half-normal distribution. The number of grains in each aliquot that have a remnant dose is drawn from the binomial distribution with parameters  $n_g$  and 1 - p. The  $D_e$  is determined by constructing a dose-response curve in the same way as measured data, i.e. one regenerative point of 3 Gy, sensitivity-corrected (although no sensitivity change is added), and subject to the same rejection criteria. Where different aliquot sizes are used in the measured data, these are replicated in the simulation. The aliquot size is approximated using the known mask size and grain size, assuming spherical grains and a 0.7 packing density.

# 2.4 Computational Bayesian solution

With the  $D_{e}$  distribution simulated by single-grain parameters, we seek to identify which values the parameters must take to result in the best match between the simulated MG distribution and the measured MG distribution. In Bayesian terms, we seek the posterior distribution, which measures how plausible we consider each possible value of the parameters after we have observed the data. For complex models such as this, the posterior density cannot be calculated directly. Instead, inferences are based on random sampling of the posterior distribution, which requires intensive computation.

In our model, the posterior is sampled using a Markov Chain Monte Carlo (MCMC) process. Single-grain parameters for four Markov chains are drawn from a starting distribution, and these parameters are then corrected to better approximate the target



posterior. The approximate distributions are improved at each step using the Metropolis algorithm. When the simulation has run long enough, each step can be considered a random draw from the target distribution. The length of the sequence is determined by the convergence of the Markov chains; this is monitored by comparing the within<sup>5</sup> chain and between-chain variance, following the procedure of Gelman et al. (2004). The first 30 % of each Markov chain is discarded to ensure that the choice of starting values dose not influence the result.

# 2.4.1 Priors

Five parameters are determined in the computational processing:  $\gamma$ ,  $\sigma$ , p, a and b. <sup>10</sup> Each of these is assigned a prior distribution, which represents our knowledge of these parameters before any measurements are undertaken. The priors could in future be determined from previous measurement data, or in the case of  $\gamma$ , from the stratigraphic order of the samples. For a and b, the priors are given by the posteriors obtained from the SG sensitivity model. The other parameters are given largely uninformative priors <sup>15</sup> (Fig. 3). For  $\gamma$  we use a uniform prior; for  $\sigma$  the prior excludes only extreme values and serves to reduce computational time. For p, the prior demands that at least some grains are well bleached. Without this, there are endless combinations of low  $\gamma$ , and

grains are well bleached. Without this, there are endless combinations of low  $\gamma$ , and high  $\sigma$ , that can lead to the MG de distribution, although this effect should disappear using smaller aliquots.

#### 20 2.4.2 Density evaluation

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Parameters with positive values ( $\gamma$ ,  $\sigma$ , a, b) are estimated on the log scale; p must lie between 0 and 1, so is estimated on the logit scale (logit  $p = \log(p/(1-p))$ ; this transforms the unit interval to the real number line). The simulated MG  $D_e$  distribution is compared to the measured distribution using the models of Galbraith et al. (1999) as summary statistics. This provides four summary statistics to compare with the measured data (three from the 3-component Minumum Age Model – MAM3, and one from



the Central Age Model – CAM). The likelihood term is defined by projecting these values onto the bootstrap likelihood distribution for the measured data (see Cunningham and Wallinga, 2012).

The model is run in two phases. The first is a short run, giving an approximate range

<sup>5</sup> of the parameter space. The output of the first run is summarised by a multivariate normal distribution, which is used to define the starting distribution and jumping distributions for phase two. The second phase is run until convergence.

# 2.5 Model validation

Here we perform a simulation-recovery test to check that the model is performing as expected. Single-grain parameters are chosen, then used to simulated  $D_e$  data for two different aliquot sizes (80 and 300 grains). Each dataset is used as input for the age model, and the SG parameters reconstructed. The results are given in Table 1, and plotted in Fig. 4 for the burial dose  $\gamma$ .

