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From authority to similarity: How Google transformed its knowledge infrastructure using computer vision

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Abstract

We investigate the impact of computer vision models, a prominent artificial intelligence tool, on critical knowledge infrastructure, using the case of Google search engines. We answer the following research question: How do search results for Google Images compare internationally with those for Google Search, and how can these results be explained by changes in Google's knowledge infrastructure? To answer this question, we carry out four steps: (1) Theorise the relationship between web epistemology, calculative technology and issue configuration, illustrating the dynamics of critical knowledge infrastructures on the web; (2) provide a potted history of Google's use of computer vision in search; (3) undertake the first international comparison of search results from Google Search and Google Images; (4) analyse the visual content of search results from Google Images. Adopting a novel research design combining a suite of quanti-quali digital methods including visual content analysis, social semiotics and computer vision network analysis, we analyse six countries' search results related to environmental change (climate change, biodiversity loss). We present two key findings. First, Google Images search results contain fewer authoritative sources than Google Search across all countries. Second, Google Images results constitute a narrow, homogenised visual repertoire across all countries. This constitutes a transformation in Google's web epistemology from ranking-by-authority to ranking-by-similarity, driven by a shift in calculative technology from web links (Google Search) to computer vision (Google Images). Our framework and findings open up new questions regarding the impact of computer vision on public access to knowledge in increasingly image-saturated digital societies.

Keywords

digital methods, search engine studies, computer vision, knowledge infrastructures, environmental communication, artificial intelligence

Introduction

In a world saturated by imagery, Google Images, a search engine sitting alongside the original text-based Google Search, is one of the world's most important online source of visual culture serving over 1.6 billion searches every day according to one estimate (Fishkin, 2025)[1]. Google's epistemic power is transforming societies, politics and cultures across the world (van Dijck et al., 2018). Yet despite Google Images' prominent role within this "critical knowledge infrastructure" (Ford, 2022: 14), it has been largely excluded from otherwise comprehensive search engine studies (Haider and Sundin, 2019; Iliadis, 2023). Within this broader context, an improved understanding of the processes used to rank Google Images search results is significant for two reasons. First, to understand how Google's knowledge infrastructure increasingly prioritises in-platform 'semantic media' such as images and knowledge panels over its traditional offer of outward-facing web links (Iliadis, 2023). Second, Google Images provides an opportunity to interrogate the impact of

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artificial intelligence on knowledge infrastructures, as it calculates search rankings using computer vision models, a widely deployed technology for image categorisation (Edwards, 2018). Yet, this research agenda faces increasing difficulties as Google's processes for ordering information have become both **more complex**, as user clicks and personalised results have assumed greater importance (Rogers, 2018), and **more opaque**, as data collection in the post-API (application programming interface) age becomes more challenging (Freelon, 2018). This presents digital media scholars with a research problem demanding both urgency and innovation.

Here, we take up this challenge by adopting a novel interdisciplinary research design combining quanti-quali digital methods including visual content analysis, social semiotics and computer vision network analysis. Our research question is:

> How do search results for Google Images compare internationally with those for Google Search, and how can these results be explained by changes in Google's knowledge infrastructure?

To answer this question, we employ a case study of two search queries related to environmental change (climate change and biodiversity loss), comparing search results from Google Search and Google Images across six countries: Australia, Brazil, China, Mexico, Netherlands, and Nigeria. This case is paradigmatic, as it highlights general characteristics and epistemological impacts of machine learning, and establishes a framework for future research into visual search engines (Flyvbjerg, 2006).

Our research contributes to four different literatures. First, search engine studies (Mager et al., 2023) including current public debates on the 'enshittification' of Google search engine results and the consequences for publicly available knowledge (Doctorow, 2025). Second, we contribute to science and technology studies research on knowledge infrastructures and artificial intelligence, discussing the development and impact of computer vision techniques that underpin Google Images (Plantin et al., 2018). Third, we extend the visual communication literature to analyse the circulation of generic, desocialised imagery on search engines (Aiello et al., 2023). Finally, our analysis provides new insights for environmental communication scholars, particularly the role of Google Images in homogenising visual configurations of environmental issues (Pearce et al., 2019).

Our argument unfolds as follows. We propose a conceptual framework of Google Search and Google Images as critical knowledge infrastructures consisting of processes (web epistemology, calculative technology) and content (issue configuration) (Ford, 2022; Haider and Sundin, 2019; Rogers, 2002). Then, we emphasise the increasing importance of Google's visual search results, as a previously under-researched example of semantic media (Iliadis, 2023) and computer vision (Crawford and Paglen, 2019). We then detail our methodological approach, grounded in coproductionist literature and digital methods research (Marres, 2017; Rogers, 2024). Findings are described in three sections corresponding to our framework of infrastructural processes and content, highlighting the divergence between web sources in Google Search and Google Images results, and the dominance of similar images. We conclude by revisiting our conceptual framework and locating our findings in wider debates on algorithmic recommendation, artificial intelligence and cultural homogenisation, as well as noting limitations in our approach which point towards a wider future agenda for visual search engine studies.

Theorising Google's knowledge infrastructure

Google Search has long since melted into everyday life, becoming a piece of critical knowledge infrastructure: robust, accessible, ubiquitous and essential (Haider and Sundin, 2019; Plantin et al., 2018). The algorithmic processes by which Google produces search results have become naturalised and are only occasionally made visible during controversies about unreliable results; for example, when Google directs users towards sources of misinformation or presents discriminatory slurs (Noble, 2018; Rogers, 2023). This embeddedness of 'googling' as an information-seeking practice means that improving publics' media and information literacy should be an important objective of search engine studies, with a research agenda that combines the critical evaluation of the content of search results, and illuminating the processes by which these results are produced (Haider and Sundin, 2019). In short, Google's processes for making search results visible, need to themselves be visualisable.

These processes are well documented for Google's original search engine, where the PageRank algorithm calculates web page quality aiming to bring order to the web (Brin and Page, 1998). From billions of web pages, Google separates "the wheat from the chaff" using a *web epistemology* ranking web sources by their authority (Rogers, 2002: 199). This contrasts with social media platforms such as Facebook and Twitter, which have previously foregrounded sociality and issue-orientation, respectively (Birkbak and Carlsen, 2016). For Google, web source authority is determined not by content, but by a *calculative technology* (Miller and Napier, 1993) which takes into account the quantity of weblinks into a given page, and the importance placed on other pages that link to it (Rogers, 2013: 113). Since the inception of search engine studies, these processes have been recognised as a matter of infrastructural politics, making different websites and issue positions more or less visible while also holding the potential to narrow the offerings and options available to citizens of digital societies (Introna and Nissenbaum, 2000; Rogers, 2002). This may give rise to digital hegemonies, which continually reinforce biases; for example, content from the Global North (Ballatore et al., 2017), or extreme right-wing sources (Norocel and Lewandowski, 2023). Subsequent updates by Google have made its means of calculating authority harder to scrutinise, as it adds ever more layers and logics atop its original PageRank approach (Haider and Sundin, 2019).

These concerns have recently sharpened as Google has moved beyond providing a range of sources, in the form of a weblink list, into more direct communication of facts and meanings through knowledge panels, autocomplete suggestions, questions and answers and, increasingly, AI text summaries. This has been conceptualised as the semanticisation of Google: processes of labelling, organising and interpreting which transform the purpose of Google's knowledge infrastructure from signposting people to information to becoming fully-fledged intermediaries, heralding the 'next era of political search' (Iliadis, 2023: 140). This has prompted a new wave of academic research focused on the impact of semanticisation on knowledge infrastructure, including how information seeking is shaped by autocompleted search queries (Rogers, 2023), how AI summaries of search results reduce source diversity (Sharma et al., 2024) and the processes by which knowledge panels appear in some search results, but not others (Iliadis, 2023). This extended scope of relevant search results is enabled by Google's Knowledge Graph, which contains over 500 billion facts related to five billion people, places and things, known collectively as entities (Iliadis, 2023). Mapping these relationships allows Google to identify entities within a search query, and then offer up to users facts connected to these entities, orchestrating these as semantic media such as knowledge panels and questions and answers (Iliadis, 2023).

