

Short Communication

SatPlat: An algorithm for the standardised determination and normalisation of saturation plateaus of luminescence rock surface dating depth profilesDaniel W. Sperlich^{1*}, Arne Ramisch¹, Michael C. Meyer^{1*}¹Department of Geology, University of Innsbruck, Austria

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Abstract

Luminescence rock surface dating has undergone recent advances and is applied in various disciplines and settings. The bleaching of the luminescence signal at rock surfaces is described by several physical models which the measurement data needs to be fitted to. In preparation for fitting, the data must be normalised to a value representing the saturated plateau region. In this study, we conduct a literature review to identify which approaches for determining the plateau region and the normalisation factor have been used. Since there is currently no standardised approach, we developed and tested SatPlat, an algorithm based on the cumulative sum of log-differences of adjacent data points. It works in a semi-automated manner needing the user to manually define two parameters. SatPlat aims to standardise and simplify the determination and normalisation of saturation plateaus in luminescence rock surface dating while also increasing reproducibility.

Keywords: Luminescence rock surface dating, Saturation plateau determination, Saturation plateau normalisation, Rock surface exposure and burial dating, Software

1. Introduction

Recent advances in luminescence rock surface exposure and burial dating and the potential application as an erosion-meter (hereafter rock surface dating RSD) have resulted in its increasing application in a wide range of geological and archaeological settings (e.g. Liritzis, 2011; Sohbaty et al.,

2015; Jenkins et al., 2018; Gliganic et al., 2019, 2024; Sohbaty et al., 2018; Lehmann et al., 2019; Smedley et al., 2021). Various physical models describe the penetration of light into rock surfaces and thus the loss of the luminescence signal with depth (Polikreti et al., 2002, 2003; Laskaris and Liritzis, 2011; Sohbaty et al., 2011, 2012b; Freiesleben et al., 2023). The currently most widely accepted model of the bleaching process of optically stimulated luminescence (OSL) into rock surfaces is the bleaching with depth model (Sohbaty et al., 2011, 2012b):

$$L = L_0 e^{-\overline{\sigma}\varphi_0 t} e^{-\mu x} \quad (1)$$

where the maximum luminescence signal at saturation L_0 is assumed to be constant at all depths prior to bleaching. L is the remaining luminescence signal at depth x (mm) following exposure for time t (a). $\overline{\sigma}\varphi_0$ (a^{-1}) quantifies the effective decay rate of the luminescence signal at the rock surface at exposure to a particular daylight spectrum, while μ (mm^{-1}) describes the attenuation coefficient as the light penetrates the rock, which controls the gradient of the bleaching front.

The bleaching with depth model of Sohbaty et al. (2011, 2012b) assumes first-order kinetics, i.e. a single trap with a corresponding recombination centre is responsible for the luminescence process. Therefore the model is strictly only applicable to quartz OSL (Polikreti et al., 2002; Sohbaty et al., 2012a). Feldspar infrared stimulated luminescence (IRSL) does not necessarily follow first-order kinetics, which was considered in general-order kinetics models (GOM) (Freiesleben et al., 2023; Biswas et al., 2023).

Luminescence depth profiles (LDP) can be derived (i) by coring and subsequent slicing or abrasion of the core, resulting in incremental point depth information (1D-approach, applicable to both OSL and IRSL; Gliganic et al., 2024), or (ii) by cutting the sample perpendicular to the targeted rock surface and obtaining images via e.g. charge-coupled device (CCD) or EM-CCD (electron multiplying CCD) cameras, resulting in high-resolution 2D luminescence-depth maps (2D-

approach); currently only applicable to samples emitting bright IRSL or IRPL signals (Sellwood et al., 2019, 2022a). Both, 1D- and 2D-RSD-approaches require the natural luminescence signal (L_n) to be sensitivity corrected either via normalisation against a test dose (T_n), or a later image of the IRPL imaging sequence (Sellwood et al., 2022b) (i.e. L_n/T_n LDP; Fig. 1). Typically, LDPs show one or more bleaching fronts and burial plateaus, depending on a rock surface's exposure and burial history. At depths where charge trapping by ionizing radiations is greater than charge detrapping by penetration of light for a specific time, the saturation plateau (with luminescence intensity L_0) persists (Fig. 1). Before fitting the LDP to the respective physical model, it is necessary to normalise the LDP to the saturated plateau region, so L_0 equals 1. Therefore, the saturation plateau needs to be determined and the central tendency for the plateau region derived on as many representative L_n/T_n data points as possible for the highest possible accuracy. The necessity for an accurate normalisation of the saturation plateau in RSD holds true regardless of (i) the number of exposure and burial events present in a given LDP, (ii) the luminescence signal that is measured (i.e. OSL, IRSL, or IRPL) or, (iii) the kinetic model that is used.

