

Conceptions of Artificial Intelligence

How Text-to-Image Models Envision Extreme Weather Events

Anne-Sophie Skarabis, 20-725-487

anne-sophie.skarabis@uzh.ch

Fall Semester 2023

Visual Communication of Climate Change

University of Zurich, Department of Communication and Media Research (IKMZ)

Xiaoyue Yan, MSc

Zurich, January 7, 2024

Contents

1	Introduction	3
2	Theoretical Foundations	4
2.1	Generative Art and Text-to-Image Models	4
2.1.1	Overview of Text-to-Image Models in AI	4
2.1.2	The Data Behind	5
2.1.3	Biases in Text-to-Image Model Outputs	5
2.2	Climate Change and Extreme Weather Events	6
2.2.1	Extreme Weather Events	6
2.2.2	Impacts of Climate Change and Extreme Weather	6
2.3	Visual Communication of Climate Change	8
2.3.1	Cognitive and Emotional Effects of Visuals	8
2.3.2	Framing Climate Change	9
2.3.3	Visual Attributes	11
2.3.4	Visual Synecdoches and Iconic Imagery	12
3	Methods	13
3.1	Designing Prompts	13
3.1.1	Image Generation	15
3.2	Sample	16
3.3	Content Analysis	16
3.3.1	Codebook	17
3.3.2	Exclusion Criteria	17

3.3.3	Formal Categories	17
3.3.4	Coding Process	18
3.4	Statistical Analysis	19

Appendix **I**

A	Prompts	II
B	Codebook	VII
C	Code Scripts	XXVI
D	Glossary	XXXIV
E	List of Figures	XXXIX
F	List of Tables	XL

1 Introduction

In recent years, climate change discourse has shifted from abstract predictions to an urgent reality with observable impacts. Among the most alarming manifestations is the increase in extreme weather events, which have intensified in frequency and severity (IPCC, 2023j). These events are disrupting ecosystems, affecting lives, and impacting economies globally (IPCC, 2023d, p. 2460). In this context, effective climate change communication is crucial (IPCC, 2023b).

Visual representations play a vital role in climate change communication. Images shape emotions and influence behaviours towards climate change (Leiserowitz, 2006). They aid in understanding complex environmental risks (Epstein, 1994; Joffe, 2008) and encourage active engagement (Keib et al., 2018). Moreover, images are more memorable than text (Coleman, 2010; Graber, 1990) and can transcend language and geographical barriers if readers share cultural references (Armfield et al., 2013).

Given this power of visual media, the emergence of advanced text-to-image models presents new prospects and challenges in climate communication. Text-to-image models harness machine-learning algorithms to transform textual prompts into visual representations (Zhang et al., 2023), offering innovative ways to depict climate change impacts and (imagined) scenarios. However, they also raise concerns about the authenticity and reliability of visual media.

Recent instances of AI-generated content used in journalism (Henrich, 2023; Kim, 2023) indicate a growing trend towards its increased use in the field. This shift is also supported by a study by Deloitte AG (2023) which, though not exclusive to journalists, shows that 61% of Swiss professionals using computers use generative technology. This highlights the importance of examining the results of generative AI to assess its accuracy and justify its use in commun-

cations.

Hence, this paper investigates the use of text-to-image models, specifically *DALL-E 3* and *Midjourney v6*¹ in visualising extreme weather events and explores how these technologies represent such events.

2 Theoretical Foundations

2.1 Generative Art and Text-to-Image Models

Generative art is the process by which an artist delegates control to an autonomous system, allowing it to either create a artwork or become the artwork itself (Galanter, 2019, p. 112). While generative art commonly incorporates computers or digital technology, it is not strictly limited to these mediums (Thomas & Thomson, 2023, p. 5). Nonetheless, this paper defines "generative imagery" as imagery produced by text-to-image models.

2.1.1 Overview of Text-to-Image Models in AI

Since 2022, text-to-image models like have seen significant advancements (Gozalo-Brizuela & Garrido-Merchan, 2023). These models, which are part of generative machine learning, transform text into images. To achieve this, they are trained on extensive data sets combining images with descriptive texts and learn to correlate text elements with visual aspects (Bie et al., 2023). For example, the word "mountain" in text is associated with certain shapes, colours, and textures in images. Through iterative adjustments during training, these models improve their ability to generate more accurate images from text.

Both *DALL-E* and *Midjourney* (Thomas & Thomson, 2023, p. 5) provide user-friendly inter-

¹hereinafter only referred to as *DALL-E* and *Midjourney*

faces, with the latter's integration into *Discord* potentially more challenging for users unfamiliar with the platform. Both models support 'prompt engineering' (Liu & Chilton, 2022), allowing iterative refinement for varied results, and can generate diverse images even from the same prompt.

2.1.2 The Data Behind

The effectiveness of text-to-image models is closely tied to their training data, which impacts the range and nature of generated images. Biased training data can result in AI-generated images mirroring and potentially reinforcing those biases. For instance, a model primarily trained on a specific newspaper's content may exhibit biases in style and thematic representation aligned with that source.

This reliance on pre-existing data for training AI models in image creation further raises ethical and legal concerns. Notably, in December 2023 *The New York Times* sued *OpenAI* for using its articles in training AI models without consent (Bradshaw & Miller, 2023). This case highlights concerns over copyright and raises questions about originality and intellectual property rights.

2.1.3 Biases in Text-to-Image Model Outputs

The field of communication science has only recently begun to examine the output of text-to-image models, reflecting the novelty of these technologies. During the literature review, only two relevant studies were found:

García-Ull and Melero-Lázaro (2023) analysed gender stereotyping in images generated by *DALL-E 2*, revealing a tendency for certain professions to be represented as either exclusively male or female, thereby echoing and potentially reinforcing traditional gender roles. Thomas

and Thomson (2023) analysed *Midjourney*'s perceptions of "what a journalist looks like", uncovering biases related to gender, ethnicity, and age, neglecting diversity in modern journalism.

This tendency of AI models to replicate biases in their outputs can be traced back to the nature of their training data, as discussed in chapter 2.1.2.