Taken together, these semanticisation processes speak to Google's enhanced, arguably dominant, role in *issue configuration*. As a conceptual device, configuration draws attention to how technologies materialise cultural representations (Suchman, 2012). For example, in their foundational study of climate change debates on the web, Rogers and Marres (2000) highlighted the role of search engines in how issues are publicly configured through the relative political positions of highly-ranked web sources. These sources in turn linked (or did not link) to further sources, forming a socio-epistemic network of organisations, texts, and users, the latter choosing which sources they will investigate and which they will ignore (Rogers and Marres, 2000). In this way, the provision of web links as the primary product of Google's knowledge infrastructure afforded users considerable agency in the configuration of an issue. Now, as Google frequently promotes in-platform AI summaries and knowledge panels above search results linking to external sources, users' epistemic agency is eroded as they are more firmly steered towards a narrower range of information.

Up to now, research into the semanticisation and epistemic power of search engines has focused on changes in the production of text. We argue that visual search results constitute a paradigmatic shift in semantic media which demand interrogation, both as an alternative means of conveying facts (Yao and Pearce, 2025) and a broader infrastructural change in which Google provides in-platform visual configurations of issues (Pearce and de Gaetano, 2021). Returning to the objective of media and information literacy, explaining Google Images search results requires methodologies for critically evaluating visual content, as well as an interrogation of the calculative devices used by Google to make some images more visible than others. Early research has importantly identified the inclusion of images in Google's Knowledge Graph, so that images found on the web can be linked to entities (Omena et al., 2021). This opens up a new research area at the intersection of search engine studies and visual communication studies, with wider significance given the rising salience of digital imagery as a resource for anti-establishment politics (Omena et al., 2024; Theisen et al., 2025; Tuters and Willaert, 2022).

Research at this intersection has great potential as visual methodologists share similar orientations to those in digital media studies, regarding how cultural representations of an issue arise from the confluence of social practices and technological processes (Rose, 2023) Researchers have long been interested in these entanglements and their role in the circulation of culture, particularly how cultural forms are rendered to convey meaning (Lash and Lury, 2007). For example, the advent of space exploration enabled the production of 'Spaceship Earth' images, circulated across national boundaries by new media technologies and giving rise to a new global environmental consciousness (Jasanoff, 2001). These images' enduring popularity has helped configure environmental issues towards a global view which looks away from the particularities of place (Jasanoff, 2004). More recently, Aiello et al. (2023) identified the importance of stock photography in shaping cultural meanings, producing an affectively flattened and desocialised visual "regime of truth" (Foucault, 1984: 74). Here, we argue that Google Images marks an important contemporary chapter in this longer story, as a knowledge infrastructure which is politically impacting the visual configuration of issues in important, but unseen, ways.

In our study, configuration serves as a device for analysing the materialities of calculative ranking technologies, and how they assemble, render visible and amplify the visual representation of issues. To this end, Figure 1 provides a simple, non-exhaustive model of Google's critical knowledge infrastructure[2].

In this section, we have conceptualised Google as a knowledge infrastructure which remains fundamental to how issues become known by publics. Next, we argue that Google Images represents a paradigmatic yet poorly

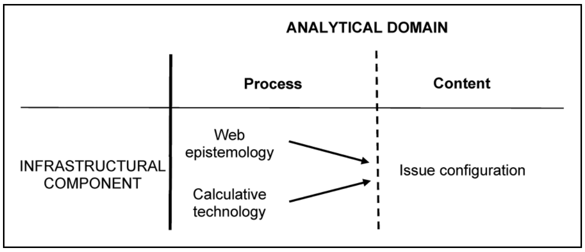

Figure 1. Conceptual framework of Google's knowledge infrastructure.

understood shift in how this infrastructure is organised, the implications being important not only for Google itself but also wider applications of artificial intelligence and computer vision.

A paradigm shift: the new knowledge infrastructure of Google images

Despite Google Images' huge reach and importance as a 'visual gatekeeper', little social scientific analysis of the platform has appeared since Safiya Noble's (2018) path-breaking analysis of discriminatory search engine image results. Ieracitano et al. (2024) found that Google Images results provide flattened and stigmatising depictions of immigrant communities, with images frequently taken from news media, highlighting that the algorithms producing these results lack public accountability. Other research has found a lack of diversity in Google Images results for dermatology (Kurtti et al., 2022) and healthcare occupations (Shamsi et al., 2022). Within our conceptual framework, this previous research focuses on evaluating content, rather than processes (the area to the right of the dashed line in Figure 1). We expand this work, evaluating not only search result content for climate change and biodiversity loss, but also the processes which produce these results. This is needed as, although the company has acknowledged its use of computer vision models in search rankings (Edwards, 2018) no foundational research paper exists for Google Images equivalent to that written by Brin and Page (1998) for Google Search[3]. Here, we trace the development of Google Images through the broader literature on computer vision; a range of techniques that seek to describe images and reconstruct their properties through pattern recognition (Crawford and Paglen, 2019; Szeliski, 2010).

Created in 2000, apparently to meet user demand for images of a Versace-clad Jennifer Lopez (Edwards, 2018), Google Images initially returned results of mixed quality (Fergus et al., 2004: 242):

> As any Google user is aware, not all the images returned are related to the search. Rather, typically more than half look completely unrelated; moreover, the useful instances are not returned first – they are evenly mixed with unrelated images. This phenomenon is not difficult to explain: current Internet image search technology is based upon words, rather than image content – the filename of the image and text near the image on a web-page

Although the search engine results were images, the calculative technology by which Google ranked results remained text-based. The authors illustrate the problem through image results for three nouns: bottles, camels, and motorbikes. Their proposed solution is based on the not-unreasonable insight that images of bottles, while heterogeneous and diverse, will possess 'visual consistency'; that is, they will look alike in fundamental ways. A subsequent article, co-authored by a Google employee, proposes a PageRank equivalent for analysing visual similarities amongst images considered relevant to a search query (Jing and Baluja, 2008). A machine learning model can identify these resemblances and, once included in search engine ranking criteria, provide images more relevant to the original query (Huang et al., 2011).

Latterly, Google has reported on the importance of computer vision models in calculating its search rankings. For example, visual 'concepts' can be identified using distinct features such as colours, objects and textures (Edwards, 2018). While it is true that 'web detection' can augment image classification using text associated with an image on the web (Omena et al., 2021; Pilipets and Paasonen, 2024), machine-readable information contained within images allows for the attribution of displayed results into more or less visually consistent clusters (Terrasi, 2019) and ultimately removes the need for any textual inputs to search. This is evident in Google Lens (n.d.), a visual search tool that allows users to search the web using user-generated photos. This suggests that visual consistency is now a central criterion for calculating search result ranking, adding to or potentially surpassing Google Search's foundational principle of ranking-by-authority.

Researchers have begun to explore the possibilities of using computer vision within digital methods for social science and humanities (Kvist Møller and Airoldi, 2025; Niederer and Colombo, 2024; Omena et al., 2021; Pearce and De Gaetano, 2021). Yet, there is little research into the changes to rankings brought about by machine learning-based tools such as computer vision. Following Plantin et al. (2018), who note that the ubiquity of Google's web search means it should be considered an infrastructure, we argue that the introduction of computer vision via Google Images represents a paradigm shift in that infrastructure, moving from a web epistemology of ranking-by-authority to ranking-by-similarity.

As explained above, while testing on apparently uncontroversial objects allowed computer vision researchers to showcase the effectiveness of their models, their real-world

Table 1. Query design with country and website domain.

