Visual Models for Social Media Image Analysis: Groupings, Engagement, Trends, and Rankings

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With social media image analysis, one collects and interprets online images for the study of topical affairs. This analytical undertaking requires formats for displaying collections of images that enable their inspection. First, we discuss features of social media images to make a case for studying them in groups (rather than individually): multiplicity, circulation, modification, networkedness, and platform specificity. In all, these offer reasons and means for an approach to social media image research that privileges the collection of images as its analytical object. Second, taking the 2019 Amazon rainforest fires as a case study, we present four visual models for analyzing collections of social media images. Each visual model matches a distinctive spatial arrangement with a type of analysis: grouping images by theme with clusters, surfacing dominant images and their engagement with treemaps, following image trends with plots, and comparing image rankings across platforms with grids.

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Social Media Image Analysis

In societies saturated with images, visual research methods gain relevance. The increasing importance of images in social, political, cultural, and commercial practices is paired with the growth of methods for visual research. While claims about the relationship between visual cultures and visual methods require careful scrutiny (Rose, 2014), recent years have seen rising interest in visual research methods, particularly in relation to the study of digital culture and online platforms. In reaction to multiple and diffuse approaches to researching (with) visual materials (Banks, 2018; Pink, 2012; Van Leeuwen & Jewitt, 2001), there have been various efforts to review, taxonomize, and develop frameworks for different approaches to visual methods research. Some focus on where in the research process visual materials are used, making a distinction between methods that gather data in visual form and those communicating findings visually (Pauwels & Mannay, 2020). Others consider "sites of meaning," distinguishing between production, image, circulation, and audiences, and evaluate methods according to their aptness to tackle each site (Rose, 2016, p. 25). Others examine the provenance of visual data, which may be found to be researchers-initiated, subjects-initiated, or a combination thereof (Pauwels, 2020). Some distinguish between the formats, for example arguing that video-capturing technologies should be treated differently (Emmison, Smith, & Mayall, 2012).

In what follows, we focus on how online images, including video thumbnails but excluding videos, may be rearranged for the purposes of—often collective—interpretative work. Our research output is also visual: We propose visual models, presented in the form of diagrams, for the study of online images through the design of other composite images. As the title suggests, in this article we focus on "social media images." Another term is "visual social media" (Highfield & Leaver, 2016, p. 1) analysis, which may imply a focus on image-driven social media platforms (such as Instagram). A broader term is "visual media analysis" (Rogers, 2021, p. 1), which expands the scope to include other online devices, spaces, and platforms (such as Google Images and Wikipedia). Our point of departure is social media images and their properties, which call for ad hoc (visual) research methods.

Studying Social Media Images in Groups

It often makes sense to study online images in groups (Colombo, 2019). In what follows, we discuss several notable features of social media images: multiplicity, circulation, modification, networkedness, and platform specificity. These features may contribute to the case for examining social media images in groups (rather than individually). First, images are often created and experienced en masse through online display formats that privilege the collection of items. Second, digital images circulate across platforms and online spaces, multiplying their sites of audiencing. Third, online images are prone to modification and remixing, giving rise to countless related image collections, variations, and visual allusions. Fourth, they are part of broader arrangements of users and platforms, generating groups of images linked by hashtags, likes, comments, and algorithmic recommendations. Fifth, the peculiar ways that each platform has in privileging particular styles and kinds of visual content can only be studied by approaching images in groups. Below we discuss each feature, together with the kind of analytical possibilities presented for studying social media images in groups.

Multiplicity

Digital images are characterized by their multiplicity, concerning both their production and audiencing. Multiplicity relates not only to a well-documented abundance of visual material online but also to ways of seeing images grouped into different formats such as threads, sets, and grids (Lister, 2013) or even in "filmic" formats such as the stream (Sze, 2018). Such display formats favoring the collection of images (as opposed to those that foreground the individual image, such as in slideshows) are both a ubiquitous and conspicuous part of networked life—from cascades of images returned by Google Image Search to carefully curated Instagram grids (with tips on how to cultivate a cohesive esthetic). Such grouping display formats are part of the esthetic of digital images: As images have to compete for "thumbnail visibility" with their neighbors, they are often designed to be legible "at a glance," at reduced size, aspiring for a "simplicity of style, content and form" (Frosh, 2013, p. 144).

Multiplicity also defines the production of digital images. Smartphone photography, characterized by heavily automated computational techniques (Taffel, 2020), generates images in bulk, often even before the user sees the result. Automated compositing, an algorithmic mechanism embedded in most modern smartphones, privileges multiple shots or live streams of photos, which are then merged to render the conventionally perfect picture.

Multiplicity invites researchers to approach images as collections. Responding to this multiplicity does not mean that visual research traditions built on a "very attentive stance" (Rose, 2016, p. 10) toward individual images should be replaced by computational analysis of massive image sets. An approach to visual research sensitive to the multiplicity of digital images shifts the focus to the collection as a research object and seeks to formulate research questions (concerning circulation, modification, and similarity—as we discuss later) that can be approached by looking closely at images in groups. Such research questions do not discard the close reading of individual images as an interpretative strategy. However, they bring an interpretive sensibility for working with image collections as a methodological entry point.

Circulation

Another characteristic feature of digital images is their proneness to circulation. Images travel across digital platforms and online spaces through screenshotting and reposting practices. With "circulationism" (Steyerl, 2013), one refers to new networked visual regimes where the circulation of images, as opposed to what they represent, is part of their meaning and reality. The primacy of circulation can also be noted in the shift from online "repositories of images," such as Flickr, based on archiving and classifying, to "infrastructures of circulation" (e.g., smartphones and social media platforms) that promote effortless sharing and fast circulation (Hand, 2020, p. 312). Sharing practices (reposting, retweeting, liking, and commenting) and "lazy" forms of image appropriation, such as the screenshot (Nešović, 2022), amplify images' "sites of audiencing" (Rose, 2016, p. 25), making image circulation an urgent object of study. Images as "circulating data" (Hand, 2020, p. 313) generate another type of image collection to be studied: multiple sites of audiencing of the same image.

Modification

Modification is an important part of digitally mediated visual cultures. Users and platforms themselves cooperate in a constant process of image manipulation: As images travel around, they get remixed, downsized, previewed, thumbnailed, and otherwise transformed. Poor image refers to the online image as a "copy in motion" (Steyerl, 2009, p. 1) whose circulation is lossy, as opposed to lossless (recalling image compression algorithms), resulting in downscaled versions of the same image (including cropped ones, of lower resolution, or ripped screenshotted content). With memes production, image manipulation may result in upscaled versions as users repackage content through mimicry and remixing. Understandings of Internet memes have shifted from thinking about them as cultural units that propagate (as the term was first used) toward thinking about them as a "group of digital items" with shared features, created with "awareness of each other" (Shifman, 2014, pp. 7–8)—adding to the case for studying images in groups.

Other types of image collections to be studied include groups of downsized copies (modified in size for thumbnails or previews) and upcycled memefied instances (resulting from mimicry and remixing practices). As visual content is often modified as it circulates, another research approach is "reuniting reused images" (Rogers, 2021, p. 5). Here one can cluster images according to their affinities and study the different versions and variations, the multiplication of poor images, and processes of meaning-making through their modification.