The determination of the saturation plateau and normalisation to L_0 is currently not standardised (section 2). Many different approaches can be found in recent literature and the methods for saturation plateau determination and normalisation are often insufficiently described or not mentioned at all.

Here we present a simple and robust algorithm that statistically determines the saturated plateau region and normalises the LDP to the median of flagged data points in a semi-automated manner. It has been tested on various datasets of different measurement approaches and luminescence types. The tool is offered as an easily applicable R (R Core Team, 2025) code. We also show the limitations and pit-falls of semi-automated saturation plateau determination and normalisation and highlight where a manual user-driven approach is still superior to automation.

2. Literature review of current approaches to saturation plateau determination and normalisation

A literature review was conducted to identify the various approaches to saturation plateau (L_0) determination and normalisation reported in recently published RSD literature. The literature review was conducted on rock surface dating articles summarised by Ancient TL's biannually issued Bibliography section from the last eight years (Ancient TL, 2018a,b, 2019a,b, 2020a,b, 2021a,b, 2022a,b,c, 2023a,b, 2024, 2025a,b), and case studies discussed in the RSD review article by Gliganic et al. (2024). Articles were rejected for literature analysis if (i) the maximum citation count from either Crossref (<https://www.crossref.org/>), Semantic Scholar (Allen Institute for Artificial Intelligence, <https://www.semanticscholar.org/>), or Web of Science™ (Clar-

ivate Analytics, <https://www.webofscience.com/>) was less than ten (as of 16 April 2026), and (ii) the article was published before 2023, to focus on the most relevant literature while still allowing for low citation count of recently published articles. Some articles that did not meet the defined criteria, were still checked due to possible relevance to the authors' remaining work. The query words that were used to scan for relevant text sections are outlined in Supplement S1. Relevant text sections in accepted articles were read and noted if details were mentioned, and later classified into (i) how the saturation plateau was identified (i.e. which data points were used for central tendency calculation) and (ii) which central tendency measure was used to calculate the normalisation factor.

Out of 84 articles considered for the literature review, 72 articles were accepted for further analysis due to recent publication or more than 10 citations (Table S1.1). Out of these 72 articles, 33 did not define which data points were used to calculate the central tendency of the saturation plateau, while in 39 articles the plateau determination approach was either loosely or well defined. Of the latter, 22 articles state that *saturated slices* were used. The *deepest x slices* ($\bar{x} = 4.75$) were considered for normalisation to saturation in ten articles. Four articles normalised the plateau to the (*calculated*) *field or lab saturation* without defining how it was derived. One article each reported the slices of the *deepest 9 mm*, the *single highest L_n/T_n value*, or *when the luminescence signal is fluctuating by less than 20%* respectively were considered for central tendency calculation (Table S1.2).

Regarding the calculation of the central tendency of the saturated plateau and therefore the normalisation factor, fifteen out of 72 articles stated that the *average* was used for central tendency calculation, six articles used the *weighted mean*, while two and one articles used the *mean (unspecified)* and *arithmetic mean* for central tendency calculation, respectively. Forty-eight articles did not mention how the central tendency was calculated (Table S1.2). The literature review demonstrates that there is no uniform way of determining the saturation plateau in luminescence depth profiles and calculating a central tendency value for LDP normalisation in the RSD community.

3. SatPlat algorithm development

3.1. Saturation plateau determination and normalisation

To identify the transition from the constant saturation plateau, representative of L_0 , towards the bleaching front, SatPlat evaluates the progressive departure of the luminescence signal from a reference value at depth. The algorithm presented herein, SatPlat (R code available here), operates on logarithmically transformed sensitivity-corrected luminescence values and calculates log-differences between consecutive observations. The cumulative sum of these consecutive log-differences reduces to the log-ratio between the reference value at depth and the value at the current posi-

tion. Consequently, the cumulative sum remains close to zero while the luminescence signal remains close to the saturation level and increases as the signal decreases towards the exposed surface. A transition is flagged when this departure exceeds a predefined threshold.

