FAIR fission track analysis with geochron@home

Pieter Vermeesch[1], Tim Band[1], Jiangping He[2], Rex Galbraith[1], and Andrew Carter[3]

[1]University College London, London WC1E 6BT, United Kingdom
[2]King's College London, London SE1 8WA, United Kingdom
[3]Birkbeck, University of London, London WC1E 7HX, United Kingdom

Correspondence: Pieter Vermeesch (p.vermeesch@ucl.ac.uk)

Abstract. Fission track thermochronology is based on the visual analysis of optical images. This visual process is prone to observer bias. Fission track datasets are currently reported as small data tables. The interpretation of these tables requires a high degree of trust between the fission track analyst and the user of the data. geochron@home is software that removes this requirement of trust. It combines a browser-based 'virtual microscope' with an online database to provide FAIR (Findable, Accessible, Interoperable and Reproducible) access to fission track data.

geochron@home serves four different purposes. It can be used (1) to count fission tracks in 'private mode', i.e. hidden from other users on the internet; (2) to archive fission track images and counts for inspection by other users; (3) to create tutorials for new students of the fission track method; and (4) to serve randomly selected selections of images to citizen scientists. We illustrate these four applications with examples that demonstrate (1) geochron@home's ability to compare and combine fission track counts for multiple users within a lab group; (2) the value of the geochron@home archive in the peer review system; (3) the use of simple tutorials in teaching novice users how to count fission tracks; and (4) the opportunities and challenges of crowd-sourced fission track analysis.

geochron@home was written in Python and Javascript. Its code is freely available for inspection and modification, allowing users to set up their own geochron@home server. Alternatively, users who would like to upload data to the archive, but do not have the facilities to set up their own server, may use the server at University College London free of charge. The archive accepts image stacks acquired on any type of digital microscope, and accomodates fission track data (counts and length measurements) from external fission track analysis suites such as Fission Track Studio and Track*Flow*.

We anticipate that the introduction of FAIR workflows will make fission track data more accurate and more future proof. Storing fission track data online will benefit future developments in fission track thermochronology. For example, archival datasets of peer reviewed fission track counts can be used to train and improve machine learning algorithms for automated fission track analysis. We invite other geochronological methods to follow the fission track community's lead in FAIR data processing. This would benefit all the Earth Science disciplines that depend on geochronological data.

1 Introduction

Science is on an irreversible trajectory towards greater openness. Geochronology is no exception to this trend, as this journal illustrates with its open access and review policies. Funding agencies increasingly demand that research results and data are shared with the public. Currently, geochronological data are generally provided as flat tables of dates or isotopic ratio estimates. However, in other fields of science such as physics, it is common practice to share the raw unprocessed measurements along with processing instructions (e.g., Abbott et al., 2016). This paper moves geochronology in the same direction. It presents a mechanism to generate and store fully FAIR (Findable, Accessible, Interoperable and Reproducible; Wilkinson et al., 2016) data in the context of fission track analysis.

Unlike most other geochronometers, which require mass spectrometers to estimate parent-daughter ratios, fission tracks are observed under an optical microscope and counted by a human observer. In recent years, digital microscopy has moved fission track data acquisition from the ocular lenses of a microscope to the computer screen (Gleadow et al., 2009; Van Ranst et al., 2019; Gleadow, 2019). Ongoing developments in artificial intelligence generate further opportunities to improve the throughput and accuracy of fission track data (Nachtergaele and De Grave, 2020). But despite the richness of the digital datasets produced by these novel tools, fission track data are still reported as small summary tables. These tables require an unnecessary degree of trust between the ‘producer’ and ‘consumer’ of the data.

geochron@home is a free and open software platform that allows geochronologists to share their raw fission track data over the internet for perusal by peer reviewers, colleagues and the general public. geochron@home is a virtual petrographic microscope connected to a database with digital image stacks of etched fission track samples. The platform can be used to acquire, archive and inspect fission track data in full adherence to the FAIR data principles. In Section 2, we will describe geochron@home’s software architecture in five steps. We will show that this architecture accommodates imagery from any type of digital microscope. It enables flexible workflows that can be adapted to four different applications.

Using image stacks of Mount Dromedary apatite, we will show how geochron@home can be used to count fission tracks in ‘private mode’ (Section 3); to archive published fission track datasets in ‘public mode’ (Section 4); to build tutorials for training purposes (Section 5); and to crowd-source fission track data on the internet (Section 6). Because geochron@home is free and open, it can be extended and improved by any interested party. We make some suggestions for future improvements in Section 7. We hope that the geochron@home’s example will be followed in other geochronological disciplines, as this will benefit not only geochronology itself, but all the other disciplines that depend on it (Section 8).

2 Workflow

The geochron@home workflow separates the acquisition of microscope images from their analysis, providing the flexibility to accommodate data from different microscope manufacturers. The workflow can be broken down into five steps.

1. Acquisition of z-stacks of microscope images in reflected and transmitted light for each of the grains in a sample and, optionally, for the accompanying external detector (Figure 1). At University College London, this first step is currently

accomplished by a Python macro within Zeiss' Zen Blue software. However, geochron@home can also accommodate imagery from other platforms, such as Fission Track Studio (Zeiss; Gleadow et al., 2009) and Track*Flow* (Nikon; Van Ranst et al., 2019).