2.2 Climate Change and Extreme Weather Events

According to the United Nations (n.d.), climate change is characterised by long-term shifts in temperature and weather patterns. Since the 1800s, human activities have become the primary driver for climate change, largely due to greenhouse gases released by fossil fuel combustion, deforestation, and agriculture (IPCC, 2023e). This anthropogenic influence has led to systemic environmental disruptions, impacting various aspects of human life (IPCC, 2023g).

2.2.1 *Extreme Weather Events*

An "extreme weather event" is a rare occurrence at a particular place and time of year (IPCC, 2023h, p. 2908). Extreme weather encompasses various phenomena, as listed in Table 1. These events, defined by their rarity compared to the 10th or 90th percentile of observations for their location (IPCC, 2023h, p. 2908), may vary in length and persist for a season or longer. Global warming is amplifying these extremes, with even a modest increase (+0.5°C) having a significant impact on global weather patterns (IPCC, 2023j, p. 1583). The frequency of unprecedented extreme events is expected to increase with ongoing global warming.

2.2.2 *Impacts of Climate Change and Extreme Weather*

Climate change and extreme weather have far-reaching impacts on various regions and communities, affecting health, livelihoods, and well-being. These events can cause deaths, injuries,

Event Type	Description
Temperature Extremes	Unusually hot or cold temperatures, significantly differing from regional historical averages.
Heavy Precipitation and Pluvial Floods	Intense, rainfall over a short period leading to rapid urban and pluvial flooding.
River Floods	Excessive river and stream levels causing adjacent land inundation, often due to extended rainfall or snowmelt.
Droughts	Prolonged low precipitation causing water scarcity, impacting ecosystems and agriculture.
Extreme Storms and Tropical Cyclones	Severe weather with strong winds and heavy rain, including tropical cyclones originating over warm oceans.
Compound Events	Concurrent or sequential extreme events, such as combined heatwaves and droughts or heavy rains with storm surges.

Table 1: Types of Extreme Weather Events according to IPCC (2023g)

ecosystem or infrastructure damage (IPCC, 2023i, p. 79). They also have long-term consequences, such as mental health issues (IPCC, 2023c, p. 1126), homelessness (IPCC, 2023f, p. 1251), and reduced availability of health services (IPCC, 2023a, p. 1632).

Financially, extreme weather can increase constraints, pushing individuals into poverty and exacerbating inequality within countries. Vulnerable groups, particularly undocumented immigrants, Indigenous populations, and marginalised communities, are most at risk. They often face displacement, income loss, and home destruction, intensifying their vulnerability (IPCC, 2023f, p. 1206). One example of this are the Caribbean, Central America and the USA, where hurricanes Katrina, Harvey, Irma, Maria and Michael have led to the displacement, destruction of homes and loss of income among the poor and marginalised (Klinenberg et al., 2020). Generally, the impacts of climate change and extreme weather events are disproportionately felt in

the Global South (IPCC, 2023f, p. 1180)².

2.3 Visual Communication of Climate Change

Visual communication can be defined as the utilisation of visual elements to convey ideas and information. It stands apart from verbal or written languages due to its more abstract nature and the interpretation of visual signs being influenced by the viewer's field of experience (Smith et al., 2004).

2.3.1 *Cognitive and Emotional Effects of Visuals*

In the area of climate change communication, visual representations are of great value. It has been shown that images not only influence people's feelings but also their behaviour in relation to climate change (Leiserowitz, 2006). Images engage the holistic, intuitive and affective experience processing system, enabling a more rapid understanding of complex environmental risks (Epstein, 1994; Joffe, 2008). This ability of images to swiftly convey information and evoke emotional responses not only increases media engagement but also shapes perceptions and behaviours towards climate change, thus catalysing the transition from passive spectatorship to active participation (Keib et al., 2018). In addition, images help readers to remember information better than text-only information (Coleman, 2010; Graber, 1990) and provided the readers have similar cultural references, images can overcome linguistic or geographical barriers, when it comes to conveying information to an audience (Armfield et al., 2013)

Returning to the topic of generative image models discussed chapter 2.1, their use in science communication offers both opportunities and challenges: For one thing, these AI tools can

²According to the Germanwatch Climate Risk Index (2021), the countries most affected by these events include Mozambique, Zimbabwe, The Bahamas, Japan, Malawi, the Islamic Republic of Afghanistan, India, South Sudan, Niger and Bolivia.

quickly produce visuals that could make scientific concepts more accessible. However, any inaccuracies could lead to misunderstandings or misinterpretations of scientific facts and generate scientific misinformation.

2.3.2 *Framing Climate Change*

According to von Sikorski and Matthes (2020), "framing refers to the idea that actors like strategic communicators, journalists but also audience members select some aspects in a particular issue and make them salient while other aspects are ignored."

Whilst a "natural" consequence of the news process, framing always leads to certain effects, whether it is intentional or not (O'Neill et al., 2022, p. 91). For example, the prevailing frames can favour certain actors, influence the focus of media coverage and affect public opinion and political decisions (Nisbet & Huge, 2006).

This concept of framing extends beyond written or spoken media and is equally applicable to visual communications. Contrary to the common belief that a camera simply captures reality as it is, the truth is that images, too, can be instruments of framing (O'Neill & Smith, 2014, p. 74). For instance, showing only a part of an image without its broader context can significantly alter the perceived story, leading to misunderstandings or misinterpretations (Fleming, 2021). Furthermore, different images can be used to portray the same underlying subject.

In framing, the narrative encompasses not just what is depicted, but also who is shown, the context provided, and the storyline conveyed. O'Neill and Smith (2014) observed that when communicating climate change, legacy newspaper oftentimes use personification, such as the portrayal of politicians. Additionally, climate impacts are frequently illustrated in these depictions. Notably, what is rarely portrayed are aspects of climate mitigation or adaptation. This can be related back to news factor theory (Galtung & Ruge, 1965), where news factors

such as "Personalisation" or "Negativity" increase the likelihood of a news story being chosen for publication, as they are more appealing to the audience. NGOs, in contrast, often focus on illustrating the dangers and triggers of climate change, using evocative polar regions to highlight environmental threats or images of renewable energy sources to emphasise the urgent need for sustainable solutions. Meanwhile, the advertising and marketing sectors use a diverse range of imagery that connects climate action with consumer behaviour, aiming to engage consumers and instill a sense of personal responsibility for climate action, influencing them to purchase their products. In each instance, the chosen frame and narrative serve the organisation's goals and influence public perception or action.