Networkedness

As visual culture (and its study) moves "from image to network" (Lister, 2013, p. 3), there has been a shift from studying images "not as solitary objects, but as a part of a network of other images, users and platforms" (Niederer, 2018, p. 12). Images are networked not only by users who tag, post, comment, upvote, regram, share, pin, and retweet but also by platforms that recommend, prioritize, and suggest, each with its own workings.

Hashtags, timestamps, comments, and other metadata link one image to another, generating networks of associated items. This networked character of online images suggests a conceptual shift that does not consider the textual and numerical as an addition to the visual but as an inherent part of the social media image itself (Hochman, 2014). The notion of "photographic document" (Neal, 2010, p. 332) captured the entanglement of visual, textual, and numerical elements involved in online images. Although the term has been developed concerning image-tagging practices on Flickr, a deep connection between visual and textual is even more relevant in today's dominant social media platforms. Researchers have noted how tags and words surrounding images should inform the analysis of online images as much as their content (Geboers & Van De Wiele, 2020a). This practice is aligned with longer media and communication research traditions that argue for multimodal approaches that examine how the interactions between verbal and visual modalities contribute to the construction of meaning in particular contexts (Jewitt, 2017).

The networked nature of digital images entails considering how users (and platforms) interacting with content online generate countless collections of linked items. Such collections may be of images posted with the same hashtags or keywords, commented on by users in the same space, or become linked thanks to algorithmic personalization logics of the platforms in which they are embedded.

Platform Specificity

The work of networking images is not just that of users interacting with content, but also of platforms linking images together. Each platform has its own "particular way of formatting, prioritizing, and recommending content" (Niederer, 2018, p. 46), as well as its platform-specific affordances catering to a variety of users' needs (Bucher & Helmond, 2018). In a networked approach to image analysis, one needs to pay close attention to how platforms and engines serve, format, rank, redistribute, and coproduce content.

The distinct ways platforms have of networking, ranking, and presenting content, as well as the specific actions they grant to users, promote platform-specific cultures of use, resulting in platform (visual) vernaculars: a combination of "styles, grammars, and logics" (Gibbs, Meese, Arnold, Nansen, & Carter, 2015, p. 257) native to (or characteristic of) a particular platform. Platform-specific affordances not only shape the emergence of particular visual styles but also determine which visualities become "elevated to prominence" (Geboers & Van De Wiele, 2020b, p. 746). The extent to which an image is seen or hidden (in one's feed or as a result of a search query) is linked to (often opaque) "ranking cultures" (Rieder, Matamoros-Fernández, & Coromina, 2018, p. 52), a mix of ranking and recommendation mechanisms put in place by social media platforms. For instance, Instagram ranks content in feeds and stories based on several different "signals," including information about the post, the user posting, and the user looking at the content (Mosseri, 2021). The opaque changes in these mechanisms force content producers to continuously fine-tune their posting strategies to keep up with platform algorithm changes. Examining and comparing groups of images across platforms can offer one entry point to the empirical elaboration of these specific dynamics.

Visual Models for Collections of Images

The features discussed above—multiplicity, circulation, modification, networkedness, and platform specificity—may be studied by starting with social media images in groups. After the data collection process, such as through query design (Rogers, 2017), images may be "analytically displayed" (Rogers, 2021, p. 1) to support interpretative work. The output can be described as a "composite image" (Colombo, 2018, p. 26) comprising multiple images in the same optical space. As a means of collection, it recalls the rhetorical format of the list, which "confer[s] unity to a set of objects" (Eco, 2009, p. 113). When collected together, disparate images comply with "contextual pressure" (Eco, 2009, p. 116), that is, they are interpreted as a group due to being found in the same place.

The analytical grouping and arrangement of image sets may also be intended as a republishing effort in that it gives collected images a new connotation. As in other projects that employ similar strategies, such as counter-archiving, rearrangement seeks to "collect, reorganize and republish" platform data against their "archival order" in a way that offers "epistemic alternatives" (Ben-David, 2020, p. 256) other than those afforded by the platform's interface.

The analytical display of image sets can also be referred to as "metapicturing" (Mitchell, 1994; Rogers, 2021), that is making pictures about pictures such that the output is an image that is used to reflect on other images. In this sense, the output should not be considered as the esthetic culmination of the analysis (Niederer & Colombo, 2019). It is instead a means to support (often collective) interpretive work. Such arrangements may also be described as visual models in that they curate a visual spread with particular interpretive and analytical sensibilities, connecting "design decisions and methodological reasoning" (Borra & Rieder, 2014, p. 262). The question is how different image arrangements may promote various interpretive procedures, and which arrangements are suitable for a particular analysis (and not for others).

What type of readings can different visual models offer researchers engaged in social media image analysis? The point of departure is that visual models are not innocent but embed specific forms of knowledge (Drucker, 2014), and different ways of arranging images support distinct analytical procedures. The display formats discussed here, that is, the visual models, make use of space as a meaning-making device. Each relies on a particular meaningful space (Engelhardt, 2016) to promote a specific way into a collection of images. For this reason, such visual models draw from cognitive studies that describe diagram-like representations displaying content spatially more efficiently for performing inferential tasks (Giardino, 2016), and those contending that spatial layouts drive (also nonspatial) reasoning (Knauff, 2013). Furthermore, they align with data visualization practices, where one prioritizes position over other visual variables, with the plane being the "mainstay of all graphic representations" (Bertin, 2011, p. 44) and location being an indispensable variable (Roth, 2017) taking primacy over others (e.g., the size or shape of the graphical marks).

In what follows, four visual models for social media image analysis are presented: image groupings with clusters, image engagement with treemaps, image trends with plots, and image rankings with grids. First, each visual model is introduced by tracing its genealogy and detailing its use in various research settings. Second, each model is illustrated through a case study that explores online visual imagery around the 2019 Amazon rainforest fires.

Image Groupings With Clusters

One way into a collection of images is to group them in clusters to observe their similarities and differences. The grouping of images may be driven by different logics, such as formal and thematic similarity, or being used with the same hashtags. As the organizing logic changes, the clusters are also interpreted differently, and the analytical focus shifts.

One approach is to group images by similarity. For example, images can be grouped based on color (hue or saturation), such as with Image Sorter (Visual Computing, 2007). There is a long history of manually curating and clustering images according to their various similarities. This has a notable precedent in the ambitious and unfinished BilderAtlas by Aby Warburg (2020), which compiles images in various plates, each dedicated to a cultural trope, allowing a comparative analysis of visual references across times and formats.

Computer vision has opened up avenues for exploring digitized cultural collections at scale. One may cluster digitized photographs (The Digital Humanities Laboratory, 2017) to compare the varying prominence of formats within a collection (the landscape vs. the portrait, "madames" vs. "suits") or the relevance of particular materials (photos, sketches, contracts, articles) in a documental archive (Colombo, 2021).

Grouping by similarity with computer vision may be applied to social media images to detect thematic clusters and dominant media formats in a set of images. It may also render marginal themes visible as one evaluates the size of one cluster of similar images compared with others. The approach has been used for exploratory work into the imagery associated with a particular place (Stefaner, 2018), issue (Ricci, Colombo, Meunier, & Brilli, 2017), or event (D'Andréa & Mints, 2021). The technique is also used to compare competing visual spaces, building on "programme and anti-programme research" (Rogers, 2017,

p. 82), such as pro-impeachment versus anti-coup content concerning Brazilian president Dilma Rousseff on Instagram (Omena, Rabello, & Mintz, 2020).

