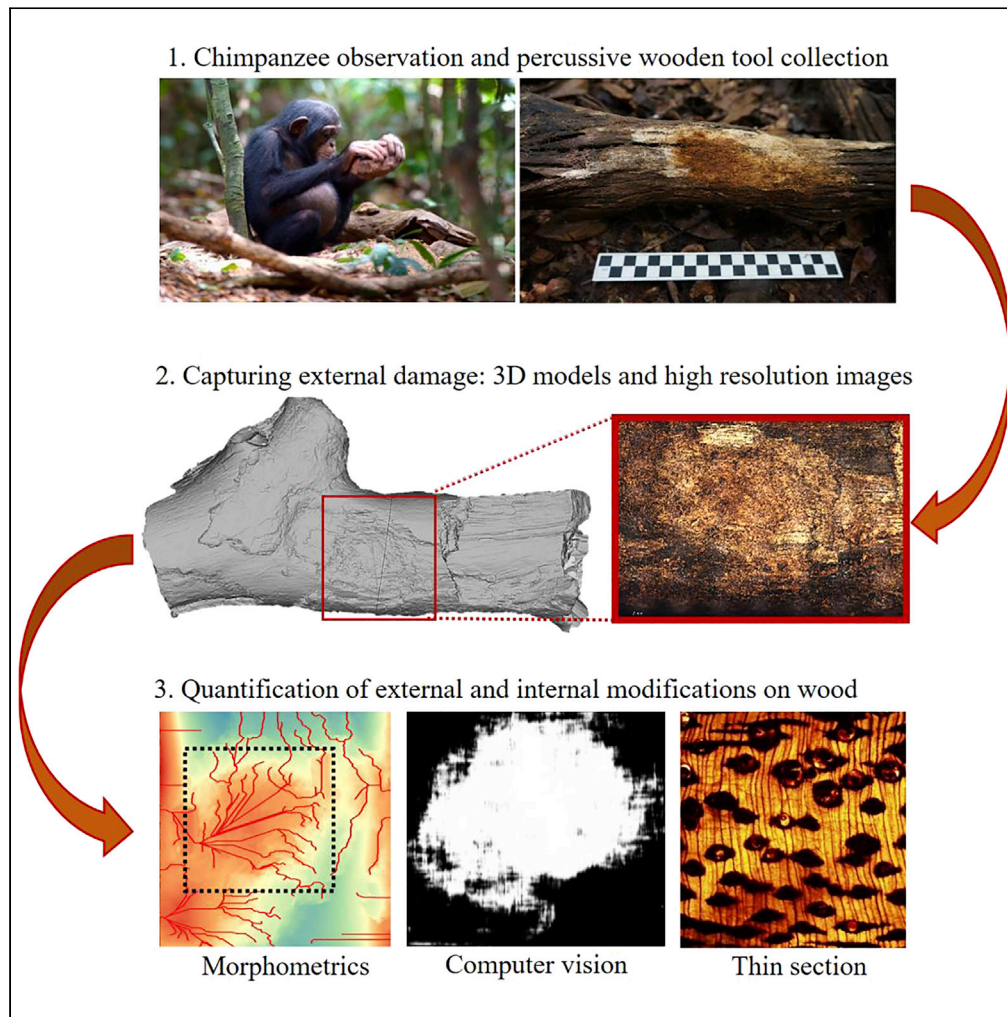


Article

Chimpanzee wooden tool analysis advances the identification of percussive technology



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Highlights

Chimpanzee percussive
foraging leaves
permanent damage on
wooden tools

Percussive activities leave
diagnostic patterns visible
in 2D images and 3D
surfaces

Machine learning can
diagnose damage
patterns even when
details are obscured

Percussive activities
produce irreversible
damage to the internal
structure of wood

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Article

Chimpanzee wooden tool analysis advances the identification of percussive technology

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SUMMARY

The ability of humans to mediate environmental variation through tool use is likely the key to our success. However, our current knowledge of early cultural evolution derives almost exclusively from studies of stone tools and fossil bones found in the archaeological record. Tools made of plants are intrinsically perishable, and as such are almost entirely absent in the early record of human material culture. Modern human societies as well as nonhuman primate species use plant materials for tools far more often than stone, suggesting that current archaeological data are missing a substantial component of ancient technology. Here, we develop methods that quantify internal and external damage pattern in percussive wooden tools of living primates. Our work shows that the inflicted damage is irreversible, potentially persisting throughout fossilization processes. This research presents opportunities to investigate organic artifacts, a significant and highly neglected aspect of technological evolution within the Primate order.

INTRODUCTION

The unparalleled abilities of humans to use tools have allowed our species to populate almost every habitat on the planet. The evolution of human material culture is visible through the archaeological record. At present, the evidence of behaviors in the deep past must rely only on those materials, which are resilient enough to survive millions of years. Taphonomic processes that modify the archaeological record render the majority of past behaviors invisible. Our technological evolution is currently visible from the early archaeological record extending over three million years ((Harmand et al., 2015), also see (Archer et al., 2020) for alternative views). The first 1–2 million years of the archaeological record are almost exclusively comprised of stone materials. Tools made from wooden materials are likely to decompose rapidly and therefore may be vastly underrepresented in the early archaeological record. Our perspective of behaviors in the deep past is therefore fundamentally incomplete (Rolian and Carvalho, 2017). Direct evidence of wood as a medium for hominin technology appears first at ~400,000 (Allington-Jones, 2015; Thieme, 1997). Younger time periods highlight the importance of wood as an essential part of the human toolkit (d'Errico et al., 2012; Dillehay et al., 2008).

The universal use of organic tools in all modern human cultures today (McGrew, 1987; Oswalt, 1976) and the widespread use of organic tools across nonhuman primates (Beck, 2011; Breuer et al., 2005; Lamon et al., 2017; Pascual-Garrido et al., 2012; Pascual-Garrido and Almeida-Warren, 2021; Pruett and Bertolani, 2007; van Schaik et al., 2003) highlights the probability that perishable tools played an important (if not substantial) role in the evolution of our material culture. Reconstructions of the palaeoenvironments indicate the woodland nature of the landscape in which tool use evolved (Bamford, 2017), adding to the potential of organic tool use in deep time (Carvalho, 2021; Rolian and Carvalho, 2017). Given the hypothesized importance of wooden artifacts in behavioral repertoire of early hominins, a focus on new methods must be put forward to interrogate the archaeological record so that such artifacts might be recognized. This would be fundamental to fully understand the adaptive dynamics and strategies, including technological systems, in early hominin behavior.

Percussive technology has been documented as a substantial component of the earliest archaeological records (Harmand et al., 2015). The technological analysis of these earliest artifacts suggests that percussive tool use may have emerged as a precursor to the deliberate production of sharp cutting flakes (Carvalho et al., 2008). Percussive tool use in the order Primates has warranted extensive discussion about the

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evolutionary pathways leading to the emergence of this behavior (Carvalho and McGrew, 2012). Historically, the interest in primate tool behavior has focused on documenting behavior in various contexts, exploring the underlying cognitive mechanisms, social learning, and the role of the environment (Koops et al., 2014; Sanz and Morgan, 2013). The advent of primate archaeology shifted the research focus, moving beyond behavior, to include the artifacts of behavioral by-products. This has revealed a rich material record of the technological behaviors of different primate species (Carvalho et al., 2008; Falótico et al., 2019; Haslam et al., 2009, 2016; Proffitt et al., 2016). Documentation of comparable tool behavior across primate species has been largely centered on technology that uses stone for two main reasons. Firstly, this medium is more durable making their identification more conspicuous. Second, the prevalence of this tool form in the hominin behavioral record allows for ease of comparisons. Stone tool use, however, is rare in nonhuman primates. Thus far, the use of stone tools has only been reported for western chimpanzees (*Pan troglodytes verus*), long-tailed macaques (*Macacca fascicularis*), and two species of capuchin monkeys (*Sapajus libidinosus* and *Cebus capucinus*) (for review see (Carvalho and Beardmore-Herd, 2019)). Stone material though is mainly used as percussive tools in a variety of contexts including foraging, communication, and hygiene and can provide valuable comparative models for the adaptive significance of percussive behavior in deep time (Proffitt et al., 2021).