For both aliquot sizes, the SG parameters can be reconstructed (Table 1). Recon-<sup>15</sup> struction of the 1 Gy burial dose is reasonably precise (8%) for the 80 grain aliquots, and very close to the bootstrapped MAM3 estimate of the burial dose on the MG aliquot dataset ( $1.03 \pm 0.08$  Gy, using  $\sigma_b$  of 0.16). For the 300 grain aliquots, the estimate of the burial dose is imprecise but accurate, and lies mostly outside the range of the MG aliquot  $D_e$  distribution. For multi-grain aliquots, it is quite possible that none of the aliquots are indicating the burial dose, if at least one grain contributing to the OSL signal on each aliquot is poorly bleached. The new age model is able to explore this possibility by making use of the MG sensitivity distribution and aliquots size. In contrast, the bootstrap MAM3 applied to the MG data, assumes some "well-bleached" aliquots exist,

so gives an overestimated burial dose of  $1.15 \pm 0.03$  Gy for this dataset ( $\sigma_{\rm b} = 0.08$ ). As a further step, it would be interesting to see how the age-model applied to multigrain aliquot data compares to single-grain data from the same sample. However, this comparison is not as simple as it sounds. Our model uses multi-grain aliquot data to estimate the assumed parameters of the SG  $D_{\rm e}$  distribution; it does not reconstruct



the SG distribution itself. Testing the model against SG data for a real sample would not distinguish between the performance of the model and validity of the assumptions about SG parameters. The way around this would be to construct an artificial sample with a known dose distribution, like Roberts et al. (2000) and Sivia et al. (2004), but
 <sup>5</sup> such an elaborate approach is outside the scope of this paper. Also, the mode of optical stimulation in single-grain measurement systems (green laser) differs from that used for MG aliguots (Blue LEDs). This prevents direct comparison between SG and MG, as

component separation is wavelength dependent (Singarayer and Bailey, 2004).

## 3 Results

- <sup>10</sup> The SG sensitivity is similar for all samples measured here, not surprising as they are all from recent Rhine deposits. The shape parameter *a* has a mean of 0.007 and standard deviation 0.003, indicating a highly skewed sensitivity distribution (more so than all of the example distributions in Fig. 2). The averaging effect on multi-grain aliquots is therefore very weak. The scale parameter *b* has a mean of 362 and standard de-<sup>15</sup> viation 274. Histograms of the bleaching parameters *p* and *σ* are shown in Fig. 5. *p* takes a wide range of values, with some well-bleached samples (*p* close to 1). The
- uncertainty on p is typically large, except for those values close to 1. The absence of low values of p is probably due to the prior (low p being defined as unlikely).

The distribution of sigma is skewed (Fig. 5b). the mean is 2 Gy, with most below 8 Gy. The high values in Fig. 5b have very poor precision, coming from samples with high p in which  $\sigma$  has little influence on the  $D_e$  distribution. The susceptibility of  $\sigma$  to outliers makes it unsuitable as an indicator of bleaching. The degree of bleaching is best defined by p, the proportion of well-bleached grains.



# Correlations

Table 2 gives the matrix of correlation coefficients, with bold print indicating significant relationships. Error terms are ignored in this analysis. Parameters a, b, and  $\sigma$  are analysed on the log scale, p on the logit scale. This is the way they are determined in

the model, and it helps to emphasise the well-bleached samples. There are multiple correlations among the predictor variables (numbers 1–12). Some predictor variables measure almost the same thing, while others are closely related. For example, deeper samples are older, and coarser, thus having lower dose rates. There are significant correlations between the sensitivity parameters *a* and *b* and several predictor variables;

these are probably due to inadequate aliquot-size estimates, as discussed in Sect. 4.
 Of most importance is the absence of significant correlation involving the bleaching parameters *σ* and *p* (see Fig. 6). However, closer inspection reveals an interesting relationship between *p* and the sample elevation above mean water level (a.m.w.l.). A number of samples have high logit *p*, corresponding to *p* greater than 0.85. When
 plotted against sample elevation a.m.w.l., it is clear that these samples were all deposited within 1 m of the modern water level (Fig. 6).

#### 4 Discussion

#### 4.1 Influences on bleaching

There appear to be significant relationships between the sensitivity parameters aand b, and several predictor variables: both a and b are correlated with sample depth/elevation, and with the depositional energy/environment. These relationships are difficult to account for in geomorphic terms, but may be a manifestation of subtle differences in grain size. Most measurements were carried out on grain-size range of 180–250 µm, with the aliquot size  $n_g$  estimated from the grain size and mask size.