Given concerns around the shortcomings and biases of machine vision, particularly regarding representation and discrimination in relation to race and gender (Buolamwini & Gebru, 2018; Crawford & Paglen, 2019), research with computer vision algorithms needs to be approached critically and carefully. This effort may include thematizing computer vision algorithms as part of the object of study, attending to their "layers of technical mediation" (Omena, Elena, Gobbo, & Jason, 2021, p. 10), and not taking for granted the kinds of associations they produce.

Digital objects (such as hashtags, emojis, and reactions) can also drive image groupings. One common output is bipartite networks of images and other digital objects. With such networks, one generates clusters using graph layout algorithms and visually explores them (Venturini, Jacomy, & Jensen, 2021). Which types of images are associated with which hashtags, accounts, Web pages, or keywords? While grouping by visual similarity enables the study of meanings at the level of the image itself, grouping images according to how social media users react to them leans toward image audience research. For example, reactions (used on Facebook to engage with content) may be used to account for the affective dimension of digital images. Which reactions (an indication of sentiment) are associated with which images? A study found that sad and angry reactions are often used with images depicting children in posts about the Syrian war, while soldiers and sign-holding activists are more associated with the love reaction (Geboers, Stolero, Scuttari, van Vliet, & Ridley, 2020).

Clustering by shared hashtags seeks to identify "hashtags publics" (Rambukkana, 2015) and their distinctive visualities. What visual materials are shared by those in favor of shale gas extraction compared with those that advocate against it (Rabello, Gommeh, Benedetti, Valerio-Ureña, & Metze, 2021)? How is the land visually constructed (as a resource commodity vis-à-vis as an object for conservation) by actors with different stances on Canada's Trans Mountain pipeline (Karsgaard & MacDonald, 2020)? Finally, grouping images by Web pages is a form of circulation research, as one studies the flows of images across online spaces (Omena et al., 2021).

Whether similarity is operationalized with computer vision, color analysis, or shared digital objects, the research requires a visual format where images sharing similar features are clustered more closely together. The process typically outputs high-dimensional data, which are computed in the two-dimensional space with statistical approximations (Van der Maaten & Hinton, 2008). The result is a "good enough" space (Perez & Tah, 2020, p. 8) characterized by topological ambiguity like other forms of relational data such as networks. Visual ambiguity, "if properly interpreted," is an analytical asset, particularly apt for exploratory work (Venturini et al., 2021, p. 1). In contrast to other visual models, such as the grid or the plot, it is a polycentric format, lending itself to multiple visual entry points (Veca, 2011). It promotes a loose and serendipitous exploration of visual material in space and forms of looking that may be equated with mind wandering.

Image Engagement With Treemaps

Repurposing engagement metrics for social research may be termed "critical analytics," in contrast to using them to measure one's success in the "theater of social media" (Rogers, 2018b, p. 454), as done by marketing professionals. The visibility of a set of images could be measured through engagement scores such as likes and retweets or by reach, that is, the number of people who scrolled by a post, regardless of whether they engaged with it in any way (Newton, 2020).

Comparing engagement (or other metrics) among images of a collection requires a format that visualizes their relative visibility. For this goal, images may be displayed in a treemap, resized according to engagement scores. Treemaps show dimensions in a "space-constrained layout" (Shneiderman, 2009, p. 1), where space is proportionally divided (Engelhardt, 2016) with tiling algorithms. They align well with this line of inquiry as they visually render the extent to which images *occupy* online space. Treemaps are a relatively recent visual model, and a natively digital one, even though the use of rectangles and area to represent data quantities can be traced back to early forms of mosaic display (Friendly, 2002). Started as a means to visualize storage space in one's hard disk (Shneiderman, 1992) or directories of photos (Bederson, 2001), they then evolved to visualize other types of space, such as the news, where stories fill the page according to how many sources report them (Weskamp, 2004). They are now a staple of data visualization, as one may note from their presence as a Microsoft Excel template (Microsoft, n.d.), mainly used for visualizing budget proposals or expenses breakdown.

Treemaps have been used to study high-engagement posts in social media research. One may compile posts from a set of pages or accounts (but the set can also be of content posted with specific hashtags), calculate their engagement, and resize them in a treemap visualization. One example is a study of Somali diaspora communities on Facebook (Kok & Rogers, 2017), which found unique content in different national chapters (the Canadian one was concerned with integration activities, the United States with transnational art, the Dutch one with host-land integration).

Visualizing engagement with treemaps focuses on the ranked visibility of images. Limiting the analysis to only highly interacted content may cause one to ignore other visualities in the long tail or the "twilight zone" (Shane, 2020, p. 7). It is also a technique that partially ignores the multiplicity of digital images as it does not always consider similar images that may add to the overall engagement score but are not included in the analysis (e.g., versions and variants). One way to address this is to first group images by similarity and resize them according to engagement, combining two visual models and analytical techniques.

Image Trends With Plots

Studying trends with Web data has been made popular by the project Google Trends, where one can gauge the popularity of search terms over time, visualized as lines trending downward or upward. Concerning images, one can study changes in visual style or the rise and fall of individual images. As a case in point, "climate change" query results from Google Image Search per year are arrayed to observe the shift (or lack thereof) in the visual representation of the issue (Pearce & De Gaetano, 2021). When applied to social media images, the analytical procedure contrasts time with engagement to see which ones stay on top and which fade down. It can be compared with the study of issue commitment, which asks "for how long is an issue a matter of concern to the actors" (Rogers, 2018b, p. 459).

The analysis requires a format for simultaneously visualizing two variables (time and engagement). For this goal, images can be plotted in a system of coordinates where "the exact positions and distances of visual objects are meaningful" (Engelhardt, 2016, p. 29). Given plots' compositional logic, which lends itself to quantitative readings, one can estimate the actual numerical difference among elements in the space.

Plots have been used to ease various inferential processes, including orientation and navigation, reference, and information retrieval (see Figure 1). In a cultural analytics approach (Manovich, 2020), one sorts images chronologically to appreciate, with a distant reading attitude (Moretti, 2013), coarse shifts in formats and visual styles. The output is dubbed PhotoPlot (Manovich, 2012) in that it is constructed as a traditional plot, but it retains images (instead of translating them into graphical marks), and for that, it is a form of "direct visualization" (Manovich, 2011a, p. 36). PhotoPlots are used to study the evolution of formats on the covers of a magazine, such as the portrait waning in favor of the composition (Manovich, 2010) or to pinpoint visual shifts in a painter's oeuvre (Manovich, 2011b). Arraying images chronologically (on one axis) also serves a narrative goal as one follows a story unfolding over time. In one example, Instagram images from the Brooklyn area posted during hurricane Sandy, sorted by time of upload and hue, reveal a "visual rhythm" (Hochman, Manovich, & Chow, 2013) through recurrent shifts of dark and light tones (indicating day and night), and point to topical moments, such as the abrupt darkening of colors (corresponding to power outage).

Studying trends with plots focuses on the visibility of images over time. Similar to studying engagement with treemaps, the approach foregrounds high-visibility images while compressing, quite literally, to the bottom those images that receive little engagement. Multiple plots with different cutting points may be designed to focus on lower engagement zones. In addition, to account for the circulation, modification, and similarity of images in a set, one can overlay the plot with coding schemes to ease the identification of recurrent images.