Ethological information indicates that across the Primate order, organic tool use is much more abundant (e.g. leaves, twigs, branches etc.). Such tool use is seen in all great apes (Breuer et al., 2005; Ingmanson, 1996; Pruett and Bertolani, 2007; van Schaik et al., 2003) and in several Cercopithecoidea and Cebidae species (Beck, 2011) predominantly used for extractive foraging (for example: termite fishing, ant dipping but also for flushing out prey from inaccessible holes and for hunting). Chimpanzees in the Taï forest, Côte d'Ivoire, however, routinely use wooden tools as hammers and anvils to crack a variety of hard-shelled nuts (Boesch and Boesch, 1983). These percussive wooden tools accrue significant damage during their use-life. Damage caused by nut cracking has thus far been described only on stone material (Benito-Calvo et al., 2015; Proffitt et al., 2018).

Primate percussive tools are not modified prior to use and as such, the only evidence of use is the presence of damage patterns on their surface. This makes the recognition of these tools more complex because of the potential for overlap with natural and post-depositional processes that could leave similar damage patterns to those observed through use (e.g., abrasion during fluvial transport). Previous work has shown that analysis of the three dimensional texture of the surface of percussive tools made from stone is able to identify and characterize use wear (Benito-Calvo et al., 2015; Caruana et al., 2014). Building a framework of percussive tool analysis will open new avenues for direct comparisons between Plio-Pleistocene artifacts and extant primate technology (Haslam et al., 2009).

Here, we develop a methodological workflow that aims to include wooden tools into the framework of percussive damage pattern. Our goal is to develop multiple diagnostic methods to robustly identify the signature of wooden percussive tools of wild chimpanzees. The methods presented here investigate damage patterns from two distinct perspectives. The first is the documentation and analysis of *superficial* or *external damage* at the location of impact, the area of the percussive tool that receives the highest impact during use. Repeated force inflicted onto a restricted area on a tool (generally at the center of mass) results in significant modifications to the surface, similar to what has previously been documented on stone material of percussive tools. The second approach seeks to identify the *structural* or *internal damage* that occurs inside the tool. Micromorphological studies of the mechanical properties of wood indicate that localized repeated percussion leads to densified internal areas (Rautkari et al., 2010). Compression of wood can cause bending and collapse of cell walls (Bodig and Jayne, 1982). Depending on the specific features of the wood (e.g. wood density) and the percussive force, we expect a substantial degree of damage to the internal cell walls as well as the capillary system of wood during percussive tool use.

Organic material, including wood, can undergo geochemical changes that replace the organic structures with a crystal matrix (Fengel, 1991). This process is analogous to the ways in which bones fossilize (Akahane et al., 2004). Fossilized wooden fragments have been identified around archaeological sites in the same sediments as stone artifacts and hominin fossils (Bamford, 2005, 2017). These fossils have been used mainly to reconstruct palaeoenvironments. Documenting the diagnostic signatures of percussive damage on extant wooden tools will allow the recognition of evidence of organic technologies in deep time.

We first describe the typical-conspicuous external features of wooden tools and explore the longevity of these features by investigating the preservation potential of modern chimpanzee tools over timeframes that might precede burial (~32 months). We use morphometric analysis of the modification of wooden fibers on the surface of tools. Three-dimensional models of the surface damage provide a high-resolution model to quantify damage patterns through the deformation of the orientation of the fiber structure.

The second approach applied computer vision techniques (Convolutional Neural Networks (CNN)) to develop a diagnostic tool that automatically differentiates between images of damaged and undamaged surface structures. The organic nature of wooden tools makes them particularly vulnerable to post-depositional weathering processes that can modify the damage patterns on the surfaces of tools. To further enhance the identification of images of tools that may have been subjected to various weathering processes, we applied the CNN to a series of images that have been artificially distorted. This analysis confirms the predictive power of CNN models even in the event that post-depositional processes obscure the signal of percussive damage on the surfaces of wooden tools.

The third approach focuses on the internal structure of the wood. This micro-morphological approach identifies the damage inflicted on the fibrous tissue inside percussive tools. These patterns were identified in thin sections of the damaged area at the center of the highest intensity of damage on the external structure of the wood. We focus on the changes inflicted to the internal wood structure through comparisons of undamaged areas of the same specimen.

Together, these interdisciplinary methods produce a robust and comprehensive analytical tool set to detect percussive damage, internally and externally, and provide a quantitative description of such processes in extant percussive wooden tools. This approach aims to be the precursor to the identification and assessment of equivalent implements in archaeological assemblages.

RESULTS

Linear measurements of tool size

In total, we identified 57 wooden tools at 30 different tool sites in the Taï National Park, Côte d'Ivoire. Wooden hammers and anvils accumulate diverse damage patterns depending on the wood species used. Often damage is characterized by deep pits on the surface of wooden tools and twisting of damaged wooden fibers. The wooden hammers of our study sample were of the species *Coula edulis* (75.5%), *Parinari exelsa* (17.5%), and other (7%): including [*Erythrophleum ivorense* (3.5%), *Klainedoxa gabonensis* (1.75%), and *Castanola paradoxa* (1.75%)]. Wooden tools were variable in size ranging from just over 200 g to up to 8 kg (mean of 1766.16 g, sd: 1658.39 g). This range is also reflected in their overall linear dimension (average length: 59.67 cm, sd: 33.92, average circumference: 20.8 cm, sd: 5.53), (Figure S1 shows general wood measurements and Table S1 lists individual measurements of the wooden tools included in the overall measurements).

Decomposition experiment

The hardness of the six wooden hammers was measured at the beginning of each month over the course of 32 months, using a standardized hardness test throughout the extent of the experiment. We inserted a nail 1 cm into the wood and measured the distance it entered the wood after dropping a 500 g weight 5 times over a distance of 50 cm through a PVC tube onto the head of the nail. This was repeated 5 times. Two hammers were removed from the experiment after 14 months to export them for further analysis. Only one hammer (*Coula edulis*) was removed from the experiment due to advanced decomposition of the wood. In this specimen, the nail completely passed through the wooden tool at multiple locations over a period of 5 months. At this advanced stage of decomposition, we considered this piece as no longer usable as a tool. We concluded that this specimen would not have survived any kind of burial and preservation process. The remaining three hammers exhibited a hardness suitable to crack nuts until the end of the experiment, after 32 months (Figure S2 displays the decay rate of wooden hammers). As such, wooden tools are durable over the course of multiple nut-cracking seasons.