2. Prepare the z-stacks for uploading to the geochron@home database. This database requires that the images are organised as a nested sequence of directories, in which a 'project' consists of 'samples' that comprise a number of 'grains'. Each grain corresponds to a numbered sequence of `.jpeg` images, one for each layer of the z-stack. Note that the raw microscope images are generally not stored as `.jpeg` files but in uncompressed `.czi` (for Zen Blue), `.tif` (for Fission Track Studio) or `.nd2` (for Nikon/Track*Flow*) formats. Conversion from these raw images to sequences of `.jpeg` files is done with a shell script using Imagemagick (Still, 2006).

   In addition to the sequence of `.jpeg` images, a low level 'grain' folder can also include an optional file called `roi.json` containing the vertices of a default region of interest for spontaneous (and/or induced) track counting. The database structure can also accommodate existing fission track counting results. For example, if a user has already counted their fission tracks in Fission Track Studio, then they can store those results in a `.json` file at the 'sample' level directory. Because Fission Track Studio stores its results in an `.xml` format, a second conversion script was created to translate those results into an equivalent `.json` format.

3. Upload the data to the geochron@home platform. geochron@home is a Django web-app with a PostgreSQL database. The database can be accessed via a Python API and a (more limited) web-based GUI. Accessing the API requires administrator privileges. Administrators can create projects, samples and grains; download data; and set the access rights of 'ordinary' users. Projects can be private or public. The source code and installation instructions for geochron@home are freely available over GitHub (see the Data Availability statement at the end of this paper). This allows fission track users to set up their own server. Alternatively, fission track labs can upload their data to the UCL server by contacting the corresponding author.

4. Analyse the images with a browser-based 'virtual fission track microscope' powered by the Leaflet library (JavaScript). This virtual instrument acts as a front-end to geochron@home. It has a simple user interface with controls to zoom, pan and focus in or out of the digital image stack. Depending on the permissions granted to the user by the administrator, the virtual microsocope offers a number of different options. Entry level 'ordinary' users are only allowed to count tracks by clicking within a pre-defined 'region of interest'. In contrast, 'superusers' are allowed to define their own regions of interest. Once the user is satisfied that they have counted all the fission tracks in a particular grain, they can submit the results to the server. They are then presented with a new set of images until all grains are counted.

5. Post-processing. The fission track data can either be downloaded as a flat data table of counts and areas, or as a `.json` file containing the locations of all the counted tracks. geochron@home does not provide any tools to post-process these files. They are meant to be passed on to other tools such as spreadsheet applications or IsoplotR (Vermeesch, 2018).

The five-step workflow can be used for several applications, including (1) conventional fission track analysis; (2) archiving published fission track results; (3) building tutorials; and (4) crowd-sourcing fission track data. The next sections of this paper will illustrate these applications with real world examples.

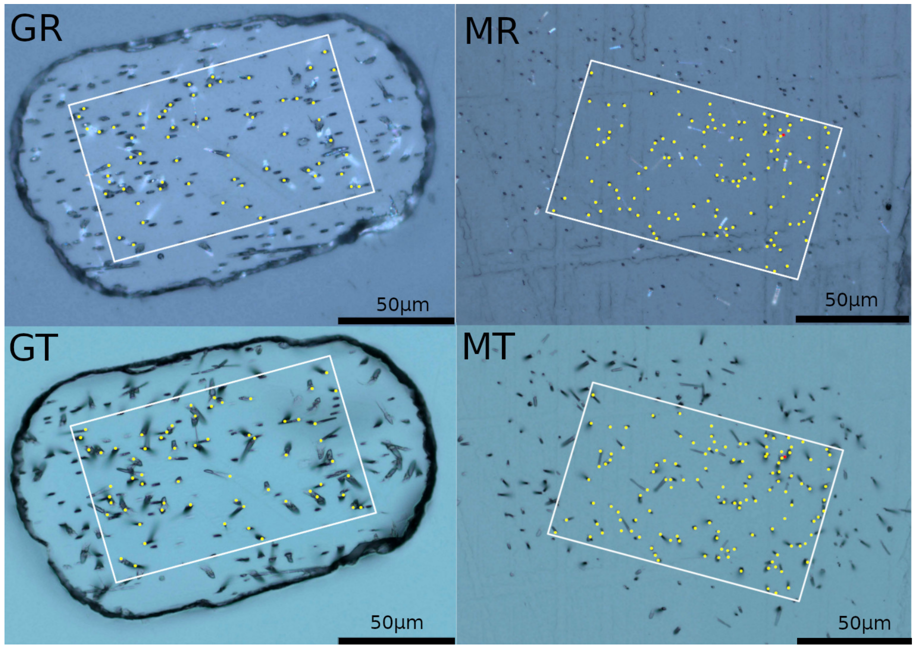

Figure 1. Screenshots of raw fission track data for the external detector method in geochron@home. GR: an apatite grain in reflected light; GT: the same grain in transmitted light; MR: the corresponding mica detector in reflected light; MT: the mica detector in transmitted light. White rectangles mark the region of interest (ROI), within which an analyst has counted fission tracks by marking their etch pits (shown in yellow). The raw data for this figure can be viewed on the geochron@home archive (https://github.com/pvermees/GaHa).