Country (VPN)	Domain	Query 1	Query 2
Australia	.com.au	Climate change	Biodiversity loss
Netherlands	.nl	Klimaatverandering	Verlies van biodiversiteit
Nigeria	.com.ng	Climate change	Biodiversity loss
Mexico	.com.mx	Cambio climático	Pérdida de biodiversidad
China	.com.hk	气候变化	生物多样性丧失
Brazil	.com.br	Mudanças climáticas	Perda de biodiversidade

implementation has proved altogether more troublesome. Discriminatory search results in Google Images have reinforced and exacerbated existing injustices (Noble, 2018), while a preference for data quantity over quality in the development of computer vision models such as ImageNet has prompted powerful critiques regarding ethical voids in machine learning (Bender et al., 2021; Crawford and Paglen, 2019; Prabhu and Birhane, 2020)[4]. Building on this scholarship, we turn our attention to the impact of computer vision on the configuration not of people and things, but of issues. In their presentation of a PageRank for images, Jing and Baluja (2008) differentiate between queries with homogeneous and heterogeneous visual concepts. Homogeneous concepts could include McDonalds results containing the 'M' logo and the Mona Lisa containing the original painting, while heterogeneous concepts include Apple (fruit and computer) or Jaguar (animal and car) (Jing and Baluja, 2008). They argue that for heterogeneous concepts, their ranking approach "is able to identify a relevant and diverse set of images as top ranking results; there is no *apriori* bias towards a fixed number of concepts or clusters" (original emphasis) (Jing and Baluja, 2008: 310–312). This claim is evaluated in our study for climate change and biodiversity loss, which are both heterogeneous concepts.

Digital methods for infrastructure studies

As noted above, our study constitutes a paradigmatic case study, as it highlights general properties of Google Images' knowledge infrastructure (Flyvbjerg, 2006). To test the impact of Google's shifting web epistemologies on issue configuration, we adopt a query design (Rogers, 2017) focused on two environmental issues of global significance: *climate change* and *biodiversity loss*. Drawing on coproductionist literature (Marres, 2017), our approach understands digital objects (e.g., search rankings, hyperlinks, Google Vision labels) not as mere passive carriers of content, but as things which exert both political and epistemic power. In a 'post-API' context where corporate platforms such as Google severely restrict researchers′ access to data sources, these digital objects are repurposed for social research in order to 'reverse engineer' digital infrastructural processes whose details are the subject of corporate control (Freelon, 2018; Rogers, 2024: 142). These objects shape what kinds of knowledge are made visible, how associations form, and what counts as authoritative. In this perspective, agency is understood as distributed and relational, i.e., emerging from the relations between different infrastructural components.

While this paper's primary focus is Google's knowledge infrastructure, we also note the power of visuals in environmental communication has been the focus of growing attention in the literature (O'Neill, 2026); for example, the emergence of iconic climate visuals such as polar bears (Born, 2019). In comparison, research into biodiversity loss images remains nascent (Hayes et al., 2025). Understanding popular encounters and engagement with environmental issues through visual representations must take seriously the digitalisation of societies (Marres, 2017) and the role of platforms in mediating the social lives of these issues (Pearce et al., 2019; Turnbull et al., 2024; Wang et al., 2018). So, in selecting these search queries, we demonstrate not only changes to Google's knowledge infrastructure, but also show why these changes matter in the visual configuration of high-stakes issues. Although we acknowledge the material dimensions of Google's infrastructure (e.g., the need for buildings and data centres) and their environmental impacts, here we focus on how Google configures issues of climate change and biodiversity loss, and discuss whether they are fulfilling the promise of a knowledge infrastructure for the Anthropocene (Edwards, 2017).

To collect our data, we accessed Google in June 2022 using a Mozilla Firefox browser in remote control mode with unlogged browsing to minimise personalisation of results (Rogers, 2017). For each issue, we obtained search results for six different countries (Australia, Brazil, China, Mexico, Netherlands, and Nigeria) to test whether results were geographically distinctive or globally homogenised. The countries were chosen for their geographical diversity, economic situations, and types of engagement with environmental issues. To obtain localised results we used CyberGhost VPN to redirect our IP geolocation, recording the top 50 results for Google Search and Google Images from the corresponding Google domain in each country. We adapted the queries for each country by translating them into the official national language, verifying the accuracy of our translations by inspecting their usage in reliable sources (see Table 1).

The ambition of our research design is for the comparison of results to be both robust (comparing results obtained via the same research protocol) and authentic (using geographically appropriate language, location and domain names). At the same time, we know that our results may not perfectly replicate what an individual Google user would see. Personalisation and advertising have made the totality of displayed search results unknowable to the researcher with any precision (Rogers, 2018). In this regard, our research has limitations compared to the research persona approach, which seeks to understand how different user behaviours bring about divergent user experiences (Bounegru et al., 2022a). However, we are confident in providing a 'baseline' view of Google results for various locations before any personalisation effects are layered on top (Rieder et al., 2018).

Data analysis is in two parts. First, for each combination of search query and country, we compare the web sources appearing in search results for Google Search and Google Images, initially using the Triangulation tool to highlight web sources common to both rankings (Digital Methods Initiative, 2008). Second, to analyse the visual results of Google Images, we use visual content analysis and social semiotics to provide both quantitative description and contextual understanding of similar images (Aiello and Parry, 2019). We use Google's computer vision model, Google Vision API, to discover the 'labels' ascribed by Google to the most prominent images in its search results (the ten labels with the highest confidence scores for each image). Computer vision models from a range of providers are increasingly used to analyse large image collections, but present social scientists with a significant challenge in the opacity of key features such as training data and algorithmic techniques (Kvist Møller and Airoldi, 2025). In the current research, and in line with our methodological approach of repurposing digital objects, we turn this challenge into a strength, using the calculative device of Google Vision API to interrogate Google's own web epistemology, analysing visual similarity using bipartite network visualisations which connect images and Google Vision labels (Omena et al., 2021). Then, through visual network analysis, we identify clusters of labels, which represent patterns of co-occurring image content (Venturini and Munk, 2021). The computer vision analysis, together with close visual reading of the image search results, provides a quanti-quali approach which complements quantitative data collection with "qualitative practices to produce thick data analyses of digital traces" (Vicari and Ditchfield, 2024: 6).

This quanti-quali approach enabled us to follow the evolution of patterns, described by Lev Manovich (2011) as determined by a projection of quantified image properties into the same optical space. However, instead of re-organising the images by an aesthetic quality, such as an image's average hue, we retained Google Images' search ranking order. Arranging images in a grid from highest to lowest rankings with columns representing country-specific style spaces provides the structure for interpreting patterns of repetition with variation. Here, rather than just representing relations of proximity between issue-specific visual styles, patterns meaningfully indicate relational shifts in relevance and visibility (Colombo et al., 2023). Maintaining the original rankings also helps keep in mind the original context for the images, which social semiotics highlights as important to understanding the story being told through visual communication (Aiello and Parry, 2019).

We describe our findings in three stages. First, we compare search result rankings in two directions: between countries and between search engines (Google Search and Google Images). This allows us to identify differences between the rankings, showing how Google Images' web epistemology dilutes the presence of authoritative web sources in comparison to Google Search. Second, we focus on the visual content of Google Images' search results across different countries to better understand how the search engine configures climate change and biodiversity loss, including the role of visual similarity. Third, we analyse the processes giving rise to visual similarity, repurposing Google Vision API labels to explore how highly-ranked search results cluster around a small number of visual genres and repeated images.

Diluting authority: The impact of web epistemologies in Google images and Google search

How Google Images orders information is poorly understood in comparison to the text-based Google Search. In particular, it is unclear *what difference Google Images makes* to the configuration of an issue. Google Images is presented as a search engine that "helps users to visually find webpages for a wide range of tasks" (SEO for Google Images, 2021), demonstrating that the image is imagined not merely as an end in itself, but as a gateway to other epistemic resources. In theory, Google Images could present an identical ranking of sources to Google Search, the only difference being that the sources would be represented by an image rather than a snippet of text. Such an approach would constitute merely a *representative* change. However, the historical development of computer vision techniques outlined above suggests an *epistemic* change in the way Google Images orders web sources, using a different calculation to produce search results. We explore this by comparing Google Search and Google Images for six countries.