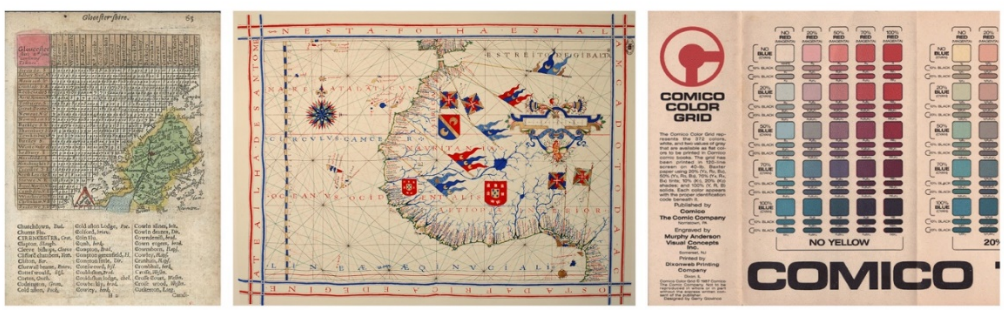

Figure 1. From left to right: Gloucestershire (Van Langeren, 1643); nautical chart (Vaz Dourado, 1571); Color Grid (Comico, 1967).

Image Rankings With Grids

Comparing image rankings across online spaces may enable the interpretation of dominant and marginal images (Rogers, 2021). The comparison may be undertaken across spaces demarcated through queries, hashtags, platforms, periods, or a combination of these. When ranking images across platforms, one should consider platforms' cultures of use, and digital objects should not be treated as equivalent across all platforms (Rogers, 2018a). Indeed, images' varying visibility may be dependent on platform-specific metrics (e.g., likes, retweets, upvotes, shares, or views), asking for the design of "platform-specific data collection protocols" (Pearce et al., 2020, p. 168).

The analysis requires a format for comparing (often small) collections of ranked images. For this goal, images are arranged in a grid from highest to lowest, with columns representing different spaces (e.g., hashtags, platforms, or time frames). The grid gathers images in the same optical space and provides the structure to appreciate "continuities and resonances" (Ahmed, 2017, para. 18) across them. It is a synoptic format as it facilitates (following the term's etymology) the *seeing together* of a group of elements in a structured way. Grids can also be a relatively accessible format, evoking classroom exercises, amateur collections, local museums, and shop displays. As a format for comparison, the grid has been used over the years for a variety of purposes (see Figure 2), including accounting, criminal identification, and statistical analysis, the latter following the principle of small multiples (Tufte, 2001), where one put side by side a series of charts to enable rapid visual comparison. In addition, the grid can be a ranked format characterized by an ordering axis (Engelhardt, 2016) where images' ranking (but not their exact position) is meaningful. Such ranked space (as opposed to the metric space of a plot) is particularly fit for comparing engagement across platforms with metrics whose sheer numbers are very different.

In social media research, grids have been used to visualize cross-space comparisons of image rankings. In one study of disinformation on Instagram during political elections (Colombo & De Gaetano, 2020), researchers curated a list of hashtags concerning political candidates and politically charged topics, collected posts, and ranked them in columns from most to least liked. Beyond single-platform analysis, grids of ranked images may also enable cross-platform visual analysis, and the study of distinctive platform visualities, termed "platform visual vernaculars" (Gibbs et al., 2015, p. 255). One study of the online representation of pregnancy (Bogers, Niederer, Bardelli, & De Gaetano, 2020) found platform-specific visual formats, such as scrollable graphics with pregnancy-related tips on Pinterest and inspirational quotes on Facebook. Another study has employed a similar visual model (Sued et al., 2022) to produce a platform-sensitive typology of Latin American feminist campaign materials, such as hand-written signs on Twitter and pastel digital flyers on Instagram. While focusing on platform specificities, the technique can also yield findings concerning image circulation, as one can follow across columns screenshots of content from one platform reposted on another.

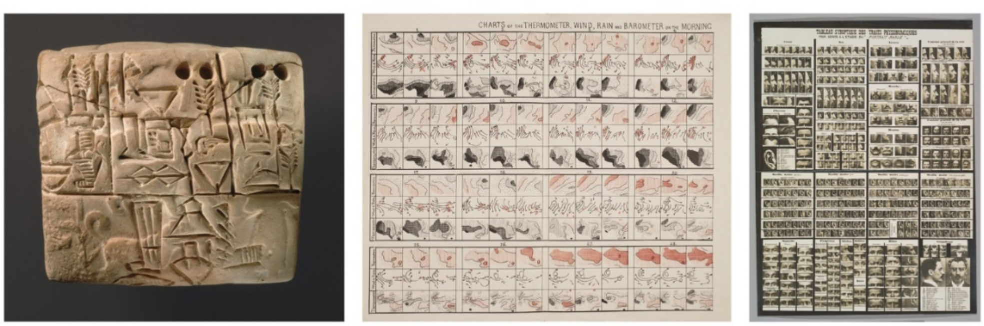

Figure 2. From left to right: Proto-Cuneiform tablet (n.d.), Galton's weather chart from Lucarelli (2014); synoptic table of physiognomic features (Bertillon, 1909).

Exploring the Visual Vernaculars of the 2019 Amazon Rainforest Fires Online With Clusters, Treemaps, Plots, and Grids

To illustrate the four visual models for social media image analysis, we use materials from a collaborative research project on the 2019 Amazon rainforest fires.[2] One of the most globally mediatized rainforest fires of the recent past, Twitter hashtags and viral images have played a prominent role in organizing worldwide public engagement around these fires (Madani, 2019; Weinberg, 2019). As most online interactions involve image sharing, visual content can play a pivotal role in surfacing different kinds of relationships among forests and various societal actors, issues, practices, politics, and cultures. To study the visual composition of the 2019 Amazon fires with social media images, we focus on the period spanning the second half of August and the first days of September 2019, corresponding to the peak of international coverage of the event. We sought to unfold the composited visualities brought to prominence online and how issues associated with and ways of relating to, experiencing, and knowing about forests in society are constituted through them.

A combination of hashtags was used to collect a set of tweets covering the period of peak activity on Twitter (and other platforms). The data were collected with the Digital Methods Initiative Twitter Capture and Analysis Toolset (Borra & Rieder, 2014). Furthermore, following platform-specific grammars, similar queries were used to collect data sets from Facebook, Instagram, Google Images, and YouTube. Each of the following analyses works with a different subset of images and offers a distinctive way into the visual composition of the event online.

Image Groupings: Dominant and Marginal Visual Formats and Themes

Image grouping is used on a collection of retweeted images, and it seeks to explore the visual registers, themes, formats, and practices associated with prominent Amazon rainforest fires related hashtags on Twitter (Figure 3). Groups are obtained with computer vision labeling and visual network analysis and subsequently annotated. The process involves four steps: (1) images are labeled with an image classification neural network (Clarifai, 2021); (2) a bipartite network (of images and labels) is visualized with the network analysis software Gephi (Bastian, Heymann, & Jacomy, 2009); (3) labels are hidden, while image position is retained; (4) clusters are manually emphasized (by tying images closer together) and named accordingly.

[2] For further details see https://publicdatalab.org/projects/out-of-the-flames/ and Gray, Bounegru, and Colombo (forthcoming).