In a first step, the natural logarithm $\ln$ of the luminescence signal L_n/T_n is taken for each data point, resulting in l_j :

$$l_j = \ln(L_n/T_{n_j}) \quad (2)$$

The SatPlat algorithm operates on the log scale so that equal proportional changes produce equal-sized differences. The log introduces symmetry into the ratio, so that changes inferred from $\ln(L_n/T_{n_j})$ are the same since $\ln(L_n/T_{n_j}) = -\ln(T_n/L_{n_j})$. Furthermore, the log transform also reduces heteroskedasticity when variability increases with signal level (Box and Cox, 1964). The choice of the natural logarithm, with base e , is immaterial, because changing the base only multiplies all log differences and therefore the threshold by a constant factor. Natural logarithms are used here as a standard convention and for notational convenience.

The data is sorted by descending depth so that change detection starts from the sample interior, so at the deepest data point of the LDP ($j = 1$; Fig. 1A), which is typically part of the saturation plateau, towards the exposed sample surface. Subsequently, the difference d of two adjacent data points j and $j + 1$ is calculated, which gives their log-ratio:

$$d_j = l_j - l_{j+1} = \ln \left(\frac{L_n/T_{n_j}}{L_n/T_{n_{j+1}}} \right), \quad j = 1, \dots, N_{\text{LDP}} - 1 \quad (3)$$

where N_{LDP} is the number of data points within one LDP that are eligible for calculation, i.e. excluding predetermined outliers (code).

In a next step, the cumulative sum S of all d up to the respective data point k is taken, starting at the second deepest value:

$$S_k = \sum_{j=1}^k d_j, \quad k = 2, \dots, N_{\text{LDP}} - 1 \quad (4)$$

which is equivalent to the log-difference of the reference value at depth l_{ref} and the value at the current position l_k :

$$S_k = l_{\text{ref}} - l_k = \ln \left(\frac{L_n/T_{n_{\text{ref}}}}{L_n/T_{n_k}} \right), \quad k = 2, \dots, N_{\text{LDP}} - 1$$

To obtain the region of the saturated plateau, the change is detected when the cumulative sum S exceeds a certain threshold T with: $S_k > T$. The threshold T is a user-defined parameter that corresponds directly to an accepted proportional departure from the relative reference value at depth l_{ref} , since S_k is equivalent to a log-ratio relative to that reference. E.g. $T = 0.25$ (Section 4.1) means that the signal has fallen to approximately 78% of the reference value, since $e^{-0.25} = 0.78$.

Since the change in the luminescence signal from the saturation plateau (L_0) to the bleaching front (the upper bend

of the sigmoidal shape; Fig. 1A) is gradual, a strict change detection at the exact point $k_{S_k > T}$ would potentially include data points that are already part of the bleaching front and therefore not necessarily in saturation anymore. To prevent the inclusion of non-saturated data points, the shallowest data point considered to still be part of the saturation plateau k_{plat} is shifted to greater depths (i.e., a lower index k) by an empirical user-defined proportion p of the number of data points within the respective LDP N_{LDP} (Fig. 1A). The absolute magnitude of the shift is therefore dependent on the number of observations per LDP.

$$k_{\text{plat}} = k_{S_k > T} - p \times N_{\text{LDP}} \quad (5)$$

Since the gradient of the bleaching front varies depending on μ (Sohbati et al., 2012b), p can be manually adjusted by the user with steeper bleaching fronts (high μ) requiring smaller values of p , while gentler bleaching fronts (low μ) may require larger values.

The normalisation factor NF is calculated as the median of L_n/T_n values flagged as part of the saturated plateau region ranging from the shallowest flagged data point $L_n/T_{n_{k_{\text{plat}}}}$ to the deepest data point L_n/T_{n_1} (Fig. 1A) with:

$$NF = \text{median}(L_n/T_{n_{k_{\text{plat}}}} : L_n/T_{n_1}) \quad (6)$$

The median is chosen since it is not skewed by outliers, which can occur in LDPs due to analytical errors or when points that are already part of the bleaching front are accidentally flagged as part of the stable saturation plateau.

For normalisation, L_n/T_n is divided by NF :

$$L_n/T_{n_{j,\text{norm}}} = \frac{L_n/T_{n_j}}{NF} \quad (7)$$

The error of L_n/T_n is also normalised by division by NF .