Building on this discussion, it is interesting to consider the role of text-to-image models. Different actors choose different frames to achieve their communication goals. These models, trained on existing datasets, have the potential to either maintain or challenge the established frames and narratives. Therefore, the following research question arises:

RQ1: What narratives do text-to-image models like *DALL-E* and *Midjourney* use when generating imagery related to extreme weather events?

This question explores the narratives constructed by these models, focusing on key aspects such as characters depicted, the types of consequences shown, and the overall context presented. The presence of a consistent frame/ narrative in generative imagery, especially if used in mass communications, could have significant impact. For example, if the images subtly embed bias or misinformation, they could unintentionally reinforce certain misconceptions and prejudices in the public consciousness.

2.3.3 Visual Attributes

The concept of framing can be further extended by looking at visual attributes or "visual modalities", defined by Kress and van Leeuwen (2020, p. 256) as the extent to which certain visual means of expression such as colour, depth or hue are used. Such visual attributes can affect an individual's emotions (Valdez & Mehrabian, 1994) or even influence their behaviour (Meier et al., 2012). Hence, the composition of visual attributes can have an impact on how an image is perceived.

This paper focuses on the aspects of colours, brightness and saturation. In their study on science conspiracy videos Chen et al. (2022) found that conspiracy videos tended to use lower colour variances and lighting compared to correction videos, noting that this was particularly noticeable in the video thumbnails and first few seconds of the video. The researchers draw parallels between the visual features of conspiracy theories and horror films. Horror movies often use low-key lighting and a more limited, less saturated range of colours than other film genres (Rasheed et al., 2005). This is typically done because dim lighting helps in building suspense, and darker colour is more fear inducing.

Previous research has demonstrated that images related to climate change tend to elicit negative emotions rather than positive ones (O'Neill, 2017). Additionally, considering that there is an intrinsically frightening component to the issue of climate change and extreme weather events in particular (Soutar & Wand, 2022), this paper investigates whether text-to-image models reinforce this narrative through their use of visual attributes associated with fear.

RQ2: Do the colour, brightness, and saturation levels typically employed in images generated by *DALL-E* and *Midjourney*, when depicting extreme weather events, align more with visual attributes that evoke fear?

2.3.4 Visual Synecdoches and Iconic Imagery

O'Neill (2019, p. 16) found that as the visual language of climate change has evolved over the past decade, certain iconic images have also become increasingly common and embedded in the visual language. O'Neill (2019, p. 17) refers to these iconic images as visual synecdoches, a kind of visual shorthand used in a particular culture to convey a certain set of ideas about climate change to the reader beyond the conceptual content directly depicted. These images often represent the broader narrative of climate change in a single, impactful visual, making them instantly recognisable and emotionally resonant (O'Neill & Smith, 2014, p. 78). For instance, the image of a lone polar bear on a shrinking ice floe has become an iconic representation of the effects of global warming (O'Neill, 2019, p. 18). Other than polar bears, O'Neill (2019, p. 16) identifies ice imagery, smokestacks and wind turbines to be common visual synecdoches.

This trend towards the use of visual synecdoches leads to the third research question:

RQ3: In what ways do *DALL-E* and *Midjourney* use visual synecdoches to represent extreme weather events?

Lastly, in light of the three specific research questions addressed earlier, an overarching question emerges:

RQ4: Do *DALL-E* and *Midjourney* exhibit distinct differences in their portrayal of climate change narratives, visual attributes, and symbolic representations in the context of extreme weather events?

This question aims to determine whether the results of the individual models are unique or whether they share common patterns in the representation of narratives about climate change.

3 Methods

The study focuses on the image-to-text models *DALL-E 3* and *Midjourney v6* due to their popularity and advanced capabilities.

The reason for choosing these models lies in their widespread public discussion in the field of AI image generation (Gibson, 2023; Gindham, 2023; Guinness, 2023).

DALL-E 3 was recently integrated into *Microsoft Bing*, which offers simple access to the model (Microsoft Bing, n.d.). The model's direct connection to *ChatGPT* further enhances its public visibility. *Midjourney*, while less accessible due to its *Discord* interface and discontinuation of its free trial in April 2023 (Weiß, 2023), still boasts over 16 million users (Krivec, 2023).

As of January 2024, *Midjourney* lacks a first-party API.

Another notable model, *Stable Diffusion*, provides free access and a first-party API, presenting some advantages over *Midjourney*. However, it lags behind in computing efficiency (Kothari, 2023) and user interest compared to *Midjourney* and *DALL-E* (see Figure 1), justifying their selection for the study.

3.1 Designing Prompts

For this study, 27 prompts were crafted, focusing on extreme weather events and their various aspects. These prompts, detailed in the appendix (see Appendix Chapter A), were designed to balance guidance and interpretative freedom, ensuring sufficient room for interpretation to ensure a wide range of responses. The aim was to provide open-ended prompts to some degree, but specific enough to generate images that were relevant and insightful in the context of extreme weather events. These prompts are mainly based on the literature review (see Chapter 2.2).