Figure 2 shows the divergence in web sources served to users by the two search engines for each search query and country. If Google Images were only a representational change, the cells would all be shaded, showing that all web sources were common to both search engines. Instead, lightly coloured cells dominate, showing web sources unique to one or other search engines for both climate change and biodiversity loss. This confirms that Google Images represents an epistemological change from Google Search; that is, users turning to Google Images are presented with a very different set of sources.

We observe that Google Search results often prioritise sources generally recognised as authoritative, in line with the epistemological principles discussed above (Tables 2 and 3). For example, the most frequently appearing sources are the official United Nations (UN) website and NASA's dedicated climate change website. Further notable sources include the Intergovernmental Panel on Climate Change (IPCC), the World Wildlife Fund (WWF) and national government websites such as Mexico's Ministerio para la Transición Ecológica y el Reto Demográfico (www.miteco.gob.es) or the Netherlands' Rijksoverheid (www.rijksoverheid.nl).

These results illustrate an important consequence of Google Images' epistemological shift: the *dilution of authority*. Authoritative sources such as the UN and IPCC appear less frequently in results for Google Images than Google Search. While some of these sources, notably the UN, remain prominent in Google Images, their dominance is reduced. Referring back to Google's Knowledge Graph, this suggests that while the links between entities (climate change, biodiversity loss) and images are giving authoritative websites visibility, the calculations involved are different to those focused only on text.

There are some differences between the results for each query, notably biodiversity loss harbours lower concentration of authority in specific web sources than climate change (e.g., the UN is top for both queries, but features only six times for biodiversity loss, compared to 16 for climate change). The concentration of authority in climate change results may be a legacy of previous controversies such as Google's alleged prioritising of climate sceptics' claims (Solon and Levin, 2016). Such controversies often result in Google providing a 'patch' to alter their algorithm to reinstate sources more generally perceived as authoritative (Cadwalladr, 2016; Rogers, 2023). This makes the dilution of authority through Google Images even more important, as it is occurring not only in less controversial issues such as biodiversity loss, but also in climate change which has been an online knowledge controversy since the 2000s (Raman and Pearce, 2020). While it is beyond the scope of this article to classify the web sources provided by Google Images in terms of their scientific accuracy, it is clear that the calculative technology for Google's ranking has shifted, leading to a *pluralisation of sources* available to users, with implications for issue configuration. Table 4 shows the total number of unique web sources for each query in each search engine, aggregated across all six countries.

Having established the divergence in web sources between Google Search and Google Images, we now turn to the impact of Google Images on the *visual* configuration of climate change and biodiversity loss. We argue that, despite the dilution of authority and pluralisation of sources demonstrated above, Google Images produces homogenised and globalised visual configurations of both climate change and biodiversity loss.

Issue configuration: A high level of visual similarity both within and between countries

In this section, we present a visual overview of the top 50 images in Google Images search results for both climate change and biodiversity loss across six countries, demonstrating the high level of visual similarity within results for each search query across all countries. A small number of visual genres and specific images are prevalent, and particularly dominant in the top 10 search results most immediately visible to Google users. Drawing on visual content analysis and social semiotics, we provide interpretations of dominant images.

Climate change

Figure 3 shows the top 10 Google Images results for each country; Figure 4 shows the detailed distribution of frequently occurring images in the top 50 results for each country. We highlight three characteristics of the results. First, there are five highly visible images across all six countries, accounting for 10% of the top 50 ranking positions and almost half (29 of 60) of the top 10 rankings. One of these images, the cartoon Earth, is specifically linked to a UN climate change campaign. Thus, the epistemological shift of Google Images does not entirely remove authoritative web sources from the rankings, with the UN maintaining a prominent position in the web source rankings (Table 2). The repeated presence of the cartoon Earth image further demonstrates, as argued in the previous section, that while authority maintains a presence in ranking calculations due to the UN's association with climate change in Google's Knowledge Graph, its authority is concentrated within a single image rather than dispersed via the multiple climate change images on its websites. The other four images (Earth in hand, landscape, tree, and triptych) are conceptual images, providing desocialised depictions of climate change, divorced from real world events, which are less closely tied to a single authoritative site (Aiello et al., 2023; Kress and van Leeuwen, 2020). Their prevalence across different countries and websites demonstrates the importance of similarity in Google Images' ranking calculations.

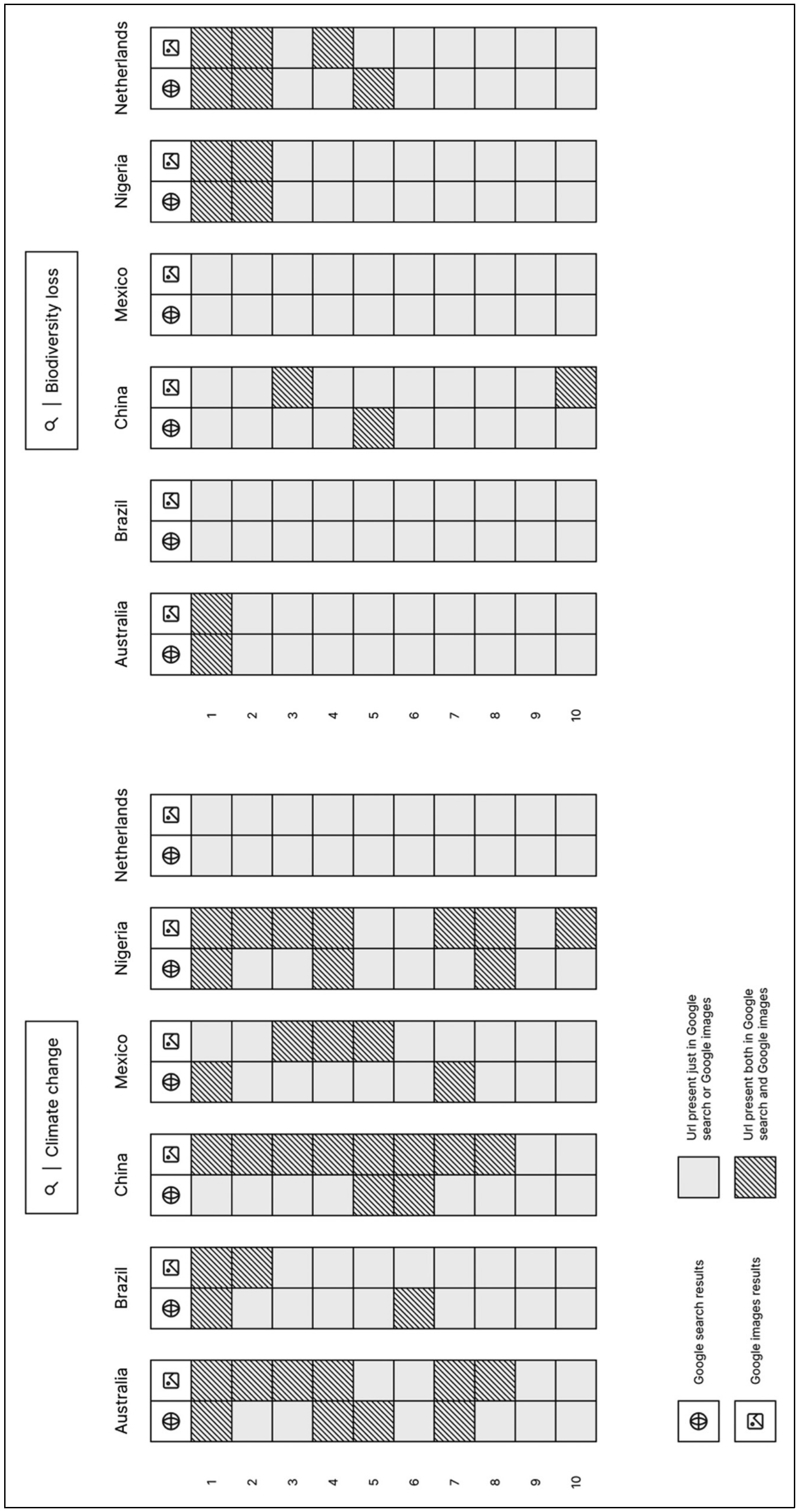

Figure 2. Cross-country comparison of ranked search results for Google search and Google images.