SatPlat is presented as a ready-to-use modular R code (R Core Team, 2025) which can be executed as-is or adapted to the user's need (code). The output of SatPlat are *.csv-files including all parameters and results and, if desired, plots of each LDP and the course of S_k as shown in Fig. 1. The normalised LDPs can be used for fitting to the various first- or general-order kinetics models.

3.2. Test data

SatPlat was tested with several 1D, 2D, and simulated datasets (Table 1). Two datasets consist of luminescence depth profiles acquired by the conventional 1D coring and slicing RSD approach, where a maximum resolution of approximately 0.5 mm can be reached (Glignani et al., 2024). The first 1D dataset ($n = 36$) comprises LDPs based on blue stimulated OSL measurements on rock slices from rock glacier RG-2 in the Uinta Mountains (Utah, USA) (Table 1; Munroe et al., 2024). The samples consist of a dark red low metamorphic subfeldsparic arenite of the Hades Pass Formation (Wallace, 1972; Bryant, 2010). The second 1D dataset is also comprised of blue OSL LDPs ($n = 4$). The samples come from the archaeological site 5GN1 close to the shore of

Table 1: Summary of datasets used for testing. LDP: luminescence depth profile. Lum. type: Luminescence type. Sim: simulated dataset.

Dataset (Source)	Data type	n LDP	Lum. type	Sensitivity normalisation	Mean N_{LDP}^a
RG-2	1D	36	OSL	24 Gy beta dose	22 $\pm$ 4
5GN1	1D	4	OSL	24 Gy beta dose	47 $\pm$ 9
DALI22	2D	11	IRPL ₈₈₀ , IRPL ₉₅₅	Later frame ^b	91 $\pm$ 24
Granite (Sellwood et al., 2022b)	2D	6	IRPL ₈₈₀ , IRPL ₉₅₅	5 kGy gamma dose	119 $\pm$ 20
Cavity (Andričević et al., 2023)	2D	35	IRPL ₉₅₅	5 kGy gamma dose	104 $\pm$ 13
Simulated	Sim	4	-	-	100 $\pm$ 0
All datasets	Sum	96		Avg	71 $\pm$ 10

^a Arithmetic mean $\pm$ 1 standard deviation.

^b Sensitivity normalised by a later frame from the IRPL decay curve (F_1/F_x ; Sellwood et al., 2022b).

Blue Mesa Reservoir in Gunnison County (Colorado, USA) (Stiger, 2001) and consist of bright fine-grained quartzite used for stone tool production in prehistory (Pitblado et al., 2013; Hedlund, 1974).

Three datasets were obtained using the 2D-approach via EM-CCD-imaging (Sellwood et al., 2019, 2022a). This approach is characterised by high resolution sub-mm data. The first 2D-dataset (DALI22) consists of 11 LDPs obtained from granitic megalith boulders from an archaeological site called Dali in the Dzhungar Mountains (Kazakhstan) (Hermes et al., 2021). These LDPs are based on infrared photoluminescence (IRPL) measurements at 880 nm and 955 nm wavelength, resulting in IRPL₈₈₀ and IRPL₉₅₅ profiles, respectively (Sellwood et al., 2019). The second 2D-dataset, termed 'Granite' (Table 1), consists of three granitic samples from different locations published by Sellwood et al. (2022b). All three samples each have an IRPL₈₈₀ and IRPL₉₅₅ L_n/L_x profile, respectively ($n = 6$). The third 2D-dataset 'Cavity' was generated by Andričević et al. (2023), from K-rich feldspar-bearing white granite samples from China. The LDPs are based on IRPL₉₅₅ L/L_n measurements ($n = 35$). The IRSL data from Andričević et al. (2023) were not further considered for testing due to the high levels of noise in the saturation plateau region making them unsuitable for semi-automated analysis using SatPlat (Discussion).