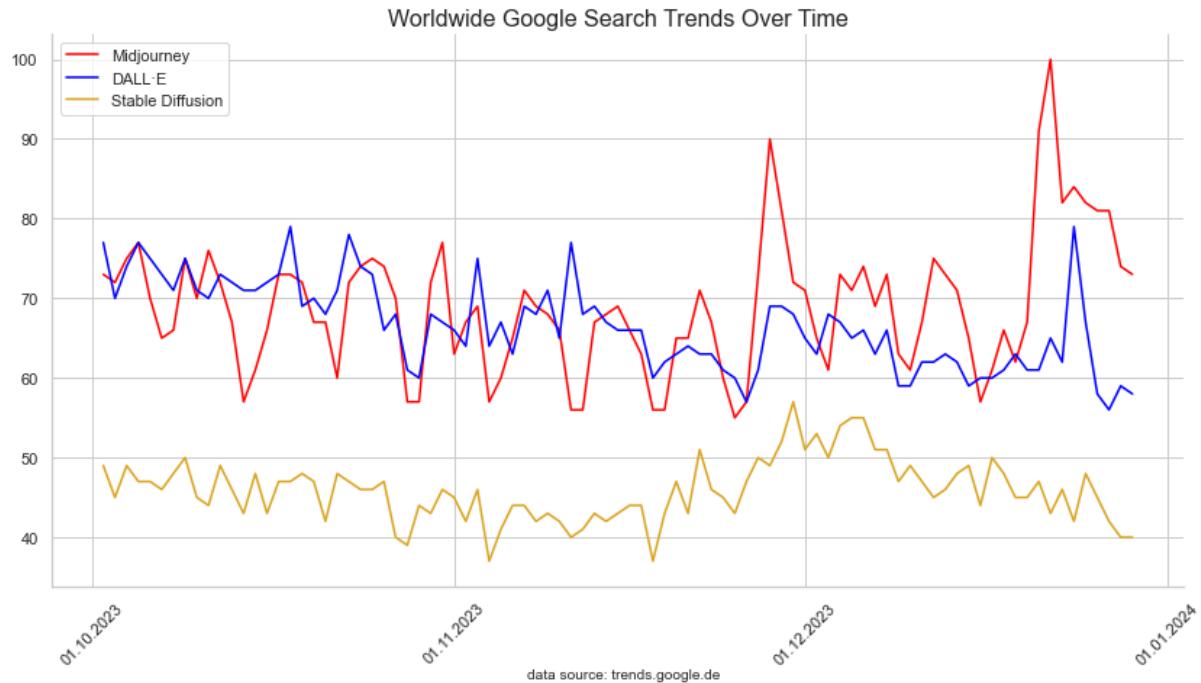


Figure 1: Worldwide Google Search Trends Over Time

The initial prompt ($n = 1$) was broad ("*Depict an extreme weather event*"), allowing for diverse interpretations and representations of extreme weather.

Building on the general prompt, a series of more specific prompts ($n = 8$) were developed, each targeting a specific type of extreme weather event as categorised by the IPCC (see table 1). This includes prompts such as "*Depict temperature extremes*". These prompts aim to analyse how the models represent different weather phenomena.

Another four prompts ($n = 4$) aim to explore the visualisation of the impacts of these events on life, landscapes, infrastructure, and cultural changes, informed by a literature review. Additionally, two prompts ($n = 2$) focus on recovery and adaptation strategies. Finally, prompts were developed focusing on the causes of extreme weather events ($n = 3$) and future climate scenarios ($n = 9$). These prompts aim to identify the models' understandings of the causes of extreme weather events and their visualisation of future weather patterns and climate change impacts.

3.1.1 Image Generation

The prompts designed for this study (as described in 3.1) will be submitted to the official *DALL-E 3* API,

while for *Midjourney* the official *Discord* interface will be used for data generation.

For generating images using the *DALL-E 3* API, the following parameters were chosen:

- **Model Specification:** 'dall-e-3' to access *DALL-E*'s latest features.
- **Image Size:** Uniform resolution of '1024x1024'.
- **Image Quality:** "standard" setting for balanced fidelity and speed.
- **Number of images:** 'n' set to 1, as per *DALL-E 3*'s one-image-per-call limit.

An example of how this API is used can be found in the appendix (see Appendix Chapter C.1).

For the creation of images with *Midjourney*, the standard *Discord* interface will be used.

The decision was motivated by the absence of an official API and potential legal and ethical implications associated with third-party APIs.

- **Model Version:** *Midjourney v6.0* (-v 6.0) for latest features.
- **Stylize Parameter:** The -stylize parameter influences the application of *Midjourney*'s default artistic style. Low values produce images closer to the prompt but less artistic, while high values yield very artistic but less prompt-aligned images (*Midjourney*, n.d.). The default and used value for this study is 100, and the parameter accepts integer values ranging from 0 to 1000.
- **Image Upscaling:** All images will be upscaled post-generation.

3.2 Sample

This study will analyse a total of 240 images, generated from 27 (+3) unique prompts with each prompt producing eight images (four from *DALL-E* and four from *Midjourney*). *Midjourney* generates four images per prompt by default, while *DALL-E* will receive each prompt four times.

The reason for creating four images per prompt is twofold: First, to capture the variability of AI interpretations, as the same model can often visualise the same prompt differently, leading to a variety of results. Second, while the first images tend to show a large variety, this tends to decrease with subsequent images (see Figure 2)



Figure 2: Comparison of the output for a single prompt by *DALL-E* 3. The first four images show diverse interpretations, while the last four indicate reduced variability.

3.3 Content Analysis

The content analysis is an essential part of this study and follows on from the collection of material as described above.

3.3.1 *Codebook*

The core of a content analysis lies in the development of a category scheme (codebook), which is necessary in order to make statements about the collected material.

The codebook contains both formal categories and content categories. Each variable defined in the codebook is accompanied by a set of coding instructions that detail the conditions under which coders should assign particular codes to the images.

3.3.2 *Exclusion Criteria*

The study's general exclusion criteria omits certain AI-generated images to maintain focus. Excluded are off-topic images clearly unrelated to prompts, images focused on text due to limitations of the models to generate coherent text within images, and images with technical flaws like poor rendering or low resolution.

3.3.3 *Formal Categories*

It was determined that only the visual content of an image would be analysed. Each image will be assigned a unique identifier, the Coding Unit (CU), which serves as a reference throughout the analysis. Information such as the model, or the prompt used will be recorded for each CU.