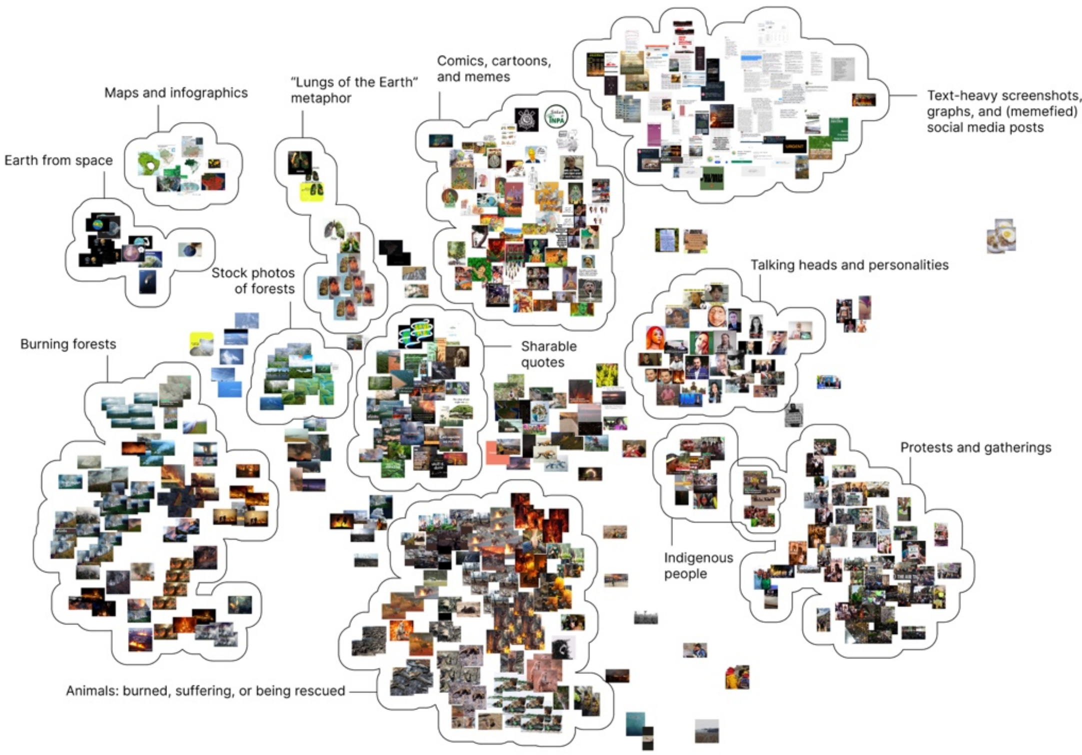

Figure 3. Images retweeted more than 10 times, grouped according to Clarifai (2021) computer vision, annotated by authors. Clusters are generated with Gephi's ForceAtlas2 spatialization algorithm (Jacomy, Venturini, Heymann, & Bastian, 2014). Time frame: 8/24/2019–9/2/2019. Source: #ActForTheAmazon, #amazonfires, #AmazonRainforest, #PrayforAmazonia, #SaveTheAmazon, and #SOSAmazonia.

In the case of the 2019 Amazon rainforest fires, among the dominant visual formats are the mainstays of Twitter and digital culture practices, such as memes, cartoons, shareable quotes, and screenshots of social media posts. Less visible is the scientific visual register, instances of which in this case include satellite images, maps, and infographics (see Figure 4). Clusters also reveal the uneven distribution of interest and care around hashtags that attract international mobilization, with affected nonhuman actors (i.e., forests and animals) dramatically more prominent than affected human actors such as Indigenous peoples (see Figure 5). Perhaps not surprisingly, emotive and sensationalist images of burning forests and suffering animals make up the most prominent clusters during the period of intense international mediatization of the event. The analysis may also be finer-grained and focus on recurrent specific visual tropes or genres (such as the "lungs of the earth" metaphor or generic forest images). Grouping by similarity also sheds light on image circulation patterns, as similar images cluster together, revealing the extensive presence of stock photography (e.g., forests) or what we called "media recycling practices" (e.g., images of burning forests from other forest fires). Finally, it may also serve as a corpus building technique, inviting in-depth multimodal analysis of selected clusters of images and their associated tweets.

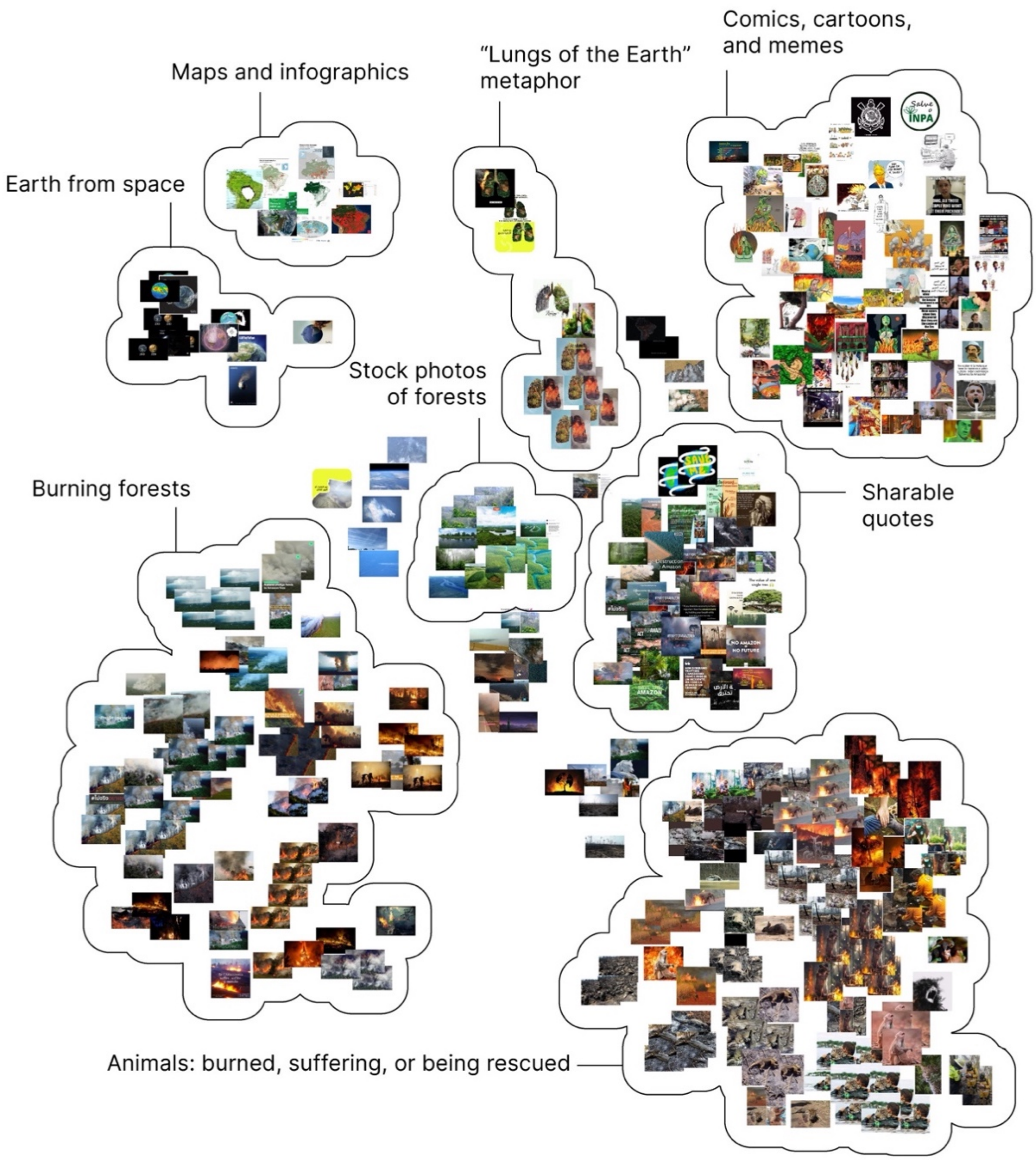

Figure 4. Images retweeted more than 10 times, grouped according to Clarifai computer vision, annotated by authors (left detail). Source: #ActForTheAmazon, #amazonfires, #AmazonRainforest, #PrayforAmazonia, #SaveTheAmazon, and #SOSAmazonia.