Table 2. Most frequently appearing climate change web sources in results for Google search and Google images (all domains appearing two or more times).

Google search		Google images	
Site	Frequency	Site	Frequency
www.un.org	16	climate.nasa.gov	6
climate.nasa.gov	9	www.un.org	5
www.ipcc.ch	4	www.itu.int	3
www.rijksoverheid.nl	3	www.noaa.gov	2
www.miteco.gob.es	3	public.wmo.int	2
www.wwf.nl	2	en.wikipedia.org	2
www.milieucentraal.nl	2		

Beyond these specific images, a broader set of visual genres dominate the results. For example, the Earth in hand, landscape, and tree images employ 'half and half' composites, which juxtapose a 'given' perspective on the left and a 'new' perspective on the right (Kress and van Leeuwen, 2020: 185–190). The positioning of the positive and negative perspectives in this layout varies between images (sometimes the same image appears reversed). Also prominent are representations of the Earth seen from an exterior viewpoint, echoing the familiar 'Spaceship Earth' images strongly associated with environmentalism (Jasanoff, 2001). Images in the search results are not grounded or contextualised within specific (local) places or landscapes, as is notable in the disconnect between particular images and the location of the Google search (e.g., searches in Australia for climate change do not retrieve images linked to Australia). This echoes Ballatore et al. (2017), who found that Google Search often fails to deliver locally produced results. We add that desocialised imagery of climate change extends across countries of all types. Images are largely devoid of human presence, in contrast to representations of climate change in other media where individuals such as Greta Thunberg have become prominent icons (Hayes and O'Neill, 2021). Overall, the marginalisation of humanity in these images configures climate change as a global issue with little regard for the particularities of place (Jasanoff, 2004).

Biodiversity loss

Figure 5 shows the top 10 search results for each country. We highlight two main findings. First, five top images are repeated across multiple datasets (see Figure 6), accounting for 4% (25 of 600) of the top 50 country-by-country rankings. These top images are more highly concentrated in top-ranked results, 26% (16 of 60) of the top 10 ranked images across all countries. Whereas climate change images were associated predominantly with expert or scientific organisations, biodiversity images had greater representation from major English-speaking newspapers, including the Guardian and New York Times (both of which are based in countries outside our sample). This echoes the finding of Ballatore et al. (2017), that content from wealthy and well-connected countries dominates search results, with the caveat that a key source of biodiversity images is Indonesia-based photographer and Getty Images contributor, Ulet Ifansasti (Ifansasti, n.d.). This highlights Getty Images' important role in the global dissemination of imagery (Aiello and Woodhouse, 2016), albeit one that also provides possibilities for local diversity.

Second, beyond specific images, five visual genres emerge from the results: Earth with animals, forest as lungs, deforestation, lonely animals and the biodiversity chart. The prominence of forests is not surprising, given their importance as biodiversity hotspots (Mittermeier et al. 1998). Issues affecting rainforests, such as wildfires, often become media spectacles, employed within NGOs campaigning and thralling public attention (Bounegru et al., 2022b). Yet other ecosystems, such as oceans, wetlands, meadows, and polar regions are equally critical for biodiversity conservation but feature rarely in search results. Notably, given the role of Global North-based media in promoting biodiversity visuals, deforestation images configure biodiversity loss as happening 'elsewhere', despite the Global North being more directly impacted by other aspects of the crisis. This detachment is enhanced in many of the images (those of the earth and many of forests) which adopt top-down long shots, allowing the viewer to observe biodiversity loss at a distance (Kress and van Leeuwen, 2020). It is beyond the scope of this article to carry out a full visual analysis of the dataset, although we do note that some images adopt a closer, more social distance between viewer and phenomenon (Kress and van Leeuwen, 2020), while the use of certain animals, such as pandas, to promote biodiversity is closely linked with their charismatic properties (Lorimer, 2007).

Calculating similarity: Repurposing google vision to understand image rankings

Having identified patterns of similarity from analysing search result content, we now turn to the processes by which these images are ranked in Google Images results; specifically, the calculation of similarity. As discussed in our Methodology, we use digital methods, in particular the notions of repurposing and reverse engineering. We repurpose Google Vision labels to interrogate how this computer vision model has categorised search result images, enabling us to identify co-occurring labels within dominant visual genres. In doing so, we use computer vision network visualisations to help reverse engineer the calculative technology of Google Vision, in order to better understand the processes by which certain visual genres come to be made visible.

Table 3. Most frequently appearing biodiversity loss web sources in results for Google search and Google images (all domains appearing two or more times).

Google search		Google images	
Sites	Frequency	*Sites*	Frequency
www.un.org	6	www.theguardian.com	3
www.europarl.europa.eu	4	www.veganaustralia.org.au	2
www.wwf.org.br	2	www.unep-wcmc.org	2
www.wwf.nl	2	www.nytimes.com	2
www.iaea.org	2	www.iberdrola.com	2
www.greenpeace.org	2	www.britannica.com	2
www.britannica.com	2	www.brinknews.com	2
www.bbc.com	2	mundoeducacao.uol.com.br	2
wwf.panda.org	2		
en.wikipedia.org	2		
biomania.com.br	2		

Climate change

Figure 7 shows the computer vision network for climate change, with prominent clusters identified using visual network analysis. The most prominent cluster (1), including labels such as ‘cloud’, ‘sky’, ‘nature landscape’ and ‘water’, is associated with landscape images often pristine and lacking recognisable human characters (see Figure 8). Where humans do feature, they are either body parts (typically, a hand) or in silhouette (often labelled as ‘people in nature’). Many of these images contain contrasting elements, either as composites of clearly delineated multiple images, or as ‘half and half’ images. The latter category contrasts images of drought or fire as a ‘given’ (on the left) with images of an idyllic green and healthy world as a ‘new’ (on the right) (Kress and van Leeuwen, 2020). Doing so prompts the audience into thinking about the direction our planet is going towards, whilst inviting us to consider potentially more positive futures.

A second cluster is associated with generic images of the Earth (Figure 9) labelled as ‘world’, ‘astronomical object’, ‘atmosphere’, or ‘circle’. The images present a view of the planet from above, often in a cartoonish style. In common with Cluster 1, these images are generally devoid of human presence. They also lack clear signifiers of place and time (contextual specificity). Images of the Earth are removed from their original context of a view from space and placed in surreal landscapes of sand or water.

A less prominent, but still distinctive, third cluster is associated with images of polar bears and ice floes which Google Vision labels ‘polar bears’, ‘ice cap’, ‘sea ice’, ‘snow’, and ‘fluid’. The prominence of polar bears in climate change imagery has been well identified in other media (O’Neill and Hulme, 2009), a trope Google Images reinforces (Figure 10). The cluster also has visual links to Cluster 1, through its use of landscapes, and Cluster 2 in its sometimes surrealist ‘Photoshopped’ aesthetic.

Table 4. Number of unique web sources for each query and search engine, aggregated across all six countries.

	Google search	Google images
Climate change	28	46
Biodiversity loss	43	51

Biodiversity loss

Figure 11 shows the computer vision network for biodiversity loss, with prominent clusters identified using visual network analysis, The most prominent cluster (1) contains images of degraded forests (Figure 12), a visual proxy for biodiversity loss. Notably, the Google Vision labels do

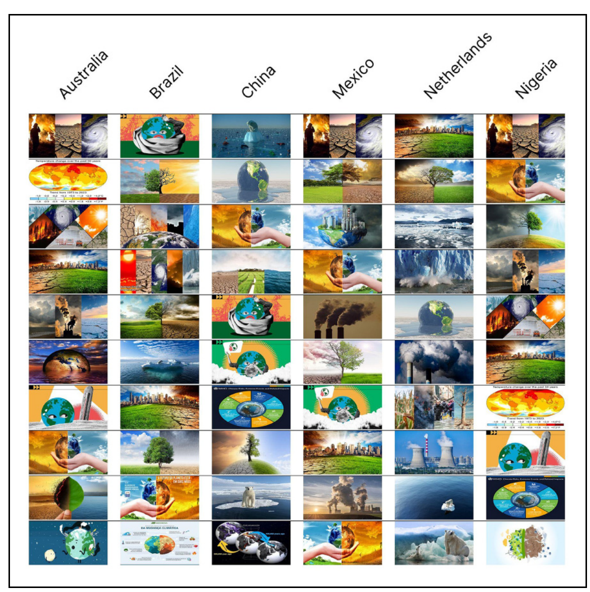

Figure 3. Cross-country comparison of top 10 Google images search results for ’climate change’, original rank maintained.