3D morphometric models

We analyzed seven individual tools using geospatial techniques. Three-dimensional models of surficial damage were transformed using a TPI transformation (Benito-Calvo et al., 2015; Caruana et al., 2014), so

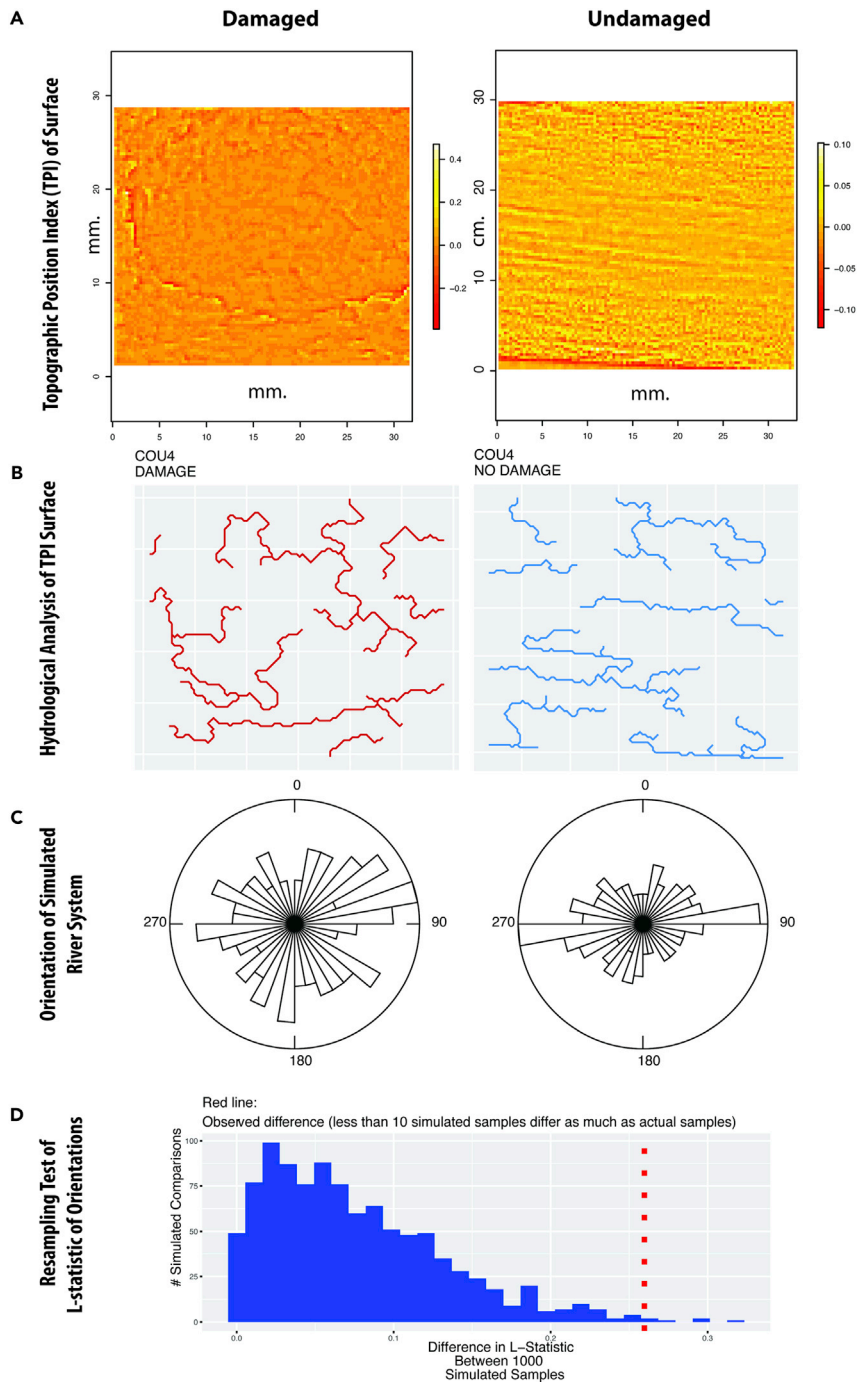


Figure 1. Morphometric analysis of surface damage on percussive wooden tools of wild chimpanzees

(A) Topographic surface model of wooden structure.

(B and C) Orientation of damaged and undamaged wooden structures visualized through hydrological surface pattern, C: the rose diagrams summarize the linear orientation of the hydrological pattern.

(D) Distribution of resampled L-statistics of the orientation of external wooden structure.

that the original grain of the wood was visible in all “undamaged” portions (Figure 1A). The rose diagrams of these undamaged areas show a linear orientation of the resulting modeled stream networks, with the highest frequency of orientations in the 80°–90° (20%–35% of orientations) or 260°–270° (20%–45% of orientations) categories (Figure 1B). This contrasts with the damaged portions of the tools that show little

Table 1. Confusion matrix of the testing dataset of 420 tool images

Confusion Matrix (un-altered test data)	Predicted Undamaged	Predicted Damaged
Actual Undamaged	201.6 ± 2.4	8.4 ± 2.4
Actual Damaged	7.2 ± 4.5	202.8 ± 4.5

The statistical measures were obtained from a 5-fold cross validation by randomly splitting five times the entire set of tool images into training dataset of 878 images and testing dataset of 420 images.

orientation of fibers (e.g. the 80°–90° categories is consistently less than 10% of all orientations). The damaged portions of the wooden tools show a variety of orientations as the fiber structure tends to point toward the center of the “pit” or the localized area of intensive percussive damage (Figure 1B). The L-statistic variation highlights this with much lower L-statistics for the areas with no damage (mean: 0.39; sd: 0.20) compared with the values seen in the damaged portions (mean: 0.212; sd: 0.05, Wilcoxon Rank Sum W: 7, $p < 0.05$) (Figure 1C). The resampling procedure also indicates that there are significant differences between damaged and undamaged portions of the same tool. When comparing resampled populations of vectors in a pooled sample of damaged vs. undamaged portions, differences between simulated samples and the actual difference in L-statistic are consistently significant in five of the seven samples. When all of the damaged portions are combined into a single population of vectors, they are significantly different at the $p < 0.001$ level compared to the undamaged portions (resampled L-statistic of damaged portions: 0.20; resampled L-statistic of undamaged portions: 0.40, Figure 1D). This method highlights that the orientation of wooden structure on the surface of damaged areas is more heterogeneous when compared to the original grain of the undamaged portions of the wood (Table S3 displays the 3D morphometric statistical analysis).

Machine learning

Convolution neural networks (using VGG16) were able to achieve an accuracy of $96.3\% \pm 1.4\%$ in differentiation between damaged and undamaged wooden parts on our test set, and an f1-score of $96.4\% \pm 1.3\%$ [the f1 score is a measure of both precision (the frequency of true positive characterizations out of possible true characterizations) and recall (the number of true positives relatives to true negatives)]. The above statistical measures on accuracy and f1 score were obtained from a 5-fold cross validation by randomly splitting the entire dataset into training and testing datasets to repeat the calculations five times. In training, we used an early stopping method and the training stopped after about 19 epochs. Early stopping is a generalization technique that helps the training process avoid overfitting the model to the training set by tracking its performance on a validation set (a proportion of the training set, which is isolated from the original training or testing set and used only for validation). When the performance on the validation set stops improving, model training stops. An average confusion matrix of test sets from a five-fold cross validation shows that an average of 15.6 samples ($8.4 + 7.2$) out of 420 images in the test set were incorrectly classified. Importantly, only 4.0% ($8.4/210$) and 3.4% ($7.2/210$) of the undamaged and damaged surfaces, respectively, were misclassified on average. This suggests low and balanced false positive and negative rates (Table 1).