<sup>25</sup> This grain-size range still allows differences in the grain-size distribution of the natural



sediment to be reflected on the disc. The finer sediments, once sieved, will contain more grains at the lower end of the range than coarser sediments. The aliquots prepared from overbank sediment will therefore contain more grains than assumed in the model, leading to an error in the model's estimate of the SG sensitivity. This error

- <sup>5</sup> would also feed through into the estimate of bleaching parameters. We should therefore ignore the correlations involving the sensitivity parameters for this dataset, and be cautious about any relationship between bleaching parameters and depositional environment or depth. Furthermore, the restriction on low *p* specified in the prior means that inferences should not be drawn from the absence of low *p* values in the posteri-
- <sup>10</sup> ors. However, this reasoning does not account for the extremely well-bleached samples clustering around mean water level.

Could the clustering reflect a real phenomenon? The data could be telling something about the comparative strengths of bleaching during transport and deposition. The attenuation of light (especially UV/blue) underwater is well-established (Berger, 1990),

- and if light intensity at deposition was the main control on bleaching we might expect shallower sediments to be better bleached (Wallinga, 2002a). The clustering of high *p* values around the mean water level may therefore reflect period of bleaching that occurs at deposition. However, close examination of the samples that are best bleached (NCL-111004, -5, -7, -8; NCL-2107157) shows that some of these are sandy channel
- deposits, whereas others are sand beds within silty overbank deposits, or silty overbank deposits with sand admixtures. All these samples are indeed within a meter from the transition of channel to overbank deposits. For the samples classified as channel deposits, deposition likely occured on top of point bars; potentially with swash/backwash operating and sub-aerial exposure likely (analogous to coastal beaches, which pro-
- <sup>25</sup> duce well-bleached quartz, e.g. Ballarini et al., 2003). For the well-bleached samples from overbank deposits, we hypothesize that sandgrains may have experienced aeolian reworing prior to final deposition and burial. Such aeolian reworking of sandy flood deposits has been documented following high-discharge events of the Waal and Lek (Isarin et al., 1995; illustrated in Fig. 8).



# 4.2 Rhine deposition

Deposition in the lower Rhine system has altered over the last 1000 years, and this can be seen in the summary age-depth plot (Fig. 7a). There appears to be a change in the mode of deposition around 300 years ago, since when about 1 m of sediment has accumulated. From Fig. 7b, it is clear that recent sedimentation has occurred above the mean water level, whereas older sediment accumulated much deeper. This shift in depositional mode can be explained by the record of anthropogenic modification of the river. Here we provide a brief summary, based on Middelkoop (1997), Hesselink (2002) and the recent work of Hobo et al. (2014) which was partly based on the same dataset that we used here. Two modifications may have affected sediment dynamics: first, the construction of dikes between AD 1000 and 1300; second, the construction of regularly spaced groynes from AD 1850. As a consequence of dike construction, the rivers changed from free-meandering to semi-natural systems that could only migrate within the embanked confines. River bends began to migrate downstream, rather than

<sup>15</sup> laterally. The cores taken from the embanked floodplains therefore show more recent overbank deposition overlying the earlier channel deposits. Implications of river training for sediment budgets in embanked floodplains of the River Waal are discussed in detail by Hobo et al. (2014).

#### 4.3 Age model

- This project necessitated a new age model for partially bleached, multi-grain aliquot data. The model we have produced uses Bayesian computational methods to estimate the parameters of the single-grain dose distribution, without the need for any single-grain measurements. Along the way, the parameters of the single-grain sensitivity distribution are estimated from multi-grain aliquot sensitivity data. Our approach has significant advantages over existing models:
  - The interaction of aliquot size and SG sensitivity is incorporated, meaning that prior quantification of the averaging effect is not necessary.



- It includes uncertainty deriving from the number of aliquots consistent with the burial dose.
- It provides an unbiased estimate of the burial dose, even when no aliquots are "well bleached". Poorly bleached samples give a very imprecise, but still accurate, estimate of the burial dose.

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- The degree of bleaching is quantified, and is independent of the SG sensitivity, aliquot size and sample age.
- Different datasets from the same sample (i.e. different aliquot sizes) can be combined to produce a single estimate of the burial dose.
- Our approach is far more complex than the alternatives, but we hope the clear advantages will spur further development. Of course the validity of the outcome rests on a number of assumptions. The parameterisation of the SG dose and sensitivity distributions must be appropriate, and crucially, the estimate of the number of grains in the aliquots should be reasonable. This paper uses archive data, so aliquot size was estimated only roughly. When applied in future, careful grain counting should take place; this could be performed manually or with a digital camera plus image-recognition software.