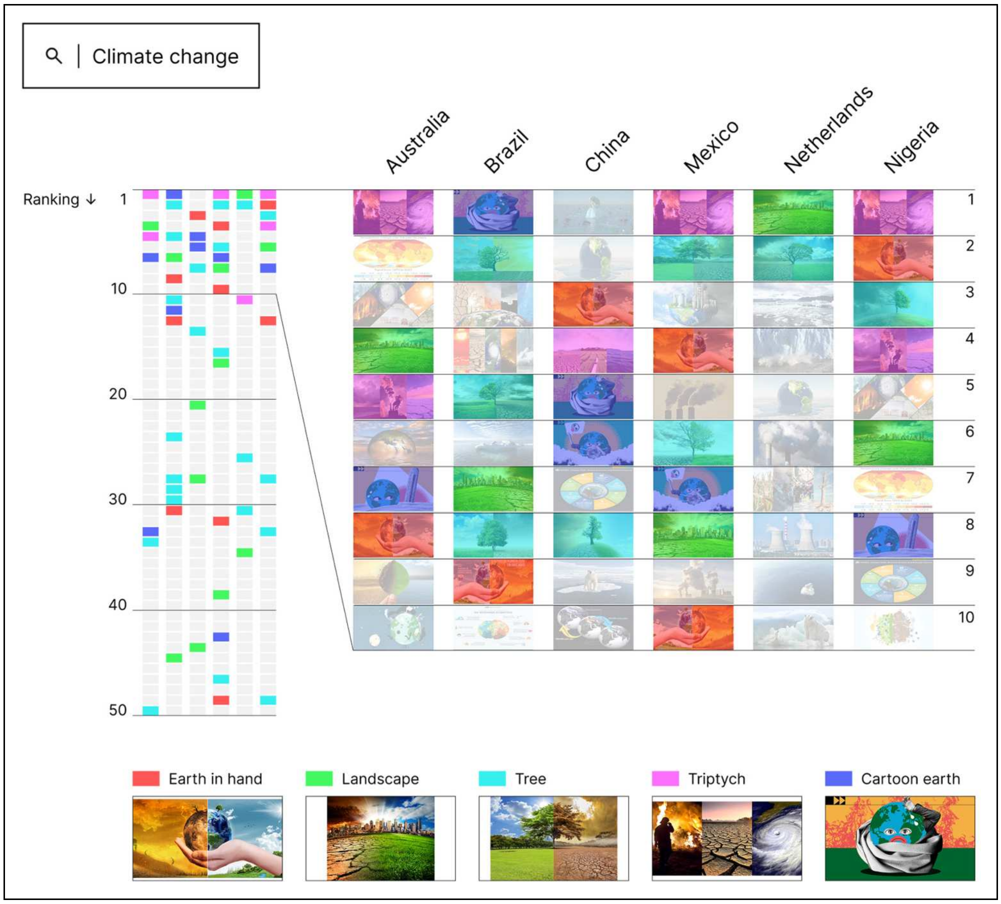

Figure 4. Frequently occurring images in top 50 results for climate change (each column represents a country).

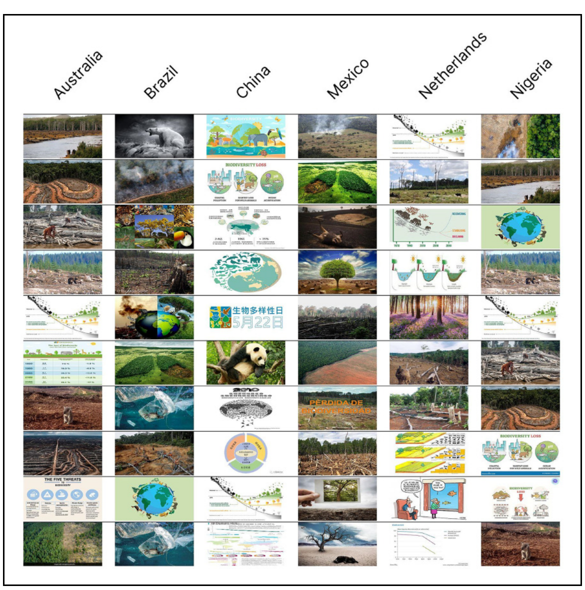

Figure 5. Cross-country comparison of top 10 Google images search results for 'biodiversity loss', original rank maintained.

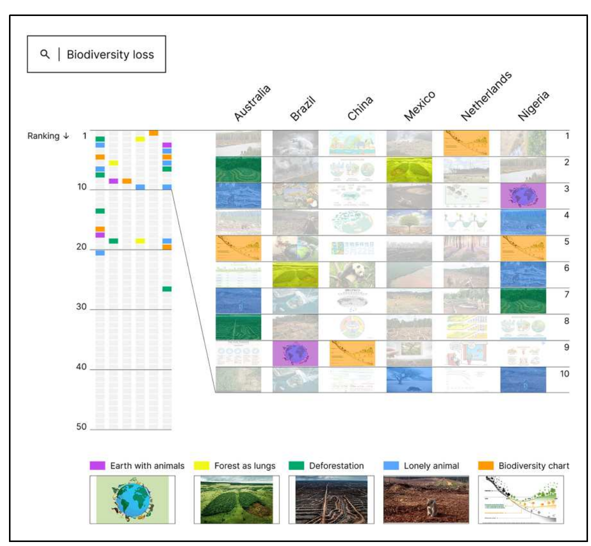

Figure 6. Frequently occurring images in top 50 results for biodiversity loss (each column represents a country).