3 Counting fission tracks in 'private mode'

Administrators can define regions of interest (ROI) and count or edit the fission track coordinates of any grain in a geochron@home database. They can also assign other users to groups, and give these groups access to a subset of the projects in the database. Administrators have fine control over the permissions of the groups. For example, they can allow the members of one group to define their own ROIs, whilst requiring members of another group to count fission tracks in predefined ROIs. Groups provide a mechanism to compare and combine the results of multiple analysts of the same sample. Figure 2 illustrates this with two sets of fission track density estimates for the same sample of Mount Dromedary apatite (Green, 1985), analysed by two users (PV and AC).

Let N_1 and N_2 be the numbers of spontaneous tracks counted by the two users over areas A_1 and A_2, respectively. Then their estimated track densities are given by $\hat{\rho}_1 = N_1/A_1$ and $\hat{\rho}_2 = N_2/A_2$. In this situation when the two areas overlap, N_1 and N_2 cannot be treated as independent Poisson counts because the two analysts will count some of the same tracks. It can be shown that, under simple (ideal) assumptions, the uncertainty of the ratio of the estimated track densities is given approximately by

$$\frac{\mathrm{se}(\hat{\rho}_1/\hat{\rho}_2)}{\hat{\rho}_1/\hat{\rho}_2} \approx \sqrt{\frac{1}{N_1} + \frac{1}{N_2} - \frac{2\,N_0}{N_1\,N_2}} \tag{1}$$

where N_0 is the number of tracks counted by both observers in the area of overlap (A_0, say) between their respective ROIs.

The combined data plots of Figures 2b and c contain two sets of counts, with $\sum N_1 = 686$ and $\sum N_2 = 679$, and a weighted mean track density ratio $\hat{\rho}_1/\hat{\rho}_1 = 0.94$ with relative standard error 0.013. PV counted 600 tracks in those common areas A_0, of which 549 were also counted by AC. Conversely, AC counted 622 tracks of which 549 were also counted by PV. The ratio of the two analysts' track density estimates based just on the common area is therefore 600/622 = 0.965 with relative standard error 0.018, calculated from Equation 1, with $N_1 = 686$, $N_2 = 679$ and $N_0 = 549$. This is close to the weighted mean ratio of 0.94 (Figure 2c), and is slightly nearer to 1. It indicates that PV under-counts the Mount Dromedary apatite by 3.5% relative to AC. The existence of 'observer bias' is well documented (Tamer et al., 2025). It is one of the reasons why fission track analysis is often done relative to age standards: observer bias does not have to be a problem provided that it is consistent between grains, and between samples.

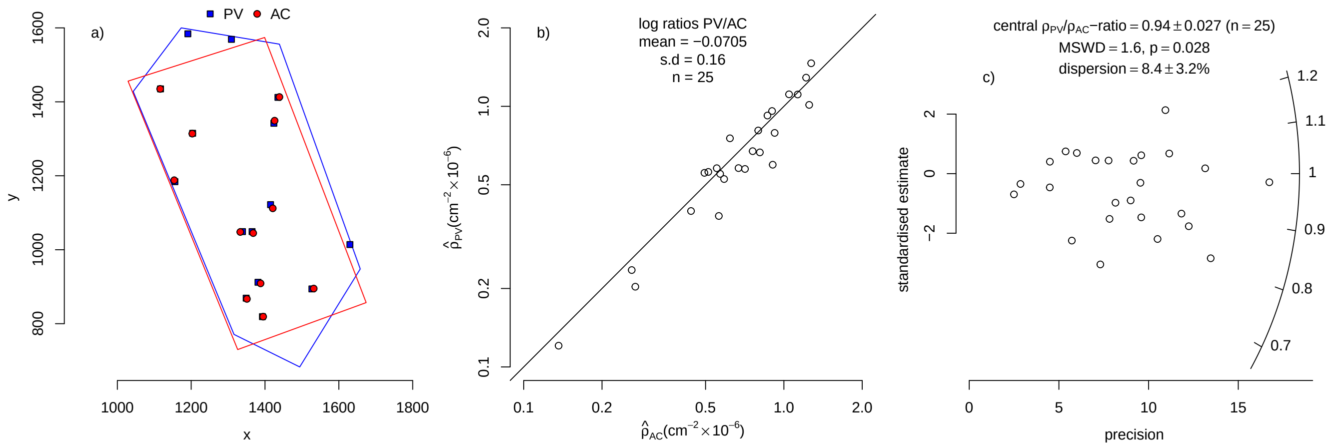

Figure 2. Comparison of fission track data for Mount Dromedary apatite by two analysts (PV = Pieter Vermeesch and AC = Andrew Carter). a) the track counts and ROIs of both users for grain 3, shown in blue (PV) and red (AC); b) comparison of the track densities for PV and AC for all 25 grains analysed by the two analysts with a reference line for $\hat{\rho}_{\mathrm{PV}} = \hat{\rho}_{\mathrm{AC}}$; c) radial plot of the same data, using Equation 1.