To display the ability of our model to identify the portions of the surface that are damaged, we used a moving window technique to classify larger images of the tool surface (these are the original images prior to the sampling procedure described in the STAR methods). In these moving window applications, a portion of the image is selected and then passed through our VGG16-based CNN model. This sub-sampled image is then assigned a classification based on the ability of the model to predict if the image reflects a damaged or undamaged part of the tool. The resulting classification “score” is displayed as a grayscale value in an overlay image. The result of this process can generate a “heat map” of the damage on the surface of the tool (Figure 2). In parts of the surface of the tool where classification is most certain, the pixels associated with this part of the image have the highest values. These “heat maps” show that the CNN model is learning generalized texture patterns that can translate to a diversity of contexts where wooden tools display similar damage patterns. These heatmaps provide an indication of where the boundary between “damaged” and “undamaged” areas are in the original wooden tool.

We applied this transfer learning model to artificially blurred images (as described in STAR methods). The machine learning classification success is rapidly impacted by increasing the window size of the blurring. Figure 3 shows the decrease in classification accuracy (% correctly classified) as window size of blurring

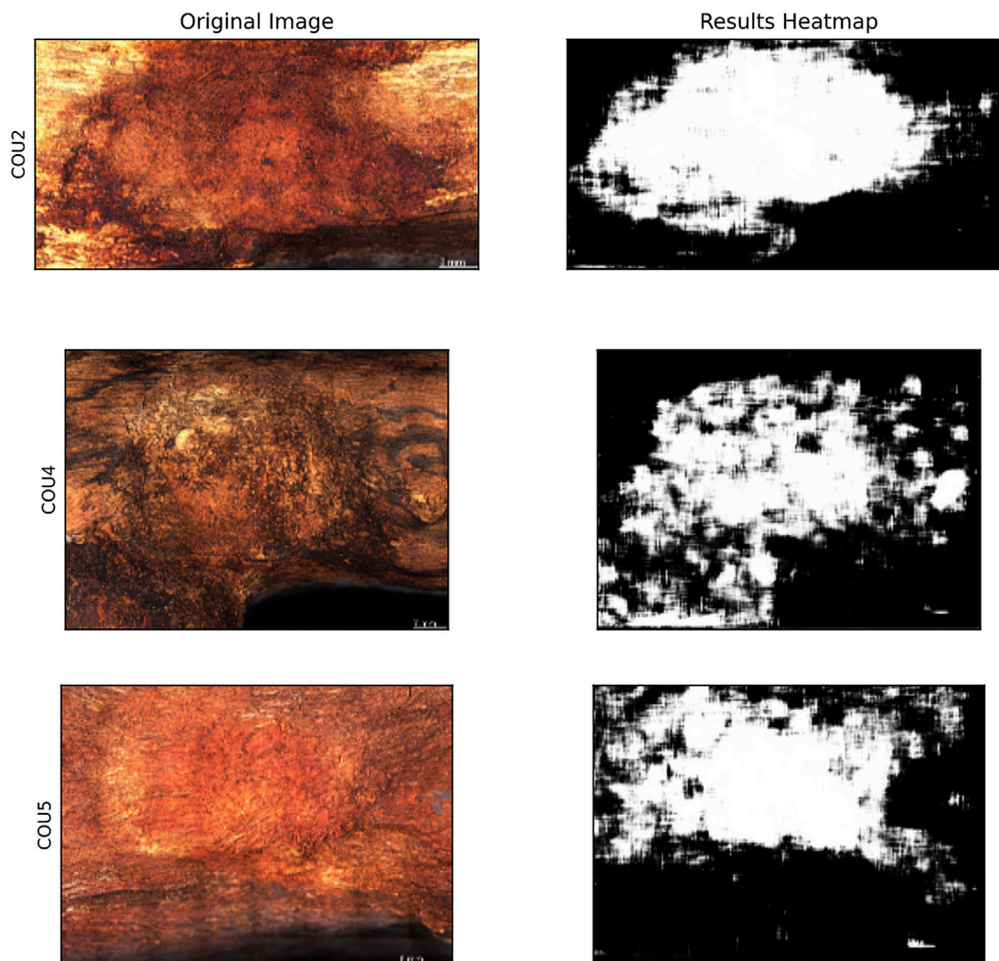


Figure 2. Image recognition of damage pattern

Left: High resolution images of the localized percussive damage in the center of wooden tools, surrounded by undamaged areas. Right: Heatmap displays the predictive classification score of damaged and undamaged areas (displayed in grayscale), location assigned by computer vision.

increases. The blurring window size represents the area over which the Gaussian weighted average blur technique was performed on the image. The accuracy of classification remains high (>90%) for blurring of size less than 0.05 mm. This suggests that even if mild weathering processes obscure the patterns that distinguish damaged surfaces, the machine learning mechanisms will be able to identify damaged portions of the tool with high probability. It should be noted that the classification success decreases rapidly as the size of the Gaussian blur increases. In particular, the accuracy approaches the level of a random guess (50%) when the blurring window size reaches 0.2 mm (Figure 3). This suggests that the CNN is sensitive to the scale of the size of damage on the surface and that small-scale texture patterns play a major role in the classification procedure.

Internal damage pattern

The external appearance of the damage formed on the three chimpanzee wooden hammers selected for thin sectioning during *Coula edulis* nut cracking confirms a round to oval indentation. These indentations are approximately 3 × 3 cm in diameter and about 1–1.5 cm deep. Microscopic analysis shows extensive surface damage of the pit with broken and distorted wood cells in the indentation/pit.

The three tools were all classified as tropical hard wood species. COU3 (Figure 4.2) has lozenge-shaped aliform parenchyma, while COU8 (Figure 4.4) has regularly spaced banded apotracheal parenchyma. In

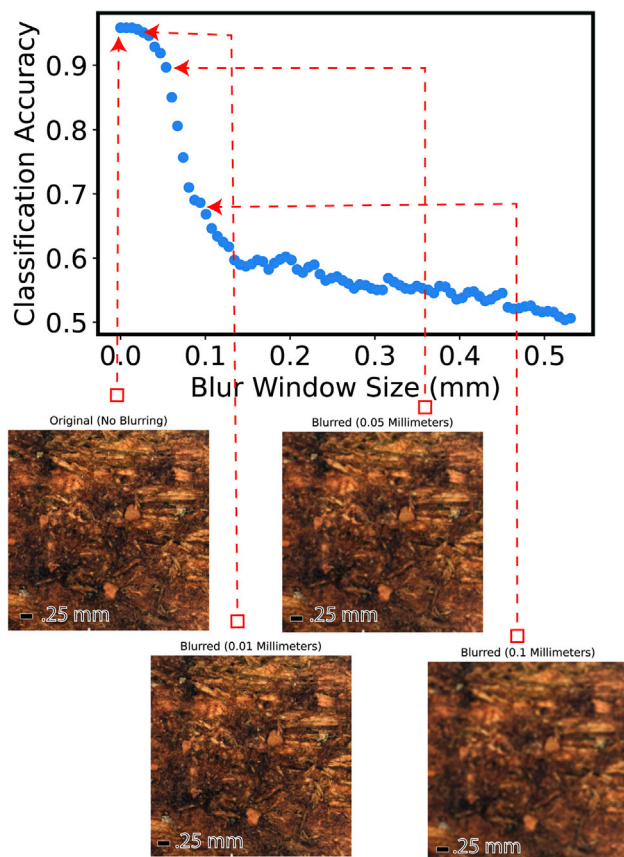


Figure 3. Gaussian blur on high resolution images of percussive wooden tool damage