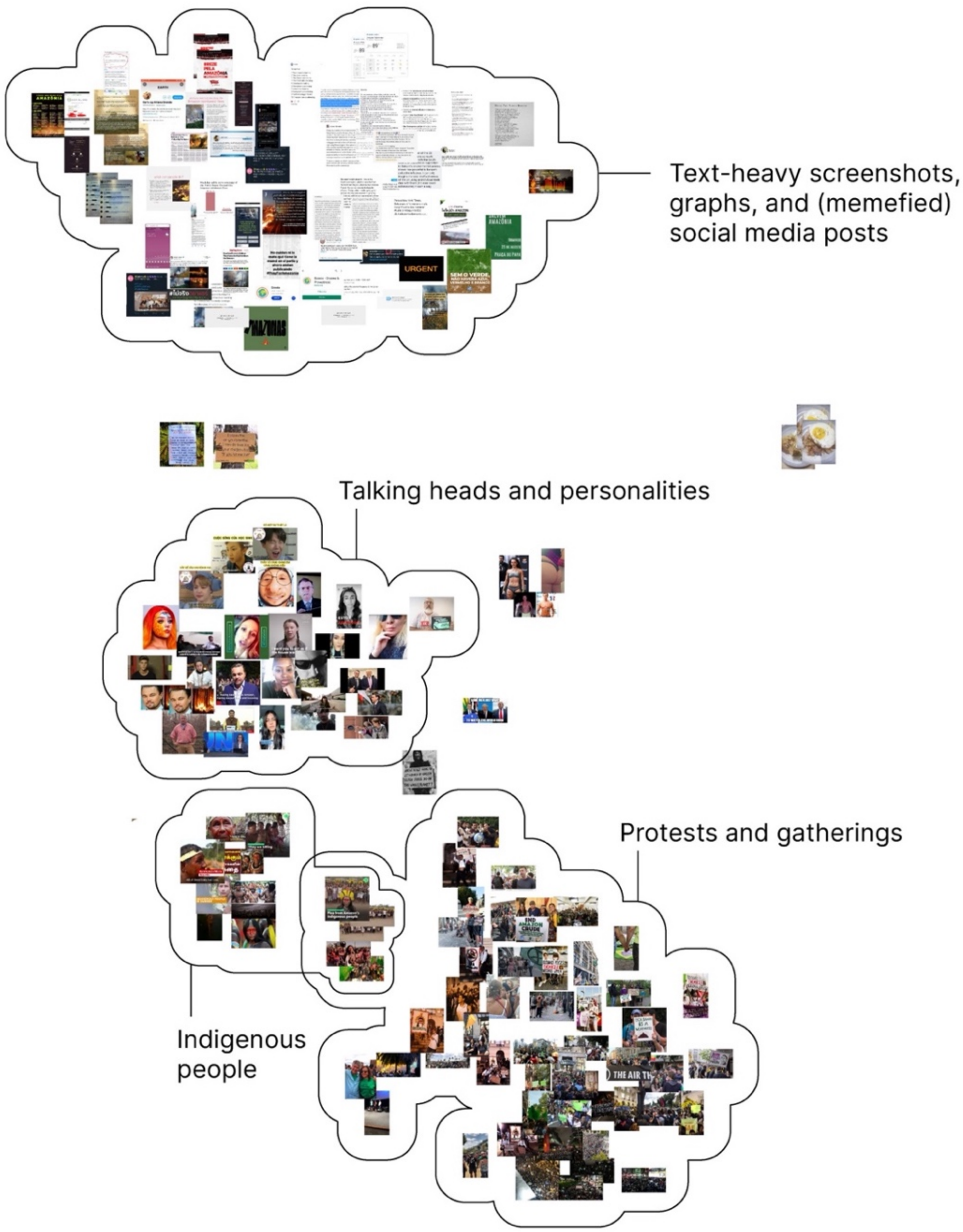

Figure 5. Images retweeted more than 10 times, grouped according to Clarifai computer vision, annotated by authors (right detail). Source: #ActForTheAmazon, #amazonfires, #AmazonRainforest, #PrayforAmazonia, #SaveTheAmazon, and #SOSAmazonia.

Image Engagement: Uneven Distribution of Attention Across Issues

The treemap visualizes images resized based on the number of retweets. It seeks to analyze prominent issues and concerns (in terms of engagement) in images associated with English-language Twitter hashtags (Figure 6). Unlike the ranking technique, which homogenizes differences in engagement, the treemap visually translates the relative visibility of images by resizing them, showing which formats and themes dominate and which become almost invisible. Compared with grouping images by similarity, the visual model focuses not only on diversity (of issues, practices, and visual formats) but also on the different degrees of attention that various issues and formats receive.

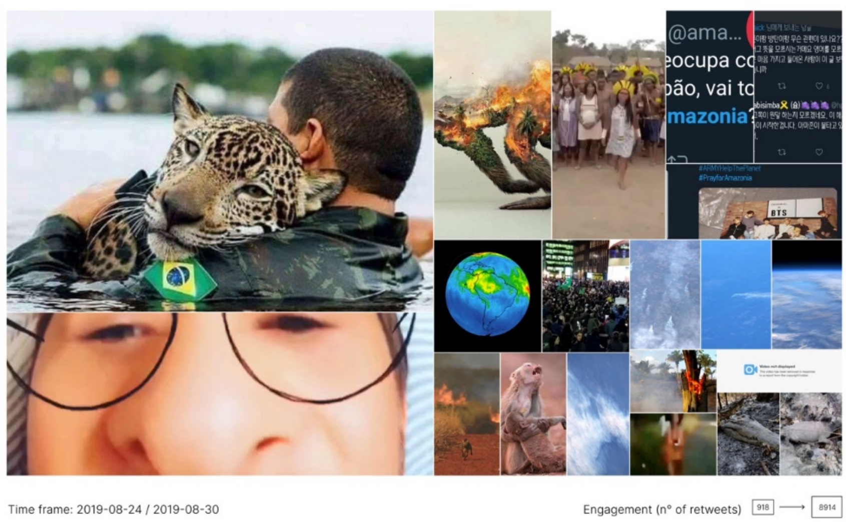

Figure 6. Twenty most retweeted images. Visualized with RawGraphs and Adobe Illustrator. Source: #ActForTheAmazon, #amazonfires, #AmazonRainforest, #PrayforAmazonia, #SaveTheAmazon, and #SOSAmazonia.