Furthermore, the SatPlat algorithm was tested with simulated datasets ($n = 4$) generated following the bleaching with depth model (Eq.1, Sohbati et al., 2011, 2012b)

3.3. Algorithm testing and comparison to other methods

We benchmarked SatPlat against another commonly used plateau determination method on our test datasets. For each LDP, normalisation factors were computed using the most widely applied approach, i.e. the median of the L_n/T_n values of the five deepest slices (Section 2), and using SatPlat. Paired estimates were compared with a two-tailed paired t -test (Student, 1908). For datasets with independent age con-

trol that passed SatPlat quality criteria (RG-2: $n = 28/36$; Cavity: $n = 31/35$; Simulated: $n = 4/4$), we fit the bleaching with depth model (Eq.1, Sohbati et al., 2011, 2012b) to estimate $\overline{\sigma\phi_0}$ and μ using the Python Time Machine (pyTM; Meyer et al., 2023, 2026). pyTM returns best-fit values with asymmetric 95% confidence intervals (CI95). We additionally assessed CI95 overlap for each parameter as a descriptive measure of the consistency of parameter estimates between normalisation methods (Eqs. S2.1–S2.4). Additionally, differences in best-fit parameters between methods were tested with a two-tailed paired t -test (Student, 1908).

4. SatPlat algorithm validation and application

4.1. Plateau determination and normalisation using SatPlat

The SatPlat algorithm determines the stable saturation plateau region (Fig. 1), calculates the normalisation factor NF , and the normalised L_n/T_n values and corresponding errors. Furthermore, SatPlat allows the non-normalised LDP with the respective NF and the course of S_k with the respective T to be plotted for visual inspection (Fig. 1).

The performance of SatPlat was tested by applying it to 6 datasets that were obtained via the 1D- or 2D-approach, respectively, and together comprise a total number of 96 LDPs (Table 2). SatPlat was passed by 96.9% of all LDP ($n = 93/96$), i.e. SatPlat successfully determined the plateau regions, calculated the NF and normalised the respective LDPs. The used parameters and the number of LDP which crossed the threshold T (i.e. where a change from the plateau into the bleaching front was detected thus normalisation to the saturation plateau conducted), are documented in Table 2. Five out of six datasets gave satisfactory results with the empirically derived parameters of $T = 0.25$ and $p = 0.10$. Due to the relatively high noise along the saturation plateaus of LDPs in dataset 5GN1 a larger threshold of $T = 0.50$ was necessary to accommodate that noise and avoid exclusion of saturated data points for the calculation of NF (Fig. 1B and