This technique demonstrates the decreasing classification accuracy with increasing Gaussian blur.

contrast, COU6 (Figure 4.3) has short lines of diffuse-in-aggregate parenchyma. In each wooden tool, the internal tissue was modified at the impact point to a depth of 1–2 mm. Farther away from the impact point (i.e. deeper and laterally), the internal wood structure was unaffected. COU3 (lozenge-shaped paratracheal parenchyma) showed the least intensive internal damage pattern. COU6 (vessels in short radial multiples) showed collapsed vessels, crooked rays, and damage to the parenchyma. However, the parenchyma in this specimen is not as abundant. COU8 (banded parenchyma) showed the greatest amount of damage with collapsed vessels, crooked rays, and heavily distorted parenchyma bands.

Photomicrographs of the thin sections of the wooden hammers show the external pits and the internal damage as seen in thin sections. The pit surface is visible in the thin sections as an indentation with fragments of broken wood cells partially removed from the wood. Within the wood (underneath the indentation), the first ~1–2 mm of vessels have been completely compressed. In this portion of the wood, the lumens are collapsed. The rays, which are normally straight in the transverse section of undamaged wood, can be observed as distorted and crooked in the thin sections of the damaged portions of the wooden tools. Furthermore, in the damaged portions of the wooden tools, the parenchyma cells around the vessels, or in bands at right angles to the rays, have been distorted. In contrast, the fibers do not appear to have been affected by the percussive force applied to the hammer.

DISCUSSION

Currently, the technological behaviors of ancient hominins can only be observed through modified bones and stones found in the archaeological record. This limits the reconstruction of technological diversity of hominins in time periods older than the Middle Pleistocene. In addition to the likely underestimation of hominin technological diversity, the lack of organic tools from ancient contexts prevents much of the

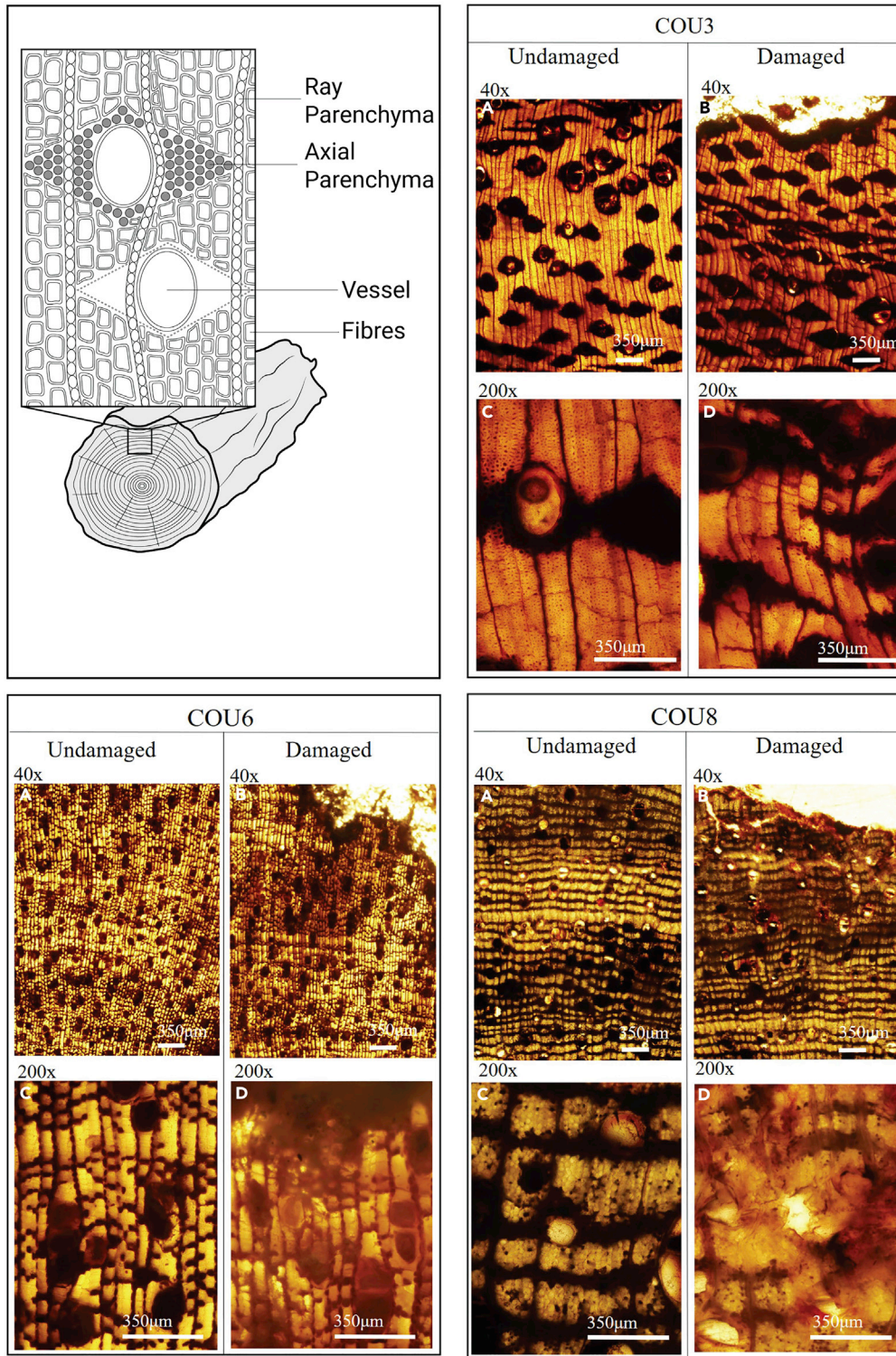


Figure 4. Internal wood structure

Upper left. Diagram of transverse sections through the wooden tools

COU 3, 6, 8: Internal structure of three wooden hammers (Transverse section): the left hand column shows the transverse section of undamaged parts of the wooden tools from a section away from the pit. The right hand column shows the areas of damaged wood at the center underneath the indentation. The undamaged areas (A and C) show straight vertical lines of the rays, open lumens of the vessels, clear short horizontal lines of parenchyma cells (dark). The damaged areas (B and D) show distorted vertical rays, compresses vessel lumens, and parenchyma.

comparison between tool use in early hominins and modern primates. Here, we provide a multi-method approach for the identification of organic percussive tools.