As a case in point, the space is overwhelmingly occupied (quite literally in the visualization) by one image depicting an animal rescue (which was from 2016 and not related to the forest fires). There are also other images of animals in danger, thereby reasserting preoccupation with nonhuman victims over affected humans in tweets associated with English-language hashtags. The issue of political responsibility (and failure to assume it) for the disaster surfaces in the second most engaging image, which is a preview image from a satirical French-language video with a father and his child criticizing Bolsonaro for his failure to take action. Less prominent formats include satellite imagery of the earth from space (which signals scientific practices and the international and planetary context of the event), Indigenous and non-Indigenous people protesting, and memefied screenshots from Twitter.

Image Trends: Persistence of Iconic Images and Satirical Content

The plot arrays images shared at least 100 times chronologically (from left to right) and by frequency (from top to bottom). The analysis is of visual practices associated with prominent English-language hashtags and focuses on how the event is articulated through images that receive high visibility over time (Figure 7). It also seeks to quantify shifts in visibility, using retweets as a measure of engagement. The visualization exposes the lack of diversity in the perspectives emerging in the space, with only a few images visible (receiving a higher number of interactions), and the rest collapsed at the bottom of the chart. One can note the prevalence across time of the same jaguar rescue image from 2016 (noted above), a thumbnail of a satirical French video clip with a father and his child criticizing Bolsonaro, and an iconic image of Indigenous groups protesting. These images shared overwhelmingly more than the others effectively dwarf other perspectives.

A second plot is designed with images shared less than 500 times to surface other less prominent visual themes (Figure 8). In the second plot, images of other endangered animals emerge as well as other formats such as call-to-actions, infographics, and Twitter screenshots (flagging visual misinformation). In general, only iconic images and satirical content stay on top of the timeline, whereas other more subtle perspectives hardly make it to the top. Both plots show how the distribution of attention across issues and formats stays mostly the same over time.

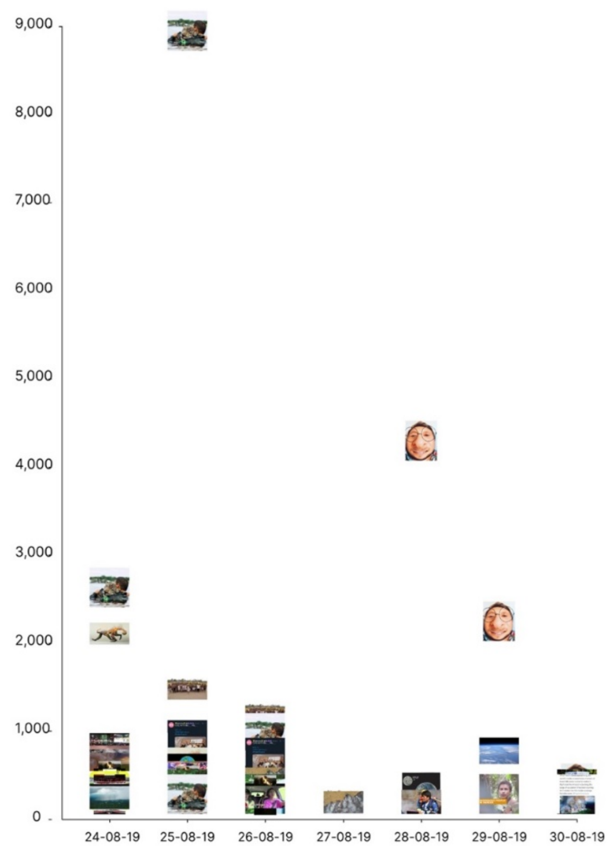

Figure 7. Top images per day shared at least 100 times on Twitter with #ActForTheAmazon, #amazonfires, #AmazonRainforest, #PrayforAmazonia, #SaveTheAmazon, and #SOSAmazonia. Time frame: 8/24/2019–8/30/2019. Visualized as a plot with RawGraphs and Adobe Illustrator.

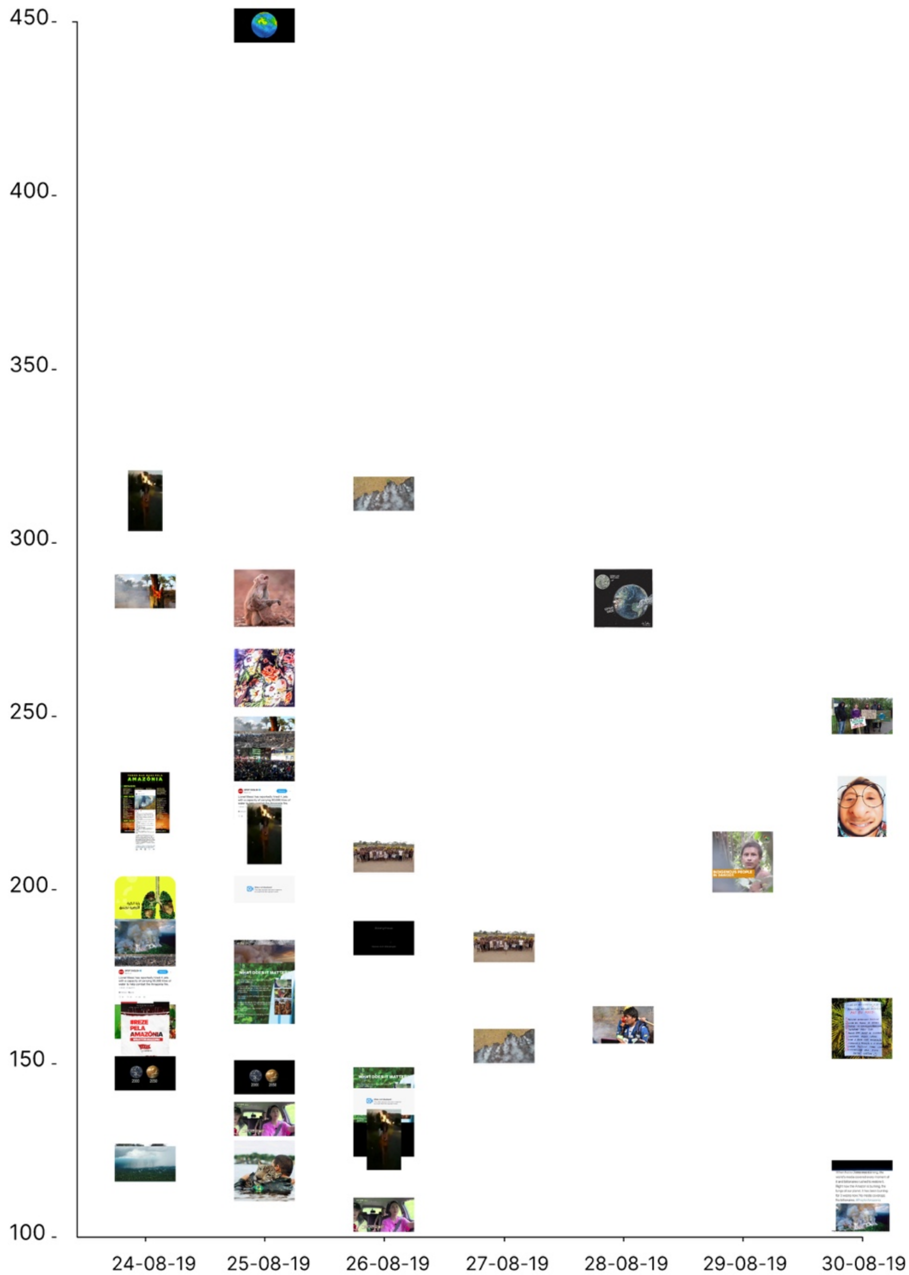

Figure 8. Top images per day shared on Twitter at least 100 times but less than 500 times with #ActForTheAmazon, #amazonfires, #AmazonRainforest, #PrayforAmazonia, #SaveTheAmazon, and #SOSAmazonia. Time frame: 8/24/2019–8/30/2019. Visualized as a plot with RawGraphs and Adobe Illustrator.