Narrative Constructs

This section is primarily focused on analysing how AI-generated images depict and contextualise extreme weather events. It examines the overall storytelling approach, including how these events are visually framed within different environmental settings, the emotional and thematic undertones conveyed, and the portrayal of impacts and potential responses.

Visual Attributes

These variables assess visual attributes such as colour, brightness, and saturation. A script (see Appendix, p. XXX) will be employed to extract these attributes from each image computationally.

Visual Synechdoches

This section focuses on discerning symbolic imagery and metaphors that encapsulate broader narratives and themes related to climate change.

3.3.4 Coding Process

Creation of a Coding Matrix

A coding matrix was created in Microsoft Excel to facilitate coding. It reflects the categories of the codebook and enforces the validity of the data through restrictions, including drop-down lists to limit entries to predefined codes and prevent invalid data entries.

Training and Reliability

Coders will be trained with sample images to ensure a shared understanding of coding instructions. Before the actual coding, a pre-test phase is carried out to assess the clarity of the coding book and refine the coding rules if necessary. Intra-coder reliability is also monitored to confirm individual coders' consistency over time. The Krippendorff's alpha statistical measure will be used to assess consistency, aiming for a reliability coefficient of 0.8 (see Appendix Chapter C.5).

3.4 Statistical Analysis

Descriptive statistics will serve as a base, especially for RQ1 and RQ3, which aim to categorise and quantify different narrative themes and elements depicted. An ANOVA is used on RQ2 to compare mean visual attributes (such as colour, brightness and saturation) across different image categories to determine whether certain attributes are more consistent with anxiety-inducing images. Furthermore, correlation and (multinomial logistic) regression analyses will be conducted to examine and potentially predict relationships between the type of extreme weather event depicted and various image attributes. For RQ4 chi-square tests are used to determine whether the distributions of narratives and visual elements differ significantly between the models.

References

- Armfield, D. M., Gurak, L. J., & Li, S. (2013). The global reach of visual communication: Pitfalls and potentials. *IEEE International Professional Communication 2013 Conference*, 1–4. <https://doi.org/10.1109/IPCC.2013.6623908>
- Bie, F., Yang, Y., Zhou, Z., Ghanem, A., Zhang, M., Yao, Z., Wu, X., Holmes, C., Golnari, P., Clifton, D. A., He, Y., Tao, D., & Song, S. L. (2023). RenAIssance: A Survey into AI Text-to-Image Generation in the Era of Large Model. <https://doi.org/10.48550/arXiv.2309.00810>
- Bradshaw, T., & Miller, J. (2023). New York Times sues Microsoft and OpenAI in copyright case. *Financial Times*. <https://www.ft.com/content/23c15ce1-16c5-4b2f-804e-2c0da64e1972>
- Broussard, M., Diakopoulos, N., Guzman, A. L., Abebe, R., Dupagne, M., & Chuan, C.-H. (2019). Artificial Intelligence and Journalism. *Journalism & Mass Communication Quarterly*, 96(3), 673–695. <https://doi.org/10.1177/1077699019859901>
- Chen, K., Kim, S. J., Gao, Q., & Raschka, S. (2022). Visual Framing of Science Conspiracy Videos. *Computational Communication Research*, 4. <https://doi.org/10.5117/ccr2022.1.003.chen>
- Coleman, R. (2010). Framing the Pictures in Our Heads: Exploring the Framing and Agenda-Setting Effects of Visual Images. In P. D'Angelo & J. A. Kuypers (Eds.), *Doing News Framing Analysis: Empirical and Theoretical Perspectives* (1st, p. 30). Routledge.
- Deloitte AG. (2023). Generative AI's fast and furious entry into Switzerland.
- Eckstein, D., Künzel, V., & Schäfer, L. (2021). *Global climate risk index 2021*.
- Epstein, S. (1994). Integration of the cognitive and the psychodynamic unconscious. *American Psychologist*, 49, 709–724. <https://doi.org/10.1037/0003-066x.49.8.709>

- Fleming, J. (2021). Pictures of Half-Truth: On Politics & Photography. *Afterimage*, 48(1), 19–27. <https://doi.org/10.1525/aft.2021.48.1.19>
- Galanter, P. (2019). Artificial Intelligence and Problems in Generative Art Theory. *Electronic Workshops in Computing*. <https://doi.org/10.14236/ewic/eva2019.22>
- Galtung, J., & Ruge, M. H. (1965). The Structure of Foreign News: The Presentation of the Congo, Cuba and Cyprus Crises in Four Norwegian Newspapers. *Journal of Peace Research*, 2(1), 64–90. <https://doi.org/10.1177/002234336500200104>
- García-Ull, F.-J., & Melero-Lázaro, M. (2023). Gender stereotypes in AI-generated images. *El Profesional de la información*. <https://doi.org/10.3145/epi.2023.sep.05>
- Gibson, D. (2023, December 28). *AI Image Generators: Midjourney v6 vs DALL-E v3*. Propeller Works. Retrieved January 1, 2024, from <https://www.propellermediaworks.com/blog/ai-image-generators-comparison-midjourney-6-dall-e-3/>
- Gindham, A. (2023, October 26). *Dall-E 3 vs Midjourney: A Side-by-Side AI Image Comparison*. Writesonic. Retrieved January 2, 2024, from <https://writesonic.com/blog/dall-e-3-vs-midjourney#:~:text=The%20showstopper%3A%20Midjourney%20vs%20Dall%2DE%203%20&text=On%20the%20other%20hand%2C%20Midjourney,be%20the%20more%20suitable%20choice.>
- Gozalo-Brizuela, R., & Garrido-Merchan, E. C. (2023). ChatGPT is not all you need. A State of the Art Review of large Generative AI models. <https://doi.org/10.48550/ARXIV.2301.04655>
- Graber, D. A. (1990). Seeing Is Remembering: How Visuals Contribute to Learning from Television News. *Journal of Communication*, 40, 134–156. <https://doi.org/10.1111/j.1460-2466.1990.tb02275.x>