Repeated percussive activity on wooden tools during nut-cracking behavior of wild chimpanzees produces a suite of diagnostic traces that are similar across different wood species. It has been shown that branches that are suitable for nut cracking are widely available at nut-cracking sites (Sirianni et al., 2015). The long-term decomposition experiments indicate that wooden tools can survive over an extended period of time (>30 months) and could be used as tools in multiple consecutive nut seasons. This persistence allows for damage to accumulate. The use of wooden tools over multiple seasons results in intense patterns of percussive damage. This confirms that robust wooden tools are not expedient tools, but rather resistant and durable parts of the chimpanzee toolkit. It is often assumed that wooden tools will not preserve because high-humidity environments (such as tropical forested conditions) will rapidly decompose these elements. The wood chimpanzees select for nut cracking is extremely hard, heavy, close-grained, and therefore resistant to water damage. Those species are also known to be more resistant to insect attack, particularly termites (Burkill, 2000). Furthermore, as we have documented here, these wooden tools preserve for extended periods of time. Indeed, the ability for wood to maintain their structural integrity over several years in a wooded habitat indicates that given potential mechanisms for burial, they have a substantial fossilization potential (Behrensmeyer, 1978). It should be noted that post-depositional degradation is substantial in wood and requires unique circumstances to allow for preservation or fossilization. However, these contexts have been documented in sediments adjacent to numerous Plio-Pleistocene archaeological sites (Bamford, 2017; Goren-Inbar et al., 2002).

Externally, the damage on percussive wooden tools is characterized by deep pits on the surface of wood and twisting of damaged fibers. Diagnostic traces can be visualized through topographic changes on the external fiber structure of the wood. The damaged areas of the tools show a significant increase in fiber distortion at the center of the percussive impact compared to undamaged areas. Our methods show that this can be quantified using three-dimensional models of damaged surfaces.

Images of these damaged areas can also be identified through computer vision and machine learning algorithms with high accuracy (96%). These superficial modifications of percussive wooden tools remain identifiable even after substantial modification of the fine-scale detail of these images. This suggests that the diagnostic features of these tools are likely to persist even in instances where fine-scale details of the surface of wooden tools have been obliterated by various taphonomic processes and leave a lasting signature of percussive technology that can be used in the absence of direct observation of behavior.

A critically innovative diagnostic feature of these wooden tools is the internal modifications to cellular structure. This is distinctive from the identification of stone percussion tools because of the anatomical features of wood that are modified during percussive activities. Repeated dynamic force applied to a localized area on a wooden tool during nut cracking damages the internal structure, which results in modifications of the wood tissues. The cross-sectioned wooden tools display a series of diagnostic features that are only present directly below the areas where percussive damage was intensive. These modifications are caused through repeated percussive force. Direct observations of hammer use by chimpanzees and the collection of material from defined nut-cracking sites diminish the likelihood that damage was the result of alternative processes. The diagnostic features include displaced rays, distorted parenchyma bands, and compressed lumens of the vessels. Areas on the same tool where no percussive activity was inflicted exhibit none of these internal modifications. Research on mechanical properties and compressive stress in wood materials shows that internal alterations, like those seen in the percussion damaged tools, are irreversible across multiple plant species (Laine et al., 2014). The elastic nature of wood makes it stress resistant until it exceeds a yield stress (depending on wood species and moisture content). However, once this threshold is surpassed, deformations caused by bending and collapse of the cell walls lead to deformations and failure of the internal wood structure (Dinwoodie et al., 1995). Force must be applied repeatedly and forcefully to inflict the distinctive damage seen in the internal wood structure of percussive tools in this study. Direct observations from ethological studies support this as chimpanzees frequently are observed to reuse the same tool to crack nuts at a given nut-cracking location (Boesch and Boesch, 1983). Fracture mechanics of commercial wooden samples shows that the densification of cell walls is only reversible to a certain degree through rehydration (Laine et al., 2016). The volume of the compressed cells can potentially return to its original form under certain conditions. However, the breakage of the internal wooden structures remains

irreparable (Laine et al., 2013). The internal features that are distinctive of percussive activity (e.g. broken cells, cracks, distorted rays, parenchyma, and lumens) are therefore permanently ingrained into the structure of the wood. This has important implications for the recovery of fossil evidence of this behavior. Previous documentation of fossilized wood indicates that internal anatomical features are visible even after extensive fossilization processes (Bamford, 2011). This strongly suggests that damage processes documented here may preserve into deep antiquity.

Understanding the diagnostic features of organic percussive tools may enable a broadening of our search lens for percussive activity in hominin technological evolution. Pounding tools have recently received an increase in research interest as they have been suggested to predate the creation of such sharp-edged tools (Rolian and Carvalho, 2017; Thompson et al., 2019). The ability to recognize different traces of percussive activity in deep time has the potential to expand the known archaeological record (Shea, 2006). The diagnostic features of percussive technology have required new methodologies to reliably identify these behaviors in the archaeological record (Mora and de la Torre, 2005). Numerous processes can produce pitting on the surfaces of stones and wood, which makes diagnostic identification of these behaviors difficult (Caruana et al., 2014). In addition, taphonomic processes can obscure diagnostic signatures on the external surface of the tool. The addition of diagnostic internal damage patterns in percussive wooden tools provides a characteristic feature of tool use, which may be more resistant to the effects of taphonomic processes.

Conclusion

The identification of primate behaviors through the description of their material culture has provided new insights into the variety of behaviors present in our closest living relatives. We provide diagnostic approaches to empirically investigate the technology of human origins by studying extant technological primates. The methodological developments described here show that 1) evidence of percussive behavior on wooden tools survives for an extended period of time so that these signatures have the potential to be buried and fossilize; 2) The signatures on the surfaces of tools can be identified through the study of three-dimensional and two-dimensional features of the surfaces of these tools; 3) Such signatures are diagnostic even when the fine-scale detail of the surface morphology is obscured; 4) These percussive activities produce irreparable and diagnostic damage to the internal structure of wood.

The development of innovative methods and the interpretation of recent discoveries require the productive discussion and collaboration between the core disciplines of primatology and archaeology (Carvalho and McGrew, 2012; Haslam et al., 2017). Advancing diagnostic features, aimed at identifying percussive damage on wooden tools, is likely to expand our insights and research avenues into a vast and almost largely ignored aspect of human cultural and technological evolution.

Limitations of the study

This study aims to identify damage patterns on organic tools in a manner that allows comparison to ancient traces of use. Patterns of use (damage on the surface and internal structure) will most likely be impacted by the physical properties of wood. These properties vary widely depending on tree species and water content at the time of use. The pattern and intensity of damage inflicted on wooden tools during percussive activities are expected to correlate with the specific material properties of the woods used. Our study has focused on the materials that were selected by chimpanzees for nut cracking in the Tai forest. As a result, we only investigated the damage pattern of the most prevalent wood species (*Coula edulis*). Chimpanzees preferably select tropical hardwoods when using organic percussive tools because of their utility in percussive actions. However, it is likely that some organic tool use may incorporate other species. Furthermore, the assessment of the modification of the surfaces and internal structures of organic tools has been identified without further quantification of damage intensity. Here, we focus on the identification of evidence of tool use, rather than the degree of tool use. Future studies that aim to quantify the degree of tool utilization, must address the critical role of physical properties in the development of these traces. The external and internal pattern of alternative sources of damage inflicted on wood needs to be assessed to allow for identification of percussive origin in the absence of observation. Among others, potential candidates that should be explored are fungal modification, insect damage, and trampling. We addressed the potential confounding factors of post-depositional modifications by applying an artificial distortion to our high-resolution images. This distortion highlighted the mechanisms associated with identifying superficial

modifications using the VGG neural network. However, this artificial distortion represents only one of many possible modifications that organic tools may be exposed to post-depositionally.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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SUPPLEMENTAL INFORMATION

Supplemental information can be found online at <https://doi.org/10.1016/j.isci.2022.105315>.