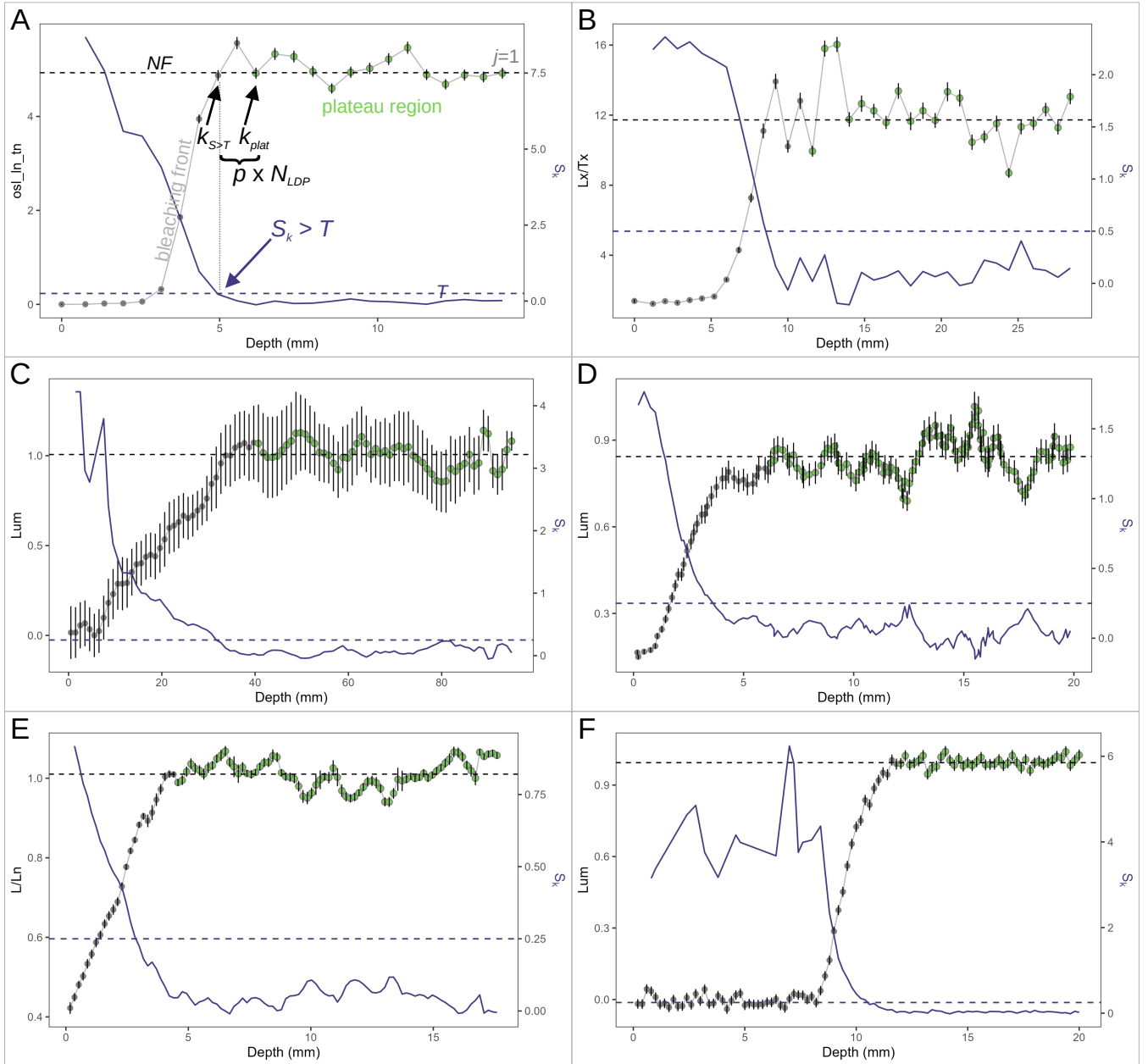


Figure 1: Output of SatPlat visualised for one representative LDP of each of the six datasets discussed in the text. A: representative LDP from dataset RG-2 (1D-approach) and visual representation of the algorithm parameters. The x-axis corresponds to the depth (mm) from the targeted rock surface. The left y-axis corresponds to the non-normalised luminescence signal, and the respective errors. The left y-axis titles correspond to the respective column headers for the luminescence signal in the input files. The dots represent the data points of the LDPs with index $j = 1$ at the deepest data point. The luminescence signal is saturated at great depth and fully bleached at the surface with the bleaching front showing how detrapping is occurring from the surface. The right y-axis corresponds to S_k . The purple solid line shows S_k while the horizontal purple dashed line shows threshold T and therefore where S_k crosses T (marked with a purple arrow). The dotted vertical line shows the data point $k_{S_k > T}$. The onset of the plateau calculation is shifted towards the right (deeper) by the proportion p of N_{LDP} to k_{plat} which is the shallowest data point considered for calculation of the normalisation factor NF . The circled green data points are flagged as part of the saturated plateau region and used for calculating NF . B: dataset 5GN1 (1D-approach). C: dataset DALI22 (2D-approach). D: dataset Granite (2D-approach; [Sellwood et al., 2022b](#)). E: dataset Cavity (2D EM-CCD; [Andričević et al., 2023](#)). F: dataset Simulated. Note the different scaling on the individual x-axes and the difference in resolution between 1D- (A-B) and 2D-approach (C-E). Note the incomplete bleaching at the surface in panel E.

Table 2: Summary of SatPlat parameters and results, and significance test results for the calibrated datasets. n overlap corresponds to the number of LDP where the calibration results have overlapping CI95 for each parameter $\overline{\sigma\phi_0}$ and μ (Supplement S2). LDP: luminescence depth profiles.

Dataset	T	p	n LDP ^a	t -test NF	n LDP ^b	n overlap $\overline{\sigma\phi_0}$	n overlap μ	t -test $\overline{\sigma\phi_0}$	t -test μ
RG-2	0.25	0.10	36/36	0.590	28	28	28	0.124	0.072
5GN1	0.50	0.10	4/4	0.463	-	-	-	-	-
DALI 22	0.25	0.10	11/11	0.639	-	-	-	-	-
Granite	0.25	0.10	6/6	0.732	-	-	-	-	-
Cavity	0.25	0.10	32/35	0.670	31	24	7	0.066	0.337
Simulated	0.25	0.10	4/4	0.607	4	4	4	0.618	0.791

^a Number of LDP (from all LDP within this dataset) that crossed SatPlat (sum = 93).