4 The geochron@home archive (GaHa)

Once a set of fission track images has been analysed and the analyst is confident that the results are accurate, the status of the results can be changed from private to public. This makes the results visible over the internet as a list of URLs, where each grain number and user ID corresponds to a unique address. The geochron@home archive (GaHa) brings fission track geochronology into the era of FAIR science. It allows peer reviewers to inspect the raw data from which thermochronological inferences are made. The archive is open to submissions from any fission track laboratory, free of charge. However, as mentioned in Section 2, it is also possible to establish a new archive elsewhere. At the time of writing, GaHa contains data for three studies:

1. Guo et al. (2025): this is an LA-ICP-MS based fission track study of detrital apatite from the northeastern Tibetan Plateau. It contains image stacks of semitracks in 1146 apatite grains from 16 different samples.

2. Tamer et al. (2025): this is a round-robin study in which digital image stacks of 44 apatite crystals were circulated among 14 different analysts. These analysts used the FastTrack image analysis software (which is part of the Fission Track Studio suite; Gleadow et al., 2009) to define their own ROIs and count the semitracks and horizontally confined fission tracks in them. GaHa presents the results of the round-robin experiment as a 44×14 grid of URLs.

3. This study: All the raw fission track data used in this article are available on GaHa, along with the post-processing software that was used to produce the figures. Together, these resources provide the reader with all the information needed to fully reproduce our results, 'from cradle to grave'. To our knowledge, this is the first geochronological study to do so.

5 geochron@home tutorials

Given the right permissions (assigned by an administrator), users can build tutorial pages by annotating features in fission track images. These features can be tracks or other objects such as scratches, inclusions, dislocations or holes. A selection of tutorial pages is presented to new users when they first log into geochron@home. They must complete the tutorial before being allowed to count fission tracks. The tutorial pages can be revisited at any time by visiting the corresponding link on the geochron@home landing page.

The annotations in the current tutorial pages were made by an experienced fission track analyst (Andrew Carter). This basic tutorial provides a quick and easy mechanism to train novice users in the art of fission track analysis. The tutorial pages are in their infancy and offer only a limited degree of interactivity. Users can click on features to read the annotations. The tutorial will grow with input from experienced analysts and future plans include the addition of fully interactive 'quizzes' (Section 8). The limitations of the current tutorials are apparent in the results of the crowd-sourcing experiment described in the next section of this paper.

6 Crowd-sourcing fission track data

In 1906, Sir Francis Galton visited a county fair in which a contest was held to guess the weight of an ox. 787 people participated in the event. Galton discovered that the median of all their estimates was within 0.8% of the true weight of the ox and more accurate than 90% of the individual estimates. Such is the 'wisdom of crowds' (Galton, 1907). Similar effects are seen in fission track geochronology. An interlaboratory comparison study by Miller et al. (1985) showed that the average of several fission track age estimates is closer to the known age of mineral standards than the age obtained by individual observers. Inspired by these previous experiments, we used geochron@home to bring fission track analysis to a proverbial 'county fair' of citizen scientists.

We here present the results of a type of 'crowd-sourcing' experiment that was carried out at UCL as part of an undergraduate course in isotope geology. 68 students were asked to create an account on the geochron@home server by selecting a unique username and password. After spending a few minutes to complete the compulsory tutorial (Section 5), they were asked to count fission tracks in randomly assigned image stacks of Mount Dromedary apatite. Each student was required to analyse at least 15 grains, using pre-defined ROIs. In a matter of hours, the students amassed a dataset of 37,331 fission track counts in 34 grains. This large dataset was parsed into separate data files — one for each student — which they processed during an assessed programming exercise.