Image Rankings per Platform: Platform Vernaculars

The grid format compares images from various platforms, ranked from top to bottom according to engagement (Figure 9). It collects the top 10 images per platform during the time frame under analysis, following platform-specific forms of engagement: Most retweeted images on Twitter, posts receiving the most interactions on Instagram and Facebook, most viewed videos on YouTube, and highest-ranked images on Google Image Search. The top 10 images are arranged in a grid, one column per platform.

In the 2019 Amazon fires case, one can note how each platform distinctively depicts the event. While Twitter shows the most diverse visual formats (including iconic photos, screenshots of other tweets, and video thumbnails), Google Images presents homogeneous visual imagery made of professional photographs of forest fires. YouTube has only images from mainstream news segments about the fires, prominently featuring the outlets' logos. On Facebook (and to a lesser extent Instagram), one image (an old photo of burning forests tweeted by Emanuel Macron) dominates the space, both in itself in various sizes and as a screenshot of tweets including it. Cross-platform visualities also emerge when one particular image (or type) recurs across columns. For example, Twitter screenshots are in several columns, denoting the centrality of the platform, whose content spills into the others. In almost all spaces, one can note a relative scarcity of images of human actors, only marginally present on YouTube and Twitter: Responders, commentators, protestors, and rescuers are visible—but not forest residents affected by the fires.

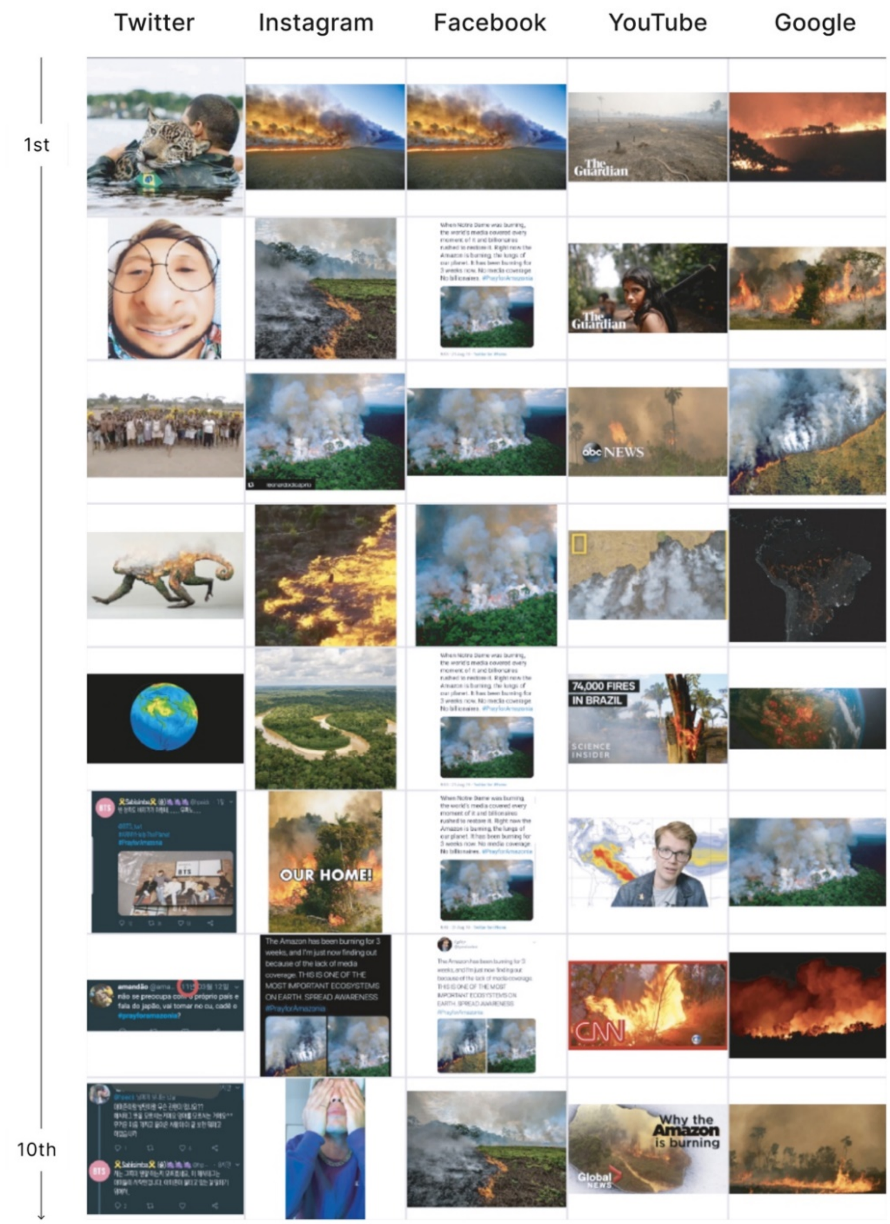

Figure 9. Top 10 images per platform. Time frame: 8/24/2019–9/2/2019. Visualized as a grid with Google Spreadsheet and Adobe Illustrator. Source: Twitter (#ActForTheAmazon, #amazonfires, #AmazonRainforest, #PrayforAmazonia, #SaveTheAmazon, and #SOSAmazonia); Instagram, Facebook, YouTube, and Google (ActForTheAmazon, amazonfires, AmazonRainforest, PrayforAmazonia, SaveTheAmazon, SOSAmazonia, "amazon fires").

Conclusions

We detailed four approaches for studying social media images. Each makes use of a visual model that displays an image set in a particular arrangement, and each arrangement structures the interpretative work in a particular way. Clusters surface thematic and formal groupings of similar images, treemaps render the uneven visibility that images receive in an online space, plots enable the ordering of image visibility over time, and grids compare ranked visualities across online spaces.

First, we made a case for studying images in groups by discussing features of online images: Multiplicity, circulation, modification, networkedness, and platform specificity. Overall, such features signal the rise of multiple kinds of image collections (or image sets) that can be demarcated through query design techniques and subsequently studied.

Second, we presented four research techniques that attend to the collection of images as a research object (rather than the individual image). We termed these techniques visual models in that they match a display mode with an analytical procedure. All of these organize analytical and interpretative affordances around relations within collections of images (as opposed to relationships between the image and its original context). The outputs are also defined as composite images, as one image is composed from many others. Such composite images are not intended as the endpoint of the analysis but rather as exploratory tools in the research process. They may open up imagination around new lines of inquiry, lead to further research questions, serve as corpus building techniques, and even become artifacts for participatory interpretation and meaning-making, where different publics are presented with an image display as a device to prompt debate and collective inquiry.

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