The age model has yet to be tested on known-age samples, and has plenty of room for improvement. In particular, it would be preferable to treat the  $\sigma_b^{SG}$  as an unknown parameter. As present, the model assumes that scatter in the single-grain burial dose population is exactly 20% (following Cunningham et al., 2011 and references therein). If it becomes possible to create a sample-specific estimate of  $\sigma_b^{SG}$  (e.g. through radiation transport modelling; Cunningham et al., 2012; Guerin et al., 2012), it could be incorporated as a prior. The posterior  $\sigma_b^{SG}$  would then be estimated along with  $\gamma$ ,  $\sigma$ and *p*. A further step would be to incorporate stratigraphic information on sample order and/or age (e.g. Cunningham and Wallinga, 2012), although this would significantly increase computational time.



# 5 Conclusions

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We have used archive data of fluvial samples from the lower Rhine floodplains to explore the controls on the degree of bleaching; for this purpose we designed a new age model which can estimate the single-grain dose and bleaching parameters from multi-grain aliguot data. It is likely that all samples contained significant numbers of

well-bleached grains, suggesting that most of the bleaching occurred before deposition. However, we found that the best-bleached samples were deposited close to the mean water level.

This result could conceivably have arisen through chance, given the small number of samples that make up the "cluster" and the large number of variables considered. Conversely, the quality of the bleaching estimates are limited by data inadequacies (with regard to aliquot size), which may be obscuring a stronger trend. In spite of these complications, we propose that the striking occurrence of well bleached samples around the transition from channel to overbank deposits is a genuine phenomenon that re-<sup>15</sup> flects additional bleaching due to reworking on or after initial fluvial deposition, due to

swash and/or aeolian processes.

Finally, we point out the shear difficulty of comparing the bleaching across different samples. This project started as a simple data-mining exercise, but eventually required an entirely new age-model to overcome the complexities involved. In light of this, it may be worth re-assessing some of the earlier work on fluvial bleaching, in which aliquot

size and/or single-grain sensitivity are ignored.

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Table	1. Result	s of th	ne si	imulation	recovery:	parameters	defined	by	the	mean	and	standard
deviatio	on of the	poster	rior d	distribution	n. N <sub>a</sub> = 40							

	true value	n <sub>g</sub> = 80	$n_{\rm g} = 300$
γ	1	$1.03 \pm 0.08$	$0.88 \pm 0.20$
σ	2.5	2.81 ± 1.66	$2.96 \pm 1.32$
р	0.7	$0.77 \pm 0.13$	$0.59 \pm 0.21$
а	0.03	$0.042 \pm 0.011$	$0.025 \pm 0.008$
b	600	$604 \pm 196$	$539 \pm 188$