^b number of LDP that crossed SatPlat and have independent age control and where therefore calibrated with pyTM (sum = 63).

Fig. 2A). The shift proportion stayed at $p = 0.10$ due to a sharp drop towards the bleaching front.

4.2. Method comparison and significance tests

All LDPs of the test datasets were normalised with two different plateau determination methods and their resulting NF compared, as outlined in Section 3.3. The SatPlat results of LDPs with independent known ages were tested by fitting $\overline{\sigma\phi_0}$ and μ to the bleaching with depth model (Eq.1, Sohbaty et al., 2011, 2012b) using the pyTM (Meyer et al., 2023, 2026). The results are presented in Table 2. The t -tests of the NF result in no significant difference between the two methods with $\alpha = 0.05$ and $t_{NF} \in [0.463, 0.732]$. The arithmetic mean of the difference between both methods ($|1 - NF_{5deepest}/NF_{SatPlat}|$) is $2.8\% \pm 4.0\%$ (1σ) for all LDPs of all datasets with a maximum value of 30.0% for a LDP of dataset DALI22. It is shown that the CI95 overlap for LDPs with a low number of data points (e.g. RG-2; 100% overlap, Table 2) and for datasets with low noise (e.g. Simulated: 100% overlap, Table 2) and therefore the difference between both methods is less pronounced than for datasets with a high number of data points and high noise. The fitting results of the dataset with high noise and many data points per LDP (Cavity; 77% overlap for CI95 of $\overline{\sigma\phi_0}$ and 23% overlap for CI95 of μ , Table 2) show higher inconsistency in CI95-overlap between the two plateau determination methods (Fig. S2.1). The two-tailed paired t -test results in no significant difference between the two methods in all three test datasets with independent age control (Table 2).

5. Discussion

The literature review showed that there is no standardised method of determining the saturation plateau of LDP in RSD, yet it has to be noted that the rejection criterion of at least ten citations is no measure for the quality of an article but an arbitrarily chosen threshold, and serves to decrease the amount of articles to be analysed. With SatPlat, we provide a reproducible framework for semi-automated plateau determination and normalisation to the central tendency of the plateau region for further fitting. The SatPlat algorithm

is fairly simple and more elaborate change-point detection methods exist and were considered and tested for determining the saturation plateau (e.g. CUSUM by Page (1954), PELT by Killick et al. (2012) or log-likelihood ratio (Basseville and Nikiforov, 1993)). However, since they did not increase performance or eradicated the need for a manually set threshold or shift of plateau onset, we chose the simpler, more comprehensible approach presented herein.

The threshold T has to be set manually by the user since the distribution of the data points within a dataset does not allow for a statistically derived threshold. The proportion p is necessary since the onset of the plateau region could lie within the bleaching front otherwise, especially for LDP with many data points (2D-approach, Fig. 1C-F) or LDPs with low resolution (1D-approach) and gently sloping bleaching fronts, such as in in very translucent lithologies (Meyer et al., 2018). The proportion p can also be adjusted manually by the user. Manually defined parameters T and p potentially increase user engagement and verification of the process.

As shown in Table 2, not all LDPs crossed the threshold and were successfully normalised by SatPlat. Not all cases can be handled by SatPlat, e.g. if the noise in the plateau region is high (Fig. 2A). Another reason for unsuccessful plateau determination with SatPlat can be insufficient bleaching at the sample surface, resulting in L_n/T_n values that are within the range of values of the saturation plateau (~ 80 – 120% of L_0 ; Fig. 2B). In both cases we suggest to manually normalise the affected LDP to the NF of other LDPs with the same measurement sequence (especially test dose/ sensitivity correction) and lithology where the assumption is met that $\overline{\sigma\phi_0}$ and μ are identical (Sohbaty et al., 2012b).