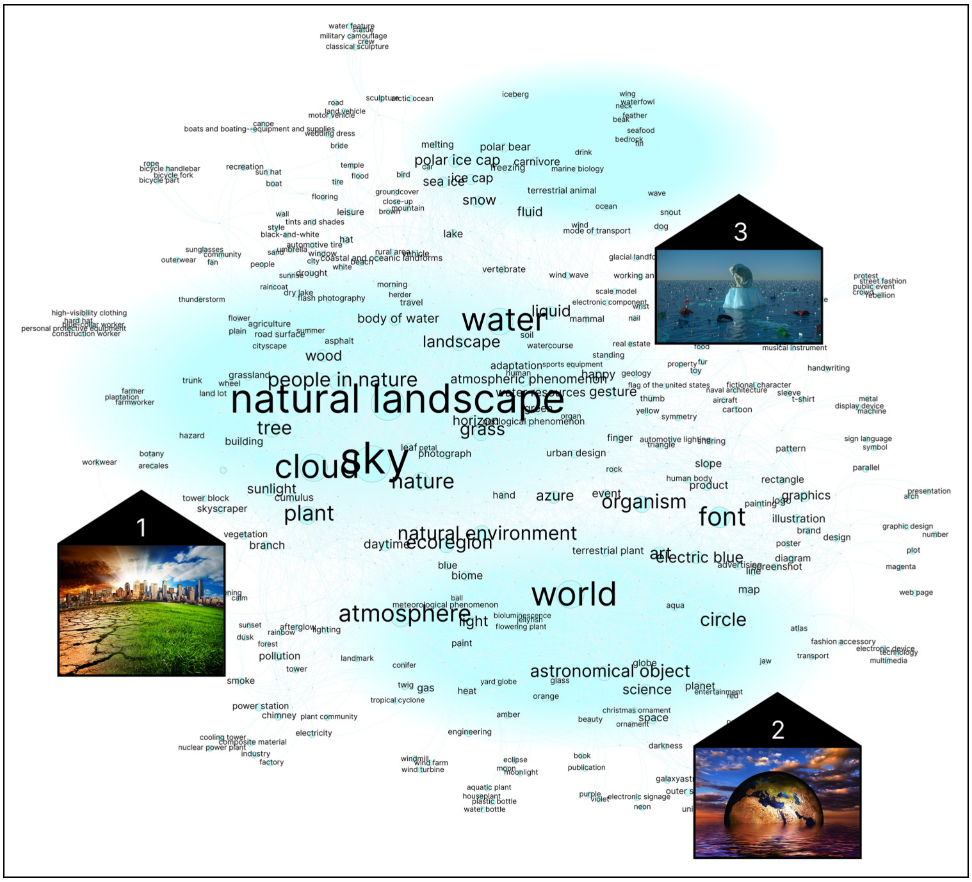

Figure 7. Computer vision network of the labels associated with climate change images ($N = 300$) with three prominent clusters, visualised in Gephi using ForceAtlas2 (Jacomy et al., 2014). Representative image shown for each cluster.

Figure 8. Composite landscape images appearing in the top 10 search results, found in cluster 1.

not include normative terms such as 'deforestation' or 'degradation'. Instead, labels include 'nature landscape', 'plant', 'wood', and 'tree'. Images predominantly include deforested forests seen from above, as well as degraded forest with individual animals wandering through them. This shows the importance of using computer and human vision

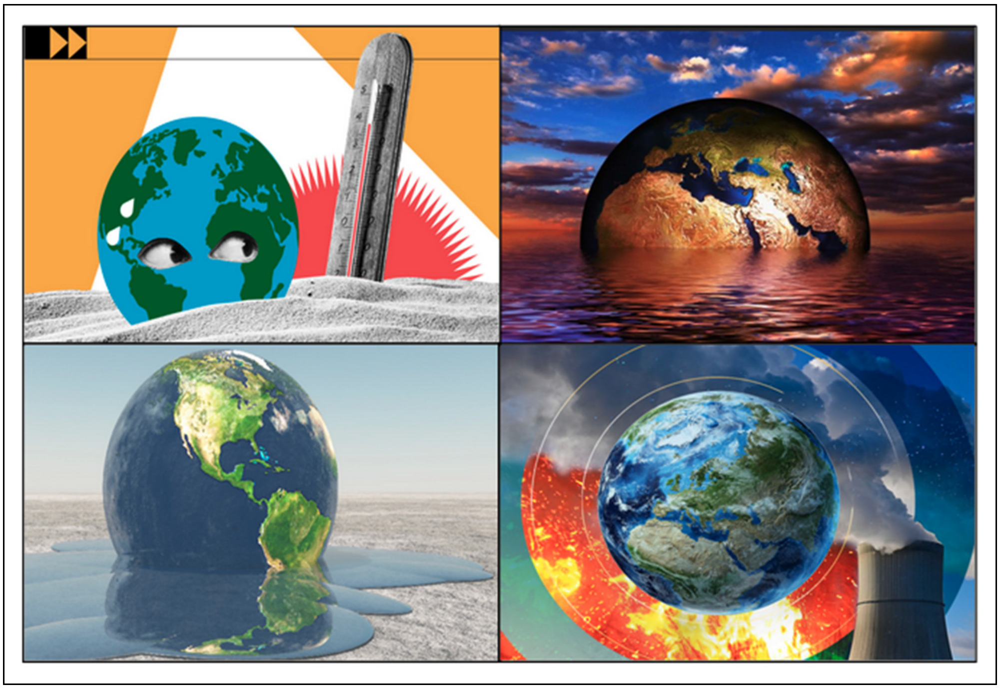

Figure 9. Generic images of the earth, removed from its original context, found in cluster 2.

Figure 10. Images of polar bears on ice floes, at least one of which (top left) is AI-generated, found in cluster 3.

in combination for interpretation: Computer vision helps identify clusters, but an additional layer of (human) interpretation is needed to identify images labelled with 'tree' as depicting deforestation and degradation.

Cluster 2 is associated with the labels 'font', 'slope', 'circle', 'graphic', and 'rectangle', referring to the significant number of charts, graphs, and diagrams present in the dataset (e.g., 46% of the Dutch top 50 results). These images often contain some bright colours and legends, contrasting with those of degraded forests. Figure 13 shows examples of these charts present across five countries.

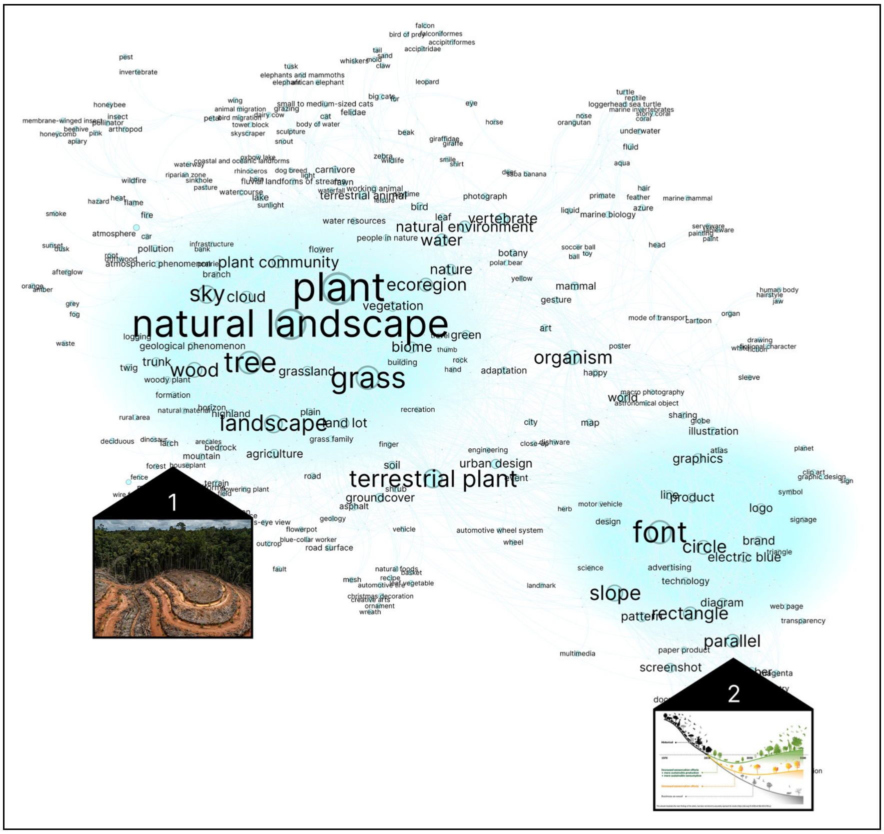

Figure 11. Computer vision network of the labels associated with biodiversity loss images ($N = 300$) with two clusters standing out, visualised in Gephi using ForceAtlas2 (Jacomy et al., 2014). Representative image shown for each cluster.

Figure 12. Images representing biodiversity loss, related to only one of its characteristics: deforestation, found in cluster 1.