- Guinness, H. (2023, December 18). *Midjourney vs. DALL·E 3: Which image generator is better? [2024]*. Zapier. Retrieved January 2, 2024, from <https://zapier.com/blog/midjourney-vs-dalle/>
- Henrich, J. (2023, May 20). *KI im Journalismus: Wie "ChatGPT" und "Midjourney" den Journalismus verändern könnten* [AI in journalism: How "ChatGPT" and "Midjourney" could change journalism]. ZDF. Retrieved December 27, 2023, from <https://www.zdf.de/nachrichten/panorama/ki-journalismus-chatgpt-midjourney-zeitschrift-burda-verlag-100.html>
- IPCC. (2023a). Australasia. In *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1581–1688). Cambridge University Press. <https://doi.org/10.1017/9781009325844.013>
- IPCC. (2023b). Framing, Context, and Methods. In *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 147–286). Cambridge University Press. <https://doi.org/10.1017/9781009157896.003>
- IPCC. (2023c). Health, Wellbeing and the Changing Structure of Communities. In *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1041–1170). Cambridge University Press. <https://doi.org/10.1017/9781009325844.009>
- IPCC. (2023d). Key Risks across Sectors and Regions. In *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment*

- Report of the Intergovernmental Panel on Climate Change (pp. 2411–2538). Cambridge University Press. <https://doi.org/10.1017/9781009325844.025>
- IPCC. (2023e). Point of Departure and Key Concepts. In *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 121–196). Cambridge University Press. <https://doi.org/10.1017/9781009325844.003>
- IPCC. (2023f). Poverty, Livelihoods and Sustainable Development. In *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1171–1274). Cambridge University Press. <https://doi.org/10.1017/9781009325844.010>
- IPCC. (2023g). Summary for Policymakers. In *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 37–118). Cambridge University Press. <https://doi.org/10.1017/9781009325844.001>
- IPCC. (2023h). *Technical Summary*. Cambridge University Press. <https://doi.org/10.1017/9781009325844>
- IPCC. (2023i). Technical Summary. In *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 37–118). Cambridge University Press. <https://doi.org/10.1017/9781009325844.002>
- IPCC. (2023j). Weather and Climate Extreme Events in a Changing Climate. In *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1513–1766). Cambridge University Press. <https://doi.org/10.1017/9781009157896.013>

- Joffe, H. (2008). The Power of Visual Material: Persuasion, Emotion and Identification. *Diongenes*, 55(1), 84–93. <https://doi.org/10.1177/0392192107087919>
- Keib, K., Espina, C., Lee, Y.-I., Wojdynski, B. W., Choi, D., & Bang, H. (2018). Picture This: The Influence of Emotionally Valenced Images, On Attention, Selection, and Sharing of Social Media News. *Media Psychology*, 21, 202–221. <https://doi.org/10.1080/15213269.2017.1378108>
- Kim, C. (2023, November 28). *Sports Illustrated accused of publishing AI-written articles*. BBC News. Retrieved December 27, 2023, from <https://www.bbc.com/news/world-us-canada-67560354>
- Klinenberg, E., Araos, M., & Koslov, L. (2020). Sociology and the Climate Crisis. *Annual Review of Sociology*, 46(1), 649–669. <https://doi.org/10.1146/annurev-soc-121919-054750>
- Kothari, S. (2023, June 23). *DALL-E vs. Midjourney vs Stable difussion: Which is Better?* Simplilearn Solutions. Retrieved January 2, 2024, from <https://www.simplilearn.com/dalle-vs-midjourney-vs-stable-difussion-article>
- Kress, G., & van Leeuwen, T. (2020, November). *Reading Images: The Grammar of Visual Design*. Routledge. <https://doi.org/10.4324/9781003099857>
- Krivec, R. (2023, September 14). *Midjourney Statistics (How Many People Use Midjourney?)* colorlib. Retrieved January 2, 2024, from <https://colorlib.com/wp/midjourney-statistics/>
- Leiserowitz, A. (2006). Climate Change Risk Perception and Policy Preferences: The Role of Affect, Imagery, and Values. *Climatic Change*, 77, 45–72. <https://doi.org/10.1007/s10584-006-9059-9>

- Liu, V., & Chilton, L. B. (2022). Design Guidelines for Prompt Engineering Text-to-Image Generative Models. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. <https://doi.org/10.1145/3491102.3501825>
- Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A Survey on Bias and Fairness in Machine Learning. *ACM Comput. Surv.*, 54(6). <https://doi.org/10.1145/3457607>
- Meier, B. P., D'Agostino, P. R., Elliot, A. J., Maier, M. A., & Wilkowski, B. M. (2012). Color in Context: Psychological Context Moderates the Influence of Red on Approach- and Avoidance-Motivated Behavior. *PLOS ONE*, 7(7), 1–5. <https://doi.org/10.1371/journal.pone.0040333>
- Microsoft Bing. (n.d.). *Bing Image Creation Tool*. Retrieved January 2, 2024, from <https://www.bing.com/images/create/>
- Midjourney. (n.d.). *Stylize*. Retrieved January 3, 2024, from <https://docs.midjourney.com/docs/stylize>
- Nisbet, M. C., & Huge, M. (2006). Attention Cycles and Frames in the Plant Biotechnology Debate: Managing Power and Participation through the Press/Policy Connection. *Harvard International Journal of Press/Politics*, 11(2), 3–40. <https://doi.org/10.1177/1081180X06286701>
- O'Neill, S. (2017, October). Engaging with Climate Change Imagery. <https://doi.org/10.1093/acrefore/9780190228620.013.371>
- O'Neill, S. (2019). More than meets the eye: A longitudinal analysis of climate change imagery in the print media. *Climatic Change*, 163(1), 9–26. <https://doi.org/10.1007/s10584-019-02504-8>