	grain ID																											
user	1	41	32	3	4	10	28	31	11	30	22	34	12	36	27	6	2	15	8	38	7	25	23	39	43	n_g	r_p	s_p
PV	9	10	11	12	14	14	18	19	21	21	22	22	25	25	27	28	32	35	37	44	46	50	52	63	66	25	1.00	.00
255			15	16	18	17	25	22			23	26		25	31		31	39	40		37	63	48	65	67	18	1.08	.84
271	9	11	14	14	16	15	23	18	22	22	23	19	28	22	27	29	31	35	34	41	46	56	54	52	56	25	.99	.61
215	10	10	12		9		25	20	19	23	22	22				35	30	34	36	34	56		44	62	62	19	.99	.85
236	9	9					18		19	18	21	20	27	23	28	30		38		41	39	55				15	.98	.49
229	8			15	11	17	26		21		30		36	24	35		31		30	29		55	50	55	30	17	.95	1.62
278	11	9	13		9	17		20	19	27		20		22	28				37		39	44		52		15	.94	.77
216	8	11				15		20	22		20	17		20	27		31		34	39	36			57		14	.91	.51
249	7	10	11	9	14	15	21	18		19	21	21	27	27	26		26	27	34	41	35	45	42	42	54	23	.88	.68
246	9	10	10	16	10	15	18	16	21	17	22	20	24	21	28	29	25	30	37	36	29	46	42	46	58	25	.88	.70
241	7	10				16	17	19						26	27	26	28	30		32	36		36		58	14	.87	.67
⋮																												
262	6	7	7	8	4	15	7	9	12	14	8	17	9	13	3	17	11	18	14	17	7	15	23	6	15	25	.39	1.13
266			5	6		9				8			10		14	11	13	11	14		13			14	24	13	.36	.56
275	4	7	12	8	2	7	5	12	12	10	15	15	2	9	13	5	8	9	6	12	4	6	26	17	32	25	.36	1.14
268	2	4	6	4	3	8	4	4	7	5	5	8	9	6	13	10	13	12	16	16	6	17	19	20	12	25	.32	.55
244		5	3		4				6	12	6			4		13					10	9		23	17	12	.30	.65
232	4	4	5	6	2	6	4	4	6	8	7	6	8	10	10	13	8	10	7	7	14	12	18	17	17	25	.29	.46
283	3	5	5	6	0	15	8	5	6	5	6	5	5	8	5	4	10	6	5	5	5	8	6	9	6	25	.21	.88
228			3	2		4	4	3	4	4		6	4	4		6	4		8	8	12	8	8		6	18	.18	.30
253	1	1			2	5	2			6	4	2	3	3	3		4	3		7	5		5			16	.13	.32
245	1	1			3	2	2	3	2	4		1	4	0		4	6	3	4	3	3	7		4	5	20	.10	.28
r_m	.89	.80	.82	.75	.57	.86	.78	.79	.62	.71	.73	.68	.64	.62	.70	.64	.61	.63	.64	.50	.43	.56	.54	.44	.57			

Table 1. Counts of fission tracks in the same ROIs of 25 grains made by PV and 68 students. Only 20 students are shown due to space constraints; the full table is provided in the GaHa. Each student counted a subset of the grains. The grains are listed in increasing order of PV's counts. The last 3 columns give, for each student, the number of grains counted n_g and the weighted mean $r_p = \sum w_i r_i / \sum w_i$ and standard deviation $s_p = \sqrt{\sum w_i (r_i - r_p)^2/(n_g - 1)}$ where r_i is the ratio of the student's count to PV's count for grain i and w_i is PV's

count for grain i. (r_p is the same as the ratio of the student's total count over the n_g grains to PV's total count over the same grains.) The students are listed in decreasing order of r_p. r_m is the ratio of the students' median count per grain to PV's count.

The raw counts for the 68 students are given in Table 1 and Figure 3, for the same selection of 25 grains that were analysed by AC and PV in Section 3, along with corresponding counts made by PV. Everyone counted tracks in the same ROIs. Variation between the mean values is to be expected because of the differing numbers of tracks due to varying areas and U contents of the grains. But the variation between counts within grains (shown by the standard deviations in Figure 3) is due entirely to differences between the students' recognising and counting exactly the same tracks. These standard deviations increase with the mean number of tracks and are considerable in size, being on average about 40% of the mean. With expert trained counters one would expect much smaller differences between counts. Furthermore, the vast majority of students counted fewer tracks than PV did, often many fewer, and on two occasions someone counted no tracks at all. PV's count is always above the students' median and nearly always above the upper quartile (Figure 3).

The rightmost three columns of Table 1 contain summary statistics (n_g, r_p and s_p) giving, for each student, the number of grains counted and the weighted mean and standard deviation of the ratios of the student's count to PV's count for each grain (definitions provided in the caption). The true number of tracks in each ROI is unknown, so we are comparing the students with PV (remembering that PV's count is also subject to error, which is the same for each student). r_p measures agreement with PV on average and s_p measures consistency over grains. For good agreement r_p should be close to 1 and s_p should be small. Perfect agreement is $r_p = 1$ and $s_p = 0$. For comparison, an $r_p = 1.04$ and $s_p = 0.69$ is obtained for PV and AC using just the counts in the common areas A_0 from Section 3. With the caveat that the ROIs are different and PV's counts are different, this calculation shows that there is a group of 6 (possibly 9) students whose agreement with PV is comparable with AC's. This group does not include student 229 whose $r_p = 0.95$ but with a large $s_p = 1.62$. Students near the bottom of Table 1 have undercounted the samples by such a large degree that their work can be qualified as vandalism. Section 7 will suggest strategies to detect and counteract this type of behaviour.

In spite of the under-counting by the students, the ratio of their pooled track counts (r_p) for two different grains is often close to PV's ratio, especially when comparing grains with similar track densities. This is illustrated in Figure 4a for grains 23 and 25. For any point, the ratio of the two counts is given by the slope of a line from the origin to that point. Although the individual slopes vary considerably, the line with slope equal to the ratio of the total counts for all students (which is 0.97) passes close to PV's pair of counts (52,50) shown by the blue dot (with ratio 1.04). It is interesting that the students with lower counts are mostly above this line and those with higher counts are all below it. There is a positive correlation between the pairs of counts, consistent with systematic observer effects (i.e., people who count a low value in one grain tend to count similarly low in the other, and vice versa). Comparing other pairs of grains shows similar results, with correlations varying between 0.4 and 0.9.