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**Table 2.** Matrix of the correlation coefficient *R*. Values in bold indicate the correlation is significant at the 95% level (i.e. the null hypothesis is rejected at p = 0.05). Numbers 1 to 10 are predictor variables; numbers 11 to 16 are model derived.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Elevation above mean water level	1	-0.16	-0.15	0.51	-0.95	-0.06	0.68	-0.36	-0.26	-0.20	-0.58	-0.36	-0.22	-0.05	0.14	0.00
2	mean water level	-0.16	1	0.97	0.76	0.08	0.57	0.09	-0.21	-0.41	-0.15	0.27	0.35	0.21	0.06	0.37	-0.55
3	Surface elevation	-0.15	0.97	1	0.74	0.15	0.50	0.09	-0.17	-0.38	-0.31	0.32	0.41	0.25	0.02	0.39	-0.59
4	Sample elevation	0.51	0.76	0.74	1	-0.55	0.45	0.52	-0.42	-0.53	-0.26	-0.14	0.07	0.04	0.02	0.42	-0.48
5	Sample depth	-0.95	0.08	0.15	-0.55	1	-0.05	-0.67	0.41	0.31	-0.01	0.61	0.41	0.26	0.00	-0.13	-0.02
6	Sample width	-0.06	0.57	0.50	0.45	-0.05	1	0.08	-0.23	-0.47	0.18	0.16	0.17	0.04	0.09	0.27	-0.26
7	Dose rate	0.68	0.09	0.09	0.52	-0.67	0.08	1	-0.63	-0.60	-0.20	-0.50	-0.20	-0.08	-0.15	0.27	-0.19
8	Depositional environment	-0.36	-0.21	-0.17	-0.42	0.41	-0.23	-0.63	1	0.61	0.04	0.07	-0.15	-0.06	0.06	-0.13	0.06
9	Grain size	-0.26	-0.41	-0.38	-0.53	0.31	-0.47	-0.60	0.61	1	0.05	0.17	0.01	-0.15	0.14	-0.33	0.32
10	Site	-0.20	-0.15	-0.31	-0.26	-0.01	0.18	-0.20	0.04	0.05	1	0.12	0.07	-0.26	0.19	-0.46	0.42
11	Age	-0.58	0.27	0.32	-0.14	0.61	0.16	-0.50	0.07	0.17	0.12	1	0.91	0.25	0.09	-0.22	0.18
12	De	-0.36	0.35	0.41	0.07	0.41	0.17	-0.20	-0.15	0.01	0.07	0.91	1	0.19	0.05	-0.14	0.05
13	$\log \sigma$	-0.22	0.21	0.25	0.04	0.26	0.04	-0.08	-0.06	-0.15	-0.26	0.25	0.19	1	-0.31	0.18	-0.18
14	logit p	-0.05	0.06	0.02	0.02	0.00	0.09	-0.15	0.06	0.14	0.19	0.09	0.05	-0.31	1	-0.15	0.08
15	log a	0.14	0.37	0.39	0.42	-0.13	0.27	0.27	-0.13	-0.33	-0.46	-0.22	-0.14	0.18	-0.15	1	-0.60
16	log b	0.00	-0.55	-0.59	-0.48	-0.02	-0.26	-0.19	0.06	0.32	0.42	0.18	0.05	-0.18	0.08	-0.60	1



**Figure 1.** Map showing the sample sites. The sites Brummen and Zwolle are along the river IJssel, whereas the other two sites (Neerijnen and OB1-3) are along the river Waal. Both are branches of the river Rhine. OB1-3 refers to two cores from the Hiensche Uiterwaarden, and one core from the Gouverneursche polder.





**Figure 2. (A)** Three SG sensitivity distributions presented by Duller et al. (2000) from SG measurements (dotted lines). Each has been fitted using the gamma distribution, with sample name and shape parameter *a* indicated. **(B)** Simple stochastic simulation of a multigrain-aliquot sensitivity distribution. The simulation uses the measured SG sensitivity dataset RBM2 (from Duller et al., 2000), with parameters  $n_g = 200$  and  $n_a = 1000$ . The MG sensitivity distribution can also be fitted using the gamma distribution, with a = 5.70. The shape of the gamma distribution is indicated in the figure, with the y-scale normalised to the peak of the histogram.





**Figure 3.** Example posterior distributions for the five parameters determined through the age model (sample NCL-2107162).  $\gamma$  is the burial dose (Gy);  $\sigma$  indicates the residual dose (Gy); p is the proportion of well-bleached grains; a and b describe the SG sensitivity distribution. The prior for  $\gamma$  is uniform, and not shown. Priors for  $\sigma$  and p are based on expert judgment. Priors for a and b are defined by the posteriors of the SG sensitivity model.





**Figure 4.** Posterior distribution of the burial dose  $\gamma$  for simulated data of aliguots of (A) 80 grains and (B) 300 grains. The "given" burial dose is 1 Gy, other parameters specified in Table 1. The simulated D<sub>e</sub> distributions are visualised using PDF plots, of the type discussed by Galbraith (2010).

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**Figure 5.** Histograms of *p* and  $\sigma$  determined from 46 samples.







**Figure 6.** Relationship between the degree of bleaching (logit p) and possible predictor variables.





**Figure 8.** A sand bar is deposited close to the river Waal shortly after high discharge (photo by Gilbert Maas, Alterra). Due to the absence of vegetation such deposits may be reworked through aeolian processes, which may enhance bleaching for deposits formed above the mean water level.

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