- O'Neill, S., Hayes, S., Strau, N., Doutreix, M.-N., Steentjes, K., Ettinger, J., Westwood, N., & Painter, J. (2022). Visual portrayals of fun in the sun in European news outlets misrepresent heatwave risks. *The Geographical Journal*, 189(1), 90–103. <https://doi.org/10.1111/geoj.12487>
- O'Neill, S., & Smith, N. (2014). Climate change and visual imagery. *WIREs Climate Change*, 5(1), 73–87. <https://doi.org/10.1002/wcc.249>
- Rasheed, Z., Sheikh, Y., & Shah, M. (2005). On the use of computable features for film classification. *IEEE Transactions on Circuits and Systems for Video Technology*, 15(1), 52–64. <https://doi.org/10.1109/TCSVT.2004.839993>
- Smith, K., Moriarty, S., Kenney, K., & Barbatsis, G. (Eds.). (2004). *Handbook of Visual Communication: Theory, Methods, and Media* (1st). Routledge. <https://doi.org/10.4324/9781410611581>
- Soutar, C., & Wand, A. P. F. (2022). Understanding the Spectrum of Anxiety Responses to Climate Change: A Systematic Review of the Qualitative Literature. *International Journal of Environmental Research and Public Health*, 19(2). <https://doi.org/10.3390/ijerph19020990>
- Thomas, R. J., & Thomson, T. J. (2023). What Does a Journalist Look like? Visualizing Journalistic Roles through AI. *Digital Journalism*, 0(0), 1–23. <https://doi.org/10.1080/21670811.2023.2229883>
- United Nations. (n.d.). *What is Climate Change?* Retrieved December 27, 2023, from <https://www.un.org/en/climatechange/what-is-climate-change>
- Valdez, P., & Mehrabian, A. (1994). Effects of color on emotions. *Journal of Experimental Psychology: General*, 123, 394–409. <https://doi.org/10.1037/0096-3445.123.4.394>

- von Sikorski, C., & Matthes, J. (2020, February 28). *Framing and Journalism*. Retrieved December 28, 2023, from <https://oxfordre.com/communication/display/10.1093/acrefore/9780190228613.001.0001/acrefore-9780190228613-e-817?d=10.1093/acrefore/9780190228613.001.0001/acrefore-9780190228613-e-817&p=emailAcIT2eSj52.cI>
- Weiβ, E.-M. (2023, March 31). *Zu viel Missbrauch: Midjourney kann nicht mehr kostenlos getestet werden*. Heise Medien. Retrieved January 2, 2024, from <https://www.heise.de/news/Midjourney-nicht-mehr-kostenlos-zu-testen-Bildgenerator-zu-oft-missbraucht-8315369.html>
- Zhang, C., Zhang, C., Zhang, M., & Kweon, I. S. (2023). Text-to-image Diffusion Models in Generative AI: A Survey. <https://doi.org/10.48550/arXiv.2303.07909>

Appendix

A Prompts

To explore the representation of extreme weather events by text-to-image models such as *DALL-E* and *Midjourney*, a set of prompts was developed. The approach starts with a general call to represent extreme weather events and then addresses specific types of events such as temperature extremes, heavy precipitation, floods, droughts, storms and hurricanes. The prompts also cover the impact of these events on human life, natural landscapes, infrastructure and cultural and social changes. Subsequent prompts address recovery and adaptation strategies, contributing factors and the presentation of future climate scenarios.

A.1 General Prompt

Prompt 1: *Depict an extreme weather event.*

Relevance: This prompt is designed to be deliberately broad, allowing the text-to-image models to generate images based on their inherent understanding and training data regarding extreme weather events.

A.2 Specific Extreme Weather Events

Following the general prompt, more specific prompts are introduced, each focusing on a particular type of extreme weather event. These prompts aim to dissect the models' portrayal of different weather phenomena and their impacts.

Prompt 2: *Depict temperature extremes.*

Prompt 3: *Depict heavy precipitation*

Prompt 4: *Depict pluvial floods*

Prompt 5: *Depict river floods.*

Prompt 6: *Depict droughts.*

Prompt 7: *Depict extreme storms*

Prompt 8: *Depict tropical cyclones*

Prompt 9: *Depict compound weather events.*

Relevance: These prompts are derived from the types of extreme weather events as defined by the IPCC (see 1) They target specific weather phenomena to understand the models' capabilities in depicting each type of event.

A.3 Impacts of Extreme Weather Events

These calls aim to investigate how text-to-image models represent the impact of extreme weather events on different aspects of life and the environment (see chapter 2.2.2).

Prompt 10: *Show the impact of extreme weather on human life.*

Prompt 11: *Illustrate the effects of extreme weather on natural landscapes.*

Prompt 12: *Visualise the infrastructural damage caused by extreme weather.*

Prompt 13: *Depict the cultural and social changes resulting from extreme weather events.*

Prompt 14: *Show a region affected by extreme weather.*

Relevance: These prompts aim to uncover the representation of the consequences of extreme weather events in the models, focusing on the human, natural and infrastructural impacts that play an important role in climate change studies.

A.4 Action related to Extreme Weather Events

This set of prompts is intended to generate imagery depicting outcomes or responses to extreme weather events.

Prompt 15: *Depict recovery efforts following extreme weather events.*

Prompt 16: *Showcase adaptation strategies to extreme weather.*

relevance: The aim here is to investigate how text-to-image models visualise post-event scenarios and highlight the human capacity for resilience and adaptation in the face of climate-related challenges.

A.5 Reasons for Extreme Weather Events

These calls focus on the underlying causes or reasons for extreme weather events as represented by text-to-image models.

Prompt 17: *Depict the reasons contributing to extreme weather events.*

Prompt 18: *Depict the human activities contributing to extreme weather events.*

Prompt 19: *Show the natural factors leading to extreme weather events.*

Relevance: These prompts are intended to understand the text-to-image models' interpretation of the causes of extreme weather events.

A.6 Future Climate and Weather Prompts

This section includes prompts designed to explore how text-to-image models envision future weather scenarios and the long-term impacts of climate change.

Prompt 20: "Depict weather patterns in a world where average global temperatures have risen by 2 degrees Celsius."

Prompt 21: "Illustrate the changes in spring weather patterns due to global warming."