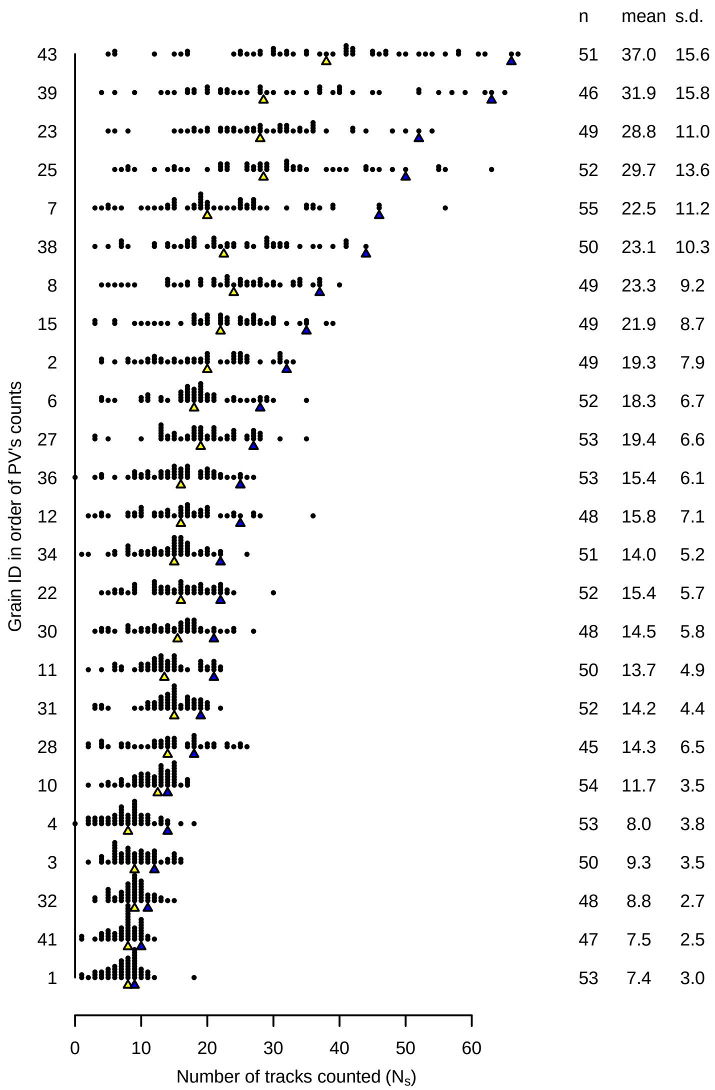

Figure 3. Strip chart of the data shown in Table 1, with the students' medians and PV's counts shown as yellow and blue triangles, respectively.

As mentioned in Section 2, geochron@home stores the actual track positions marked by the users. This raw data can be downloaded as a `.json` file and inspected in detail. Figure 4b shows two-dimensional histograms for the x-y positions of all the track positions generated by the students in grains 23 and 25. Visual comparison of the histograms with the optical images confirms that the students unanimously identified the most obvious semitracks, which contain a clearly visible etch pit and tail. Shorter and fainter tracks received fewer clicks. Datasets like this can be used to replace integer counts of fission tracks with probabilities, reflecting the ambiguity of some fission track datasets. Figure 4 also shows that some students counted the tails of the fission tracks rather than their etch pits, despite being told the opposite in the tutorial. Fixing this issue will require some improvements to the tutorial pages (Section 7).