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DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

We support inclusive, diverse, and equitable conduct of research.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
R computing language (v. 3.6)	R Core Team (2020)	https://www.R-Project.org
Cloud compare (v 1.4)	Cloud Compare (2022)	www.cloudcompare.org
GRASS GIS (v. 7.8.3)	GRASS Development Team 2017	http://grass.osgeo.org
CNN (VGG16)	Simonyan and Zisserman (2015)	https://arxiv.org/abs/1409.1556
TensorFlow Library	Abadi et al., (2016)	www.tensorflow.org

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Lydia_Luncz@eva.mpg.de.

Materials availability

This study did not generate new unique materials or reagents.

Data and code availability

- Data: http://cdna.eva.mpg.de/Organic_Tool_Data/
- Code: http://cdna.eva.mpg.de/Organic_Tool_Data/

METHOD DETAILS

Data collection

Fieldwork to collect percussive tools used by chimpanzees was carried out during December 2017 and March 2018 in the North Group of the Taï Chimpanzee Research Project in the Taï National Park (Côte d'Ivoire). To identify suitable tools for our study we conducted transects in areas that have high *Coula edulis* tree density. We identified 30 nut cracking sites where wooden tools were used. The criteria for the identification of tool sites was established prior from direct observations of chimpanzee behavior and the collection of tools directly after use. A nut cracking site is defined as a combination of a tool located within the vicinity of 50 cm to an anvil (a root that shows fresh indentations in the form of one or multiple round pits). Nut cracking sites are defined by the presence of broken nut shells that had to be within the same vicinity as the tool (Luncz et al., 2018). We classified wooden tools by the clear discoloration of the tool surface where the nut was hit. We measured the length and the circumference of the wooden hammer at three different places (the center and approximately at 10 and 90% across the length of the tool). We weighed each wooden tool using a digital hanging scale (accuracy 0.1 g). We collected and exported a representative sample of chimpanzee wooden hammers for further investigations. To increase sample size we included four wooden hammer from the tool collection at the Max Planck Institute. To create 3D models of the exported wooden tools we used an AICON smart scan HeR8/C8 8 Megapixel (Fields of view 450 mm) scanner. High-resolution 2D images of the damaged area, localized at the centre of the percussive damage (i.e., pit) were taken with a ZEISS smartZoom5 (Objective: ZEISS: Plan ApoD1.6x/0.1 FWD 36 mm).

Wooden tool preservation

To assess the use life of wooden tools in forested conditions, the possibility for extensive reuse and the accumulation of percussive damage we carried out a longitudinal study of hammer hardness over the course of three years. We exposed used wooden tools to the natural climatic conditions of the Taï Forest and continuously measured their hardness (and consequently the effectiveness as pounding tools). Wood hardness often relies on the structural integrity of wooden fibers in the face of a dynamic load (Welzbacher et al., 2008). Dynamic milling of wooden tools was not possible in field contexts. To create an analogous

measure of wood structural integrity we devised field methods that identified the ability of wooden fibers to resist a dynamic load (a falling weight on the head of a nail). We selected six wooden tools (*Coula edulis*) that showed intense external percussive damage (Table S2 lists the wooden tools included into the decay study). We recorded size and weight of each tool. The initial measurement of hardness was measured within two days of collection (December 2017). We placed the wooden tools in a shaded area directly on the forest floor, each 50 cm apart from each other. The tools were kept in the same place during the duration of the experiment. Measurements of hardness was collected on the same side of the tool each month for 32 months. To assess hardness we inserted a 5 mm wide nail 1 cm into the wood using a hammer. We then dropped a 500 g weight over a distance of 50 cm through a PVC tube onto the head of the nail, repeatedly for 5 times. We recorded the distance the nail entered the wood (above the pre-inserted 1 cm). Wooden hammers were removed from the experiment when the nail passed through the entire thickness of the wooden tool at 5 different locations. This standardized method allowed for a comparable measure of wood structural integrity between the tools for 32 consecutive months between December 2017 and February 2021. This approach is essential to assess the possibility of reuse and damage aggregation over time, as well as the potential to preserve the wooden structure for long enough to get buried, an essential first step towards fossilization.

Internal wood structure

To analyse the internal wood damage that percussive activity might cause, we selected three chimpanzee wooden tools for thin sectioning. These tools were cut vertically (perpendicular to the grain of the wood) through the center of the pit (i.e. localized area of intense surficial damage) and with a rotary saw. One half of the tool was retained intact. The other half of the tool was sectioned again, parallel to the first section but 5 mm away from it to create a 5 mm thick cross section of the wooden tool. We applied the same method to undamaged components of all experimental pieces to provide a control. To preserve the internal structure of the wood during the thin sectioning process the slices were embedded in epoxy resin (Epofix® from Struers). The epoxy was guaranteed to penetrate all wooden cells by placing the cup piece in a container of the resin, which was then placed in a small desktop vacuum chamber until all the air bubbles had escaped. Once the epoxy was completely hardened, the thin slice was mounted on a petrographic glass slide and the outer surface was ground and polished to form a thin section. Thin sections were studied under a Zeiss Axiophot microscope and photographs taken with an Olympus DP72 digital camera and Stream Essentials® software.

QUANTIFICATION AND STATISTICAL ANALYSIS

3D morphometric models

Previous investigation of percussive technology capitalized on the ability of geospatial techniques to characterize landscapes e.g., the use of the topographic position index to highlight percussive damage on stone tools (Benito-Calvo et al., 2015; Caruana et al., 2014). This approach explores three-dimensional patterns on the surface of tools and characterizes them as landscapes. Here we employ a similar measure to explore the variability in the surface texture of wooden tools by identifying the reorientation of fibers on the surface of damaged pieces of wood. These surfaces are explored as hydrological landscapes using techniques that predict drainage from the variation in topography. Here we explore this methodology by extracting a portion of the surface of a wooden tool and follow a standard protocol to test the method's capacity to differentiate between damaged and undamaged surface areas.

Wooden tool surfaces were captured using a structured white structured light scanner at a high resolution (field of view: 450 mm, 108 μm point-to-point distance). Scans were saved as standard three-dimensional point clouds (e.g. .PLY). These three-dimensional models were then oriented using the three-dimensional visualization software CloudCompare (2022) v 1.4. We extracted a portion of the surface of each tool in an area where we identified percussive damage through visual inspection of the tool. We then extracted a portion of the undamaged surface on the same tool (Figure 1A). Portions of each tool that reflect damaged and undamaged surfaces were extracted at standard sizes (3 × 3 cm). These extracted portions were then isolated and oriented in CloudCompare so that the texture of the sample was reflected in the z-value. In other words, the surface of the tool was reflected as a surface "elevation". Extracted portions were positioned so that the natural grain of the wood was oriented in an "east-west" direction (Figure 1A). The isolated portion of the surface was translated into standard point cloud format for analysis (.xyz). These point clouds were converted into a raster surface through an inverse-distance weighting method (using the R computing language (R core team, 2020) (v.3.6) and the packages *sp* v.1.4, *spatstat* v.1.64, and *raster*

v.3.4). Many of these wooden tools are damaged on rounded areas; therefore, it was necessary to remove the natural convexity of the surface to explore the variation in surface morphology that was exclusively the result of surficial damage. This was done using the topographic position index (De Reu et al., 2013) which allows for a surface to be displayed using only local variations in topography (using the *terrain* function in the *raster* package). This is a moving window technique and here we employed a 3 × 3 pixel window because it provided the best estimation of local topographic variation without the development of “noise” created by minute variations in surface morphology.