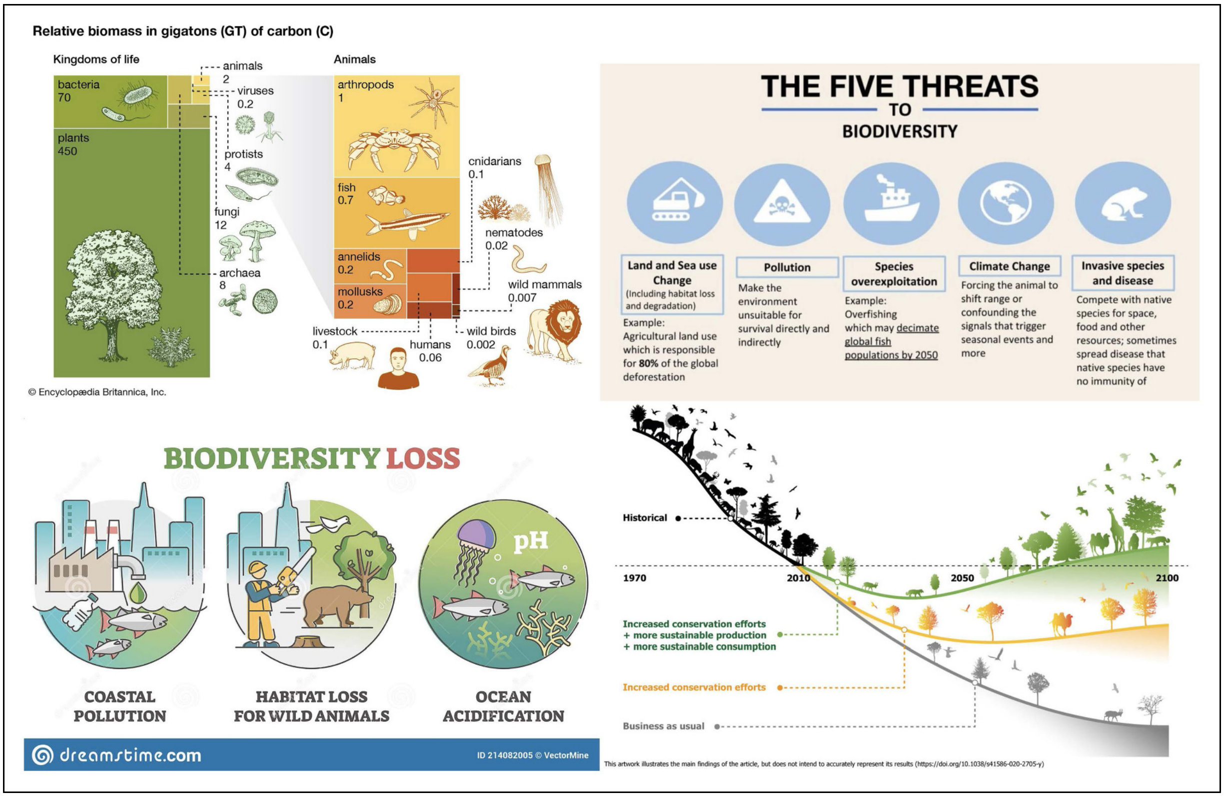

Figure 13. Scientific and educational materials related to biodiversity loss, including infographics and cartoons, found in cluster 2.

Table 5. Knowledge infrastructures of Google search and Google images, for examples of climate change and biodiversity.

		Search engine	
Infrastructural component		Google search	Google images
Process	Web epistemology	Ranking-by-authority	Ranking-by-similarity
	Calculative technology	Web links	Computer vision
Content	Issue configuration	Authoritative expertise: Usually global, occasionally national	Divorced from place: issues occurring 'elsewhere' or on a stylised Earth

Conclusion: The epistemic impacts of Google images

Google Images is a critical everyday mediator of visual culture, yet to date has been the subject of little empirically-informed social science or humanities research. By demonstrating how Google Images homogenises visual culture, both within issues and across different countries, we highlight a previously unacknowledged impact of computer vision models: how they transform the configuration of issues on search engines, a foundational source of public knowledge in digital societies. Our search queries focused on environmental change constitute a paradigmatic case, with a research approach and design which can be applied more broadly to analyse the infrastructural components through which search engines organise knowledge, and the issue configurations which these give rise to (Flyvbjerg, 2006; Haider and Sundin, 2019).

Returning to our research question, we found that Google Search adopts a ranking-by-authority epistemology, consistent with its founding principle of providing web sources with high numbers of in-links, ranking authoritative web sources such as the UN, NASA and IPCC consistently highly across multiple countries, occasionally alongside more local sources. Authoritative sources were less visible in Google Images results. Moving from web sources presented by Google Images to its visual content, we found a high degree of similarity between search results across different countries for each query (climate change, biodiversity loss) with specific images repeated multiple times. Using a relational approach to computer vision analysis, we also found results across different countries to be dominated by a small number of visual genres, such as pictures of the Earth and degraded forests.

Based on these results, we argue that Google Images' use of computer vision has brought about an emerging web epistemology of ranking-by-similarity, operating in parallel with the ranking-by-authority approach of Google Search. This epistemology operates across national boundaries, prioritising visual similarity over locally contextualised relevant visuals, so globally homogenising the visual configuration of environmental change. Table 5 locates our empirical findings within our conceptual framework for understanding knowledge infrastructures.

As well as providing novel knowledge about Google Images, our research findings also contribute to wider debates in search engine studies and digital media. We provide further evidence of the degradation, or 'enshittification', of Google search results (Doctorow, 2025), and put in perspective Google's claim that page authority has been given increased importance in determining Google Images search results (Edwards, 2018). We also note the divergence between our results and the claim that Google's PageRank for images can return diverse and relevant results for heterogeneous concepts, such as those in our study (Jing and Baluja, 2008). While we do not doubt that page authority continues to play some role, we have shown how this authority has been significantly diluted by the turn to visual similarity, with impacts on the quality of images and information provided to societies. Our research also contributes to wider debates on the epistemic impacts of algorithms; for example, in homogenising music and film recommendations (Hallinan and Striphas, 2016) and uniformity in AI image generation model outputs (Katirai et al., 2025). We show how these dynamics are also changing knowledge infrastructures, and in turn impacting both the public visibility and visuality of important issues such as climate change and biodiversity loss. By highlighting these processes, we also seek to improve media and information literacy of how search engines impact public understanding of important issues (Haider and Sundin, 2019). Determining whether such ranking processes can be described as fair or transparent, the criteria for rankings required by the European Union Digital Markets Act 2022, will require further research.

We conclude with some limitations to our study which also illuminate opportunities for future research. First, we recognise that climate change and biodiversity loss are issues often primarily configured by institutional actors, NGOs, and expert communities (Veltri and Atanasova, 2017). As a consequence, these topics may rely not only on business-driven discourses, but also on standardised and institutionalised images, which may affect the findings of our research. While the knowledge infrastructure of Google Images is very likely to have homogenising effects across other issues, future studies covering a more diverse range of search queries and languages are necessary, particularly as this remains an understudied area. Second, our analysis is limited to a specific set of countries and queries. We selected the six countries based on their geographical diversity, economic contexts and varying levels of engagement with environmental issues. While this choice allowed us to have a broader look into our topic, we recognise that it also constitutes a limitation as we may have overlooked other cultural, political, and linguistic differences. Third, our study of Google Search looks only at 'organic' results of web sources and not the increasing amount of semantic media such as knowledge panels and AI summaries which are often given greater visibility. Fourth and finally, we have highlighted how highly ranked results in Google Images look similar to each other. The further question that arises, but is beyond the scope of our study, is how Google Images has come to represent climate change and biodiversity loss in these ways, and not others. In short, how does Google Images decide what a concept looks like in the first place? Answering this larger question, at the intersection of algorithmic authority and visual culture, is an important priority for future research in order to better understand the epistemic impacts of both search engines and machine learning.

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Supplemental material

Supplemental material for this article is available online.

Notes

1. Fishkin's US-focused study estimates 5.9 trillion Google searches during 2024, equating to 16.4 billion per day, of which Google images accounts for approximately 10%. Google estimates over 5 trillion searches taking place annually, without providing a breakdown for different Google products (Srinivasan, 2025).
2. An example of an infrastructural component not included here is Google's employees, particularly given the homogeneity of its workforce and how this characteristic can impact decision making (Seaver, 2021)
3. The closest equivalent is a paper focused on product image search, published eight years after Google Images' launch (Jing and Baluja, 2008).
4. In a move mirroring the development of Google web search, researchers have claimed improved search engine results are obtained through the integration of user click data (Yu et al., 2015). In theory this provides a more 'democratic' image ranking, but does nothing to address critiques regarding ethical voids in machine learning development.

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