The t -test results show no significant difference in NF as well as $\overline{\sigma\phi_0}$ and μ . It is notable that the results of the CI95-overlap-tests between the two tested plateau determination methods in dataset Cavity are deviating more than in datasets RG-2 and Simulated (Table 2 and Fig. S2.1). For example, the mean number of data points flagged as part of the saturation plateau for data set Cavity is 74 ± 26 (1σ) when using SatPlat at a mean N_{LDP} of 104 ± 13 (1σ). This is a higher ratio of data points compared to the five deepest data points and the difference is much higher than to dataset RG-2, where a mean number of 12 ± 5 (1σ) data points were flagged as

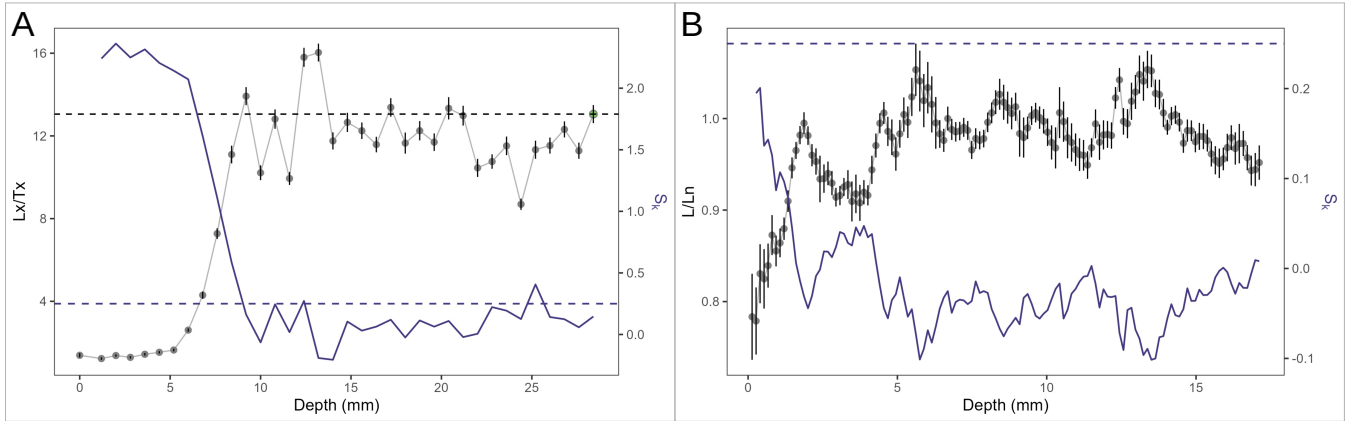


Figure 2: A: The same LDP as shown in Fig. 1B (dataset 5GN1) but with $T = 0.25$ instead of $T = 0.50$. Due to the noise along the saturation plateau, S_k crossed the threshold T quite deep in the LDP and with the shift of $p \times N_{\text{LDP}}$ only the single deepest data point was flagged for NF calculation. B: LDP from dataset Cavity. S_k did not cross T , so SatPlat was not passed due to incomplete bleaching at the surface. One could argue that a change can be detected with a smaller threshold T , but that could potentially be oversensitive to other LDPs in the dataset and deter the purpose of SatPlat to be applied to whole datasets.

part of the saturation plateau at a mean N_{LDP} of 22 ± 4 (1σ). This implies that it is even more important for LDPs with a large number of data points (i.e. long cores in 1D-approach or high resolution 2D-approach) to reliably determine the saturation plateau. Although the t-test results show no strong statistically significant difference either in NF or $\overline{\sigma\phi_0}$ and μ , it is shown that different NF , resulting from different plateau determination and normalisation approaches, can have an impact on fitting results. Fig. S2.1 suggests that there clearly is a substantial offset between CI95 for individual LDPs.

We conclude that SatPlat has the potential to standardise the normalisation of LDPs to the saturation plateau across the luminescence rock surface dating community. It is a simple, easily comprehensible algorithm, that works in a semi-automated manner and increases reproducibility.

Data availability. The test data cannot be published. Data for datasets RG-2 and 5GN1 is available on request from the corresponding author. The R software code is available at <https://github.com/danielsperlich001/SatPlat>.

Declaration of the use of artificial intelligence and generative technologies in the writing process. During the preparation of this article, the authors used OpenAI Chat GPT-5 (<https://chat.openai.com/>) and Anthropic Claude Sonnet 4.6, Haiku 4.5 and Opus 4.6 (<https://claude.ai/>) as large language models in browser or in Visual Studio Code 1.112.0 (<https://code.visualstudio.com/>) to help with coding and materialising statistical concepts and writing. The authors carefully reviewed the final version of the article and supplemented code and take full responsibility for its content.

Conflict of interest. The authors declare that they have no conflict of interest that could have biased their scientific

work.

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Supplement S1

Literature Review

Supplement S2

Method comparison and significance tests

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