We used these TPI landscapes to apply a standard geomorphic technique known as ‘stream extraction’ which calculates watersheds within the landscape by estimating the surface of the landscape as a series of triangles connecting points of elevation data (Holmgren, 1994). The flow accumulation is then used to develop watersheds that determine the number and direction of possible streams on a landscape based on the topography of the landscape. The end result is a stream network that uses the relative topography of the surface to identify general patterns in the topography. This analysis was done in the open-source software GRASS GIS ((GRASS GIS, 2017)v.7.8.3) using the *r.stream.extract* function. As this technique tends to produce hundreds of smaller rivers we only extracted those that could be classified as Strahler Order 1 (Hughes et al., 2011). These represent the major axes of orientation of the fibers on the surface of the wood (and not smaller deviations in the orientation of fibers).

To assess the statistical differences between the damaged and undamaged portions we employed a method that capitalizes on the use of circular statistics as well as resampling methods. The orientation of the “stream network” was calculated with functions that use the beginning and end of two straight river system and calculate the length of each river and the angle between two rivers (McPherron, 2018). The orientations of the stream networks can then be compared using standard circular statistics (using the R package *circstats* v.0.6). We calculated a standard measure of the general trends in orientation using an L statistic. This measure calculates a generalized trend in the orientations of aligned objects within a given sample. As such we calculated an L statistic value for each sample of “streams” (streams extracted from the topography of each 3 × 3 cm sample of damaged and undamaged wood surface) (McPherron, 2005). We used a resampling technique to assess statistical differences between the portions of the tools that were damaged (by the force of percussive activity on the surface of the tools) versus those that retained the original structure of the wood fibers (undamaged). We calculated the difference in the L statistic between the “undamaged” sample of “stream networks” and those from the damaged portions of the tools. All of the orientation values were then pooled into a single population. We sampled this pooled population (without replacement) randomly 1000 times using sample sizes that were identical to the unpooled samples. We compared the L-statistic between each of these randomly sampled populations. The number of times that the difference in L-statistic between randomly selected population exceeded that of the original damaged and undamaged portions was used as an estimation of the statistical differences between the damaged and undamaged portions of the tools. Although this is not technically a P-value it acts similarly to Monte-Carlo estimations of significant difference (Carsey and Harden, 2013).

Computer vision (machine learning image analysis)

We used a convolution neural network (CNN) to classify images of the damaged and undamaged portions of chimpanzee wooden tools. CNNs are particularly suitable for this task as the convolutional filters can identify different layers of abstraction across multiple spatial scales. CNNs can simultaneously identify large-scale patterns (lines or texture distinctions) as well as smaller scale patterns in the fine-grained detail of an image. Two-dimensional images of wooden tools were used to reflect the changes to the surface morphology of the damaged and undamaged portions of the wooden tools. The damaged portions of the wooden tools vary in shape and size, and can sometimes overlap, due to repeated impacts, creating composite damaged regions. These complexities require a method that can explore the variety of signatures and variable modifications of the textures across different scales including large-scale patterns (lines or texture distinctions) as well as small-scale patterns that exist in the fine-grained detail of an image.

The 2D images used for the CNN were captured using a ZEISS smartZoom5 to collect high quality images of the surfaces of 16 chimpanzee tools (resulting in images that are approximately 12,000 by 8000 pixels). Images were captured systematically so that the center of a single defined damaged area was facing the lens (Figure 2, left). These original images also captured enough of the surrounding surface of the wooden tool so that the images included both damaged and undamaged portions of the tool surface. We created a

custom script in the Python computing language to allow standardized smaller images that were focused on a portion of the image that reflected either percussive damage or the absence of damage. These smaller images were selected from within the original larger images. These resampled images were scaled so that each resampled image maintained the same physical size (6 × 6 mm). The pixel number for these images varies slightly because some tools were photographed at slightly different distances from the smartZoom5 camera (so that 6 mm represents a slightly different number of pixels). On average the resampled image dimensions were about 893 × 893 pixels (Figure S3 shows the resampled images from 2D wooden images). This resampling procedure resulted in 1298 images that could be used to train and test the machine learning model.

The CNN we employed to differentiate between the damaged and undamaged portions of the wooden tools was created using a transfer learning technique. A transfer learning technique is when an existing machine learning model that was originally developed to solve a certain classification problem is then augmented with a final supervised layer. This transfers the knowledge of general pattern recognition from a known (and highly trained model) to a specific classification problem. In our example we utilized an existing deep CNN model known as VGG16 (Simonyan and Zisserman, 2015) that was designed and trained to perform well on the classification of millions of images into 1000 distinct categories. This enabled us to repurpose the classifying capabilities of the more complex VGG16 model towards smaller datasets of percussive wooden tool images in binary classification task (“damaged” vs. “undamaged”). The VGG16 model, with a total of 134,264,641 parameters, was originally intended for use with the ImageNet classification dataset (Deng et al., 2009). The VGG16 model has been successful in classification experiments for the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). ILSVRC rates model performance against the ImageNet dataset, which consists of over 14 million images labelled with 1000 classes (Russakovsky et al., 2015). Our implementation utilized a minimally modified VGG16 while keeping the ‘ImageNet’ pre-trained weights available from the TensorFlow library (Abadi et al., 2016). The only modification made was replacing the final layer in the model with a fully connected layer. More specifically, we use the pre-trained VGG to extract 4096 features from any given image that are to be used as inputs to a sigmoid activation function with 4097 parameters (one weight for each of 4096 features plus one overall bias) to train our final machine learning model into a binary classification task (“damaged vs. undamaged”).

In our model, 4097 parameters were trained by supervised machine learning that is characterized by the use of a corrective feedback loop, which iteratively improves a model based on comparing the model outputs to desired outputs of known values provided in a labeled training dataset. Binary classification problems are characterized by defining a mapping from an input to a binary output. In our present analysis of chimpanzee tools, the output classification indicates whether the image contents are reflective of damage caused by chimpanzee percussive tool use.

We divided the 1298 resampled images into a training data set (which is used to develop the components of the convolutional neural network) and a test set (which is used to identify the classificatory strength of the model). We used 67.6% (878 images evenly distributed between damaged and undamaged samples) of the data for the training dataset. We then used 32.4% of the dataset (420 images evenly distributed between damaged and undamaged images) to test the machine learning model. Finally, in preparing the images we resized them to (244 × 244) pixels required as an input to VGG16 model (a requirement of the VGG16 model process).

As noted earlier, CNNs are particularly suited to classifying components of images by identifying both large-scale patterns and fine scale details simultaneously. The computer aided image classification process is developed on modern chimpanzee tools, which more than likely preserve all the details necessary for classification. However, many of these fine scale details may not preserve in other contexts. To simulate the processes that remove some of these fine scale details we artificially obscured the details in the 2D images. The artificially modified images were only included in the “test” set of the supervised machine learning classification procedure. In this subsequent analysis, the CNN is initially trained using the unmodified images and then the artificially modified images are classified in the “test” set. The artificial modification of the images was caused by using a Gaussian-weighted average to blur fine-scale distinctions within an image. We applied different degrees of artificial modification to assess the degree to which artificial modification reduces classification accuracy. The degree of artificial modification is increased by expanding the window size that the Gaussian blur is applied to. Figure 3 shows an example of the original images (no blur) and the subsequent three modified images with an increasing larger blurring window size.