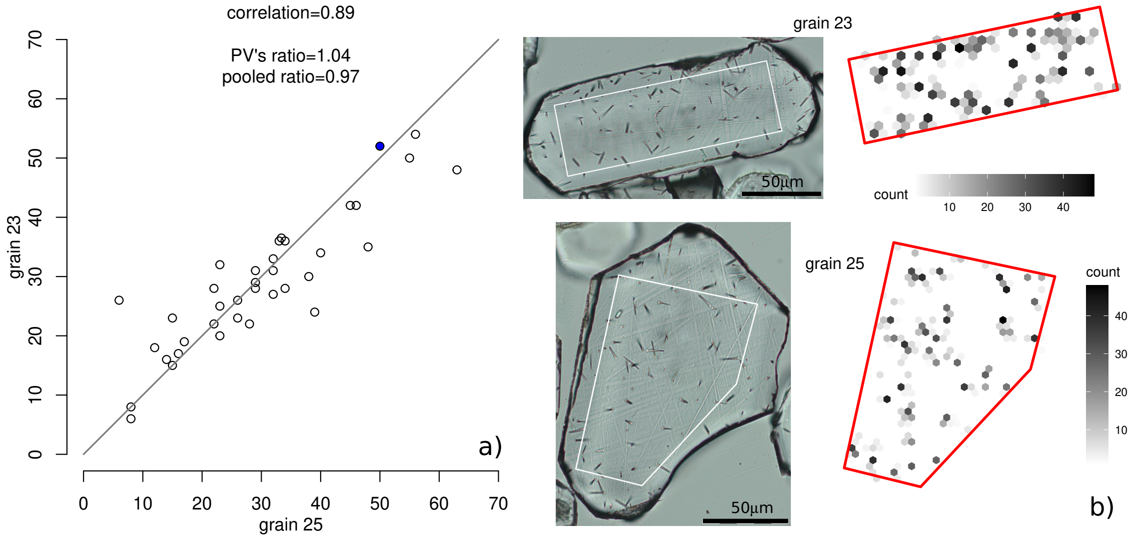

Figure 4. a) The track counts for grain 23 plotted against those for grain 25 for 36 students who counted both of those grains. The grey line through the origin has slope 0.97, equal to the ratio of the students' total counts for each grain. The blue dot shows PV's counts for those two grains. b) Optical images in transmitted light of Mount Dromedary apatites 23 and 25 in the crowd-sourcing experiment, along with two-dimensional histogram of the track locations for the two grains, as identified by the citizen scientists.

7 Outlook

geochron@home has been in development for a decade and remains a work in progress. Planned improvements include:

1. Length measurements. The geochron@home archive already contains horizontally confined fission track measurements (Tamer et al., 2025). However, these results must be generated externally (e.g., using Fission Track Studio) and uploaded via a `.json` file. The virtual microscope curently lacks the functionality to generate length data within geochron@home. This functionality will be added in a future update.

2. Dpar and Dper. Etch pits are currently stored as simple sets of x- and y-coordinates. In reality, etch pits have a finite length ('Dpar') and width ('Dper'), which serve as useful indicators for the horizontal etch rates along the c-axis and parallel to it (Donelick, 1993). Functions will be added to measure and visualise this type of data in geochron@home.

3. Interactive tutorial pages and embedded quality control. Section 6 shows that the crowd-sourcing idea is not yet ready for general use. Two improvements will be made to make its results more reliable. First, a 'quiz' will be added to the tutorial pages to ensure that novice users do not count the tails but the etch pits of fission tracks. Only users who click on the 'correct' features in an unlabelled set of images will be allowed to count new samples. Second, future citizen scientists will occasionally be served reference images of known track density. Their counts for these 'test' images will be used to identify trustworthy analysts (top of Table 1) and flag unreliable ones (bottom of Table 1).

4. Machine learning. Data science is experiencing an artificial intelligence (AI) revolution that has already started to transform the fission track method (Nachtergaele and De Grave, 2020). Convolutional neural networks must be trained with example data. geochron@home is ideally suited for this task. Section 6 showed how the opinion of multiple fission track analysts can be combined to label fission track images with probabilities rather than counts. This data format is close to the form in which data are treated within an AI algorithm.

5. Inverse counting. Once trained on historical data, AI algorithms can be used to count fission tracks automatically. Following the model of Fission Track Studio (Gleadow et al., 2009; Gleadow, 2019), machine learning can be used to reverse the fission track counting process. Instead of asking users to count the fission tracks in a sample, the software can ask them to check the results proposed by an AI algorithm, and to remove any features that are *not* fission tracks. Regardless of whether fission tracks were counted manually or with a machine, the value of the geochron@home archive remains the same. It is important to document data so that samples can be reanalysed in the future, for example when a new and improved generation of machine learning algorithms becomes available.

These improvements will be made by ourselves pending additional funding. However, because geochron@home is free and open software, we invite any interested parties to join the effort and extend or improve our code.

8 Conclusions

This paper introduced geochron@home, a software platform for FAIR fission track analysis. We demonstrated four different applications of this platform using real data. Putting the FAIR data paradigm into practice, all the imagery, counts and source code for this paper are publicly available on the geochron@home archive. Using these resources, the reader can reproduce all the results that were presented in this publication. We encourage other geochronologists to follow this example. FAIR workflows promise to address the reproducibility crisis in science (Miyakawa, 2020).

geochron@home's rich archive of raw data can be reanalysed in the future. We anticipate that the adoption of FAIR data processing workflows will open up new research opportunities. For example, archived pairs of peer-reviewed fission track images and counts could be used to train the next generation of automated machine learning algorithms. Conversely, it is also possible that future improvements in fission track images analysis will be used to update the count data for published datasets, improving their accuracy.

Another advantage of the geochron@home workflow is the separation of image acquisition and image analysis. This separation reduces the hardware requirements for fission track geochronology. It opens up the possibility to share resources. State-of-the-art digital microscopes are expensive. Using geochron@home, a single microscope can serve multiple users and make fission track analysis more affordable.

The fission track method has always been a test bed for new geochronological developments. Because fission track data are imprecise, the fission track community has sollicited the help of statisticians and mathematicians to develop its analytical protocols. Other geochronological communities are still catching up with concepts and tools such as overdispersion, mixture modelling and radial plots, which have been commonplace in fission track analysis for decades (Vermeesch, 2019). In a similar vein, the subjective nature of fission track identification has prompted the fission track community to organise inter-laboratory comparisons and round-robin studies long before other geochronological communities (Miller et al., 1985; Tamer et al., 2025).

With the development of geochron@home, fission track thermochronology is once again ahead of the pack in terms of FAIR data analysis. geochron@home currently only stores images and counts. This is enough to reproduce the results of fission track studies using the external detector method, but not for LA-ICP-MS based data. FAIR data processing of LA-ICP-MS data requires a new generation of mass spectrometer data reduction software. We are currently working on this (Vermeesch, 2025). The development of FAIR ICP-MS data pipelines will not only benefit fission track analysis but other chronometers as well, such as in-situ U–Pb, Rb–Sr and Lu–Hf.

With the establishment of FAIR data, geochronology will be well placed to avoid the reproducibility problems that have plagued other fields of science.

Code and data availability. geochron@home is free software released under the GPL-3 license. The package and its source code are available from https://github.com/pvermees/geochron-at-home (last access: August 21, 2025). The raw data (imagery) are available at the geochron@home archive (https://github.com/pvermees/GaHa, last access: August 21, 2025). R-scripts to reproduce the figures are provided in the supplementary information (https://github.com/pvermees/supplements, last access: August 21, 2025).

Author contributions. PV designed the study, acquired the funding and counted fission tracks. JH created geochron@home. TB expanded geochron@home and wrote the accompanying microscope image acquisition software. RG derived Equation 1, designed Table 1 and verified the other calculations. AC provided the samples, prepared the training data and counted fission tracks. PV and RG wrote the paper with input from the other authors.

Competing interests. PV is an Associate Editor of *Geochronology*.

Acknowledgements. This research has been supported by the Natural Environment Research Council (grant no. NE/T001518/1), awarded to Pieter Vermeesch. We would like to thank the students of GEOL0017 (‘Isotope Geology’) for their contribution to the crowd-sourcing experiment of Section 6.

References

Abbott, B. P., Abbott, R., Abbott, T. D., Abernathy, M. R., Acernese, F., Ackley, K., Adams, C., Adams, T., Addesso, P., Adhikari, R. X., et al.: Observation of gravitational waves from a binary black hole merger, Physical Review Letters, 116, 061 102, 2016.

Donelick, R. A.: Method of fission track analysis utilizing bulk chemical etching of apatite, uS Patent 5,267,274, 1993.

Galton, F.: Vox Populi, Nature, 75, 450–451, 1907.

Gleadow, A.: Future developments in fission track thermochronology, in: Fission track thermochronology and its application to geology, edited by Malusà, Marco and Fitzgerald, P., chap. 4, Springer, 2019.

Gleadow, A. J., Gleadow, S. J., Belton, D. X., Kohn, B. P., Krochmal, M. S., and Brown, R. W.: Coincidence mapping – a key strategy for the automatic counting of fission tracks in natural minerals, Geological Society, London, Special Publications, 324, 25–36, 2009.

Green, P.: Comparison of zeta calibration baselines for fission-track dating of apatite, zircon and sphene, Chemical Geology: Isotope Geoscience Section, 58, 1–22, 1985.

Guo, C., Zhang, Z., Lease, R., Malusà, M. G., Chew, D., Lu, H., Wu, L., Xiang, D., Wang, N., Grasemann, B., et al.: Apatite geo-thermochronology and geochemistry constrain oligocene-miocene growth and geodynamics of the northeastern Tibetan Plateau, Geophysical Research Letters, 52, e2024GL113 157, 2025.

Miller, D. S., Duddy, I. R., Green, P. F., Hurford, A. J., and Naeser, C. W.: Results of interlaboratory comparison of fission-track age standards: fission-track workshop – 1984, Nuclear Tracks and Radiation Measurements, 10, 383–391, 1985.

Miyakawa, T.: No raw data, no science: another possible source of the reproducibility crisis, 2020.

Nachtergaele, S. and De Grave, J.: AI-Track-tive: automated fission track recognition using computer vision (Artificial Intelligence), Geochronology Discussions, 2020, 1–12, 2020.

Still, M.: The Definitive Guide to ImageMagick, Definitive Guide Series, Springer, 1st edn., ISBN 978-1-59059-590-9, https://www.apress.com/gp/book/9781590595909, a comprehensive guide to ImageMagick, covering installation, usage, and scripting., 2006.

Tamer, M. T., Chung, L., Ketcham, R. A., and Gleadow, A. J. W.: The need for fission-track data transparency and sharing, Geochronology, 7, 45–58, https://doi.org/10.5194/gchron-7-45-2025, 2025.

Van Ranst, G., Baert, P., Fernandes, A. C., and De Grave, J.: Technical note: TRACK*Flow*, a new versatile microscope system for fission track analysis, Geochronology Discussions, 2019, 1–25, https://doi.org/10.5194/gchron-2019-13, 2019.

Vermeesch, P.: `IsoplotR`: a free and open toolbox for geochronology, Geoscience Frontiers, 9, 1479–1493, 2018.

Vermeesch, P.: Statistics for fission-track thermochronology, Fission-track thermochronology and its application to geology, pp. 109–122, 2019.

Vermeesch, P.: KJ: A Julia package for physics-based LA-ICP-MS data processing, in: Goldschmidt Conference, Prague, 2025.

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.-W., da Silva Santos, L. B., Bourne, P. E., et al.: The FAIR Guiding Principles for scientific data management and stewardship, Scientific data, 3, 1–9, 2016.