Prompt 21b: "Illustrate the changes in summer weather patterns due to global warming"

Prompt 21c: "Illustrate the changes in autumn weather patterns due to global warming"

Prompt 21d: "Illustrate the changes in winter weather patterns due to global warming"

Prompt 22: "Showcase the impact of sea-level rise in a coastal city in the future."

Prompt 23: "Depict the future state of polar regions (if current warming trends continue)."

Prompt 24: "Visualise future agricultural landscapes affected by changing climate conditions."

Prompt 25: "Illustrate the transformation of urban areas in response to future extreme weather events."

Prompt 26: "Depict human life adaptation in a future with frequent extreme weather events."

Prompt 27: "Visualise future solutions to combat extreme weather challenges."

Prompt 28: "Visualise the development of future solutions to combat extreme weather challenges."

Relevance: These prompts focus on the visualisation of possible future scenarios influenced by ongoing climate change. They aim to stimulate text-to-image models to generate images that reflect possible changes in weather patterns, environmental conditions and human adaptations.

This research is critical to understanding the potential long-term impacts of climate change and the effectiveness of AI in visualising these future possibilities.

B Codebook

This codebook serves as a guide for analysing the images generated by *DALL-E* and *Midjourney*. It provides a structured approach to understanding how these models represent extreme weather events, focusing on answering the research questions defined in chapter 2. In this attempt, the codebook categorises different aspects of the images, allowing for a systematic and detailed examination of the narratives and visual elements depicted in the AI-generated images.

B.1 Coding Unit

The primary coding unit (CU) in this study is the single image generated by AI models (*DALL-E* and *Midjourney*). Each image created in response to a specific text prompt is considered a separate unit of analysis.

Characteristics of the Coding Unit:

- **Completeness:** Images are sourced directly from the AI models and are considered complete as rendered by the AI model, with no subsequent changes or additions.
- **Uniqueness:** Each image is treated as a unique entity, distinct from others generated, even from similar prompts.
- **Relevance:** The image must be relevant to the prompt.

This definition ensures that each AI-generated image is analysed in its entirety, focusing on its relevance and alignment with the research themes.

B.2 General Exclusion Criteria

In the analysis of AI-generated images, certain categories of content are systematically excluded to maintain focus and relevance to the research questions. The following types of content will not be coded:

- **Off-Topic Imagery:** Images that do not directly correspond to the specific prompts. The focus is on excluding images that are clearly not related to the context or topic of the specific prompt, such as images that show completely unrelated topics or environments.
- **Ineffective Text Generation:** Given the limitations of the AI models *DALL-E* and *Mid-journey* in generating coherent and relevant text within images, this study excludes images where the primary focus is on text content. While images simply containing text (without it being the primary focus) are not excluded, the text itself is not analysed. The emphasis is on the visual elements and representations, not on the textual content within the images.
- **Technical Inadequacies:** Images suffering from poor rendering, low resolution, or other technical flaws that significantly hinder their analysis.

B.3 Formal Categories

CU (Coding Unit)

This represents a unique identifier for each individual image generated by the AI models. The ID is derived from the image's filename **ImageID_PromptID_Model_Date_PromptExcerpt**, where **ImageID** refers to the coding unit's ID (CU).

CODER

This category lists the coders involved in the image analysis, each assigned a specific number for identification purposes.

1 Anne-Sophie Skarabis

2 Linda Murray

MODEL

This category indicates the AI model used to generate each image, distinguishing between the two different platforms used in this study. The model is derived from the image's filename `ImageID_PromptID_Model_Date_PromptExcerpt`, where **Model** refers to the model used for the creation of said image.

1 *DALL-E 3*

2 *Midjourney v5.2*

IDPROM (Prompt ID)

The ID for each specific text prompt used for generating each image. The Prompt ID is derived from the image's filename `ImageID_PromptID_Model_Date_PromptExcerpt`, where **PromptID** refers to the ID of each prompt used for the creation of said image. Here are the IDs for each of the prompts.

1 Depict an extreme weather event.

2 Depict temperature extremes.

- 3** Depict heavy precipitation.
- 4** Depict pluvial floods.
- 5** Depict river floods.
- 6** Depict droughts.
- 7** Depict extreme storms.
- 8** Depict tropical cyclones.
- 9** Depict compound weather events.
- 10** Show the impact of extreme weather on human life.
- 11** Show the impact of extreme weather on human life.
- 12** Visualise the infrastructural damage caused by extreme weather.
- 13** Depict the cultural and social changes resulting from extreme weather events.
- 14** Show a region affected by extreme weather
- 15** Depict recovery efforts following extreme weather events.
- 16** Showcase adaptation strategies to extreme weather.
- 17** Depict the reasons contributing to extreme weather events.
- 18** Depict the human activities contributing to extreme weather events.
- 19** Show the natural factors leading to extreme weather events.
- 20** Depict weather patterns in a world where average global temperatures have risen by 2 degrees Celsius.

- 21 Illustrate the changes in spring weather patterns due to global warming.
- 22 Illustrate the changes in summer weather patterns due to global warming.
- 23 Illustrate the changes in autumn weather patterns due to global warming.
- 24 Illustrate the changes in winter weather patterns due to global warming.
- 25 Showcase the impact of sea-level rise in a coastal city in the future.
- 26 Depict the future state of polar regions (if current warming trends continue).
- 27 Visualise future agricultural landscapes affected by changing climate conditions.
- 28 Illustrate the transformation of urban areas in response to future extreme weather events.
- 29 Depict human life adaptation in a future with frequent extreme weather events.
- 30 Visualise future solutions to combat extreme weather challenges.
- 31 Visualise the development of future solutions to combat extreme weather challenges.

PROMPT

DATE

The date on which the image was generated. The Prompt ID is derived from the image's file-name `ImageID_PromptID_Model_Date_PromptExcerpt`, where **Date** refers to the date on which said image was created.

B.4 Narrative Constructs

This section of the codebook is devoted to the analysis of the narratives constructed by the AI models in the imagery related to extreme weather events. It aims to identify how these events are visually represented in terms of event, setting, mood and thematic focus.

EVENT (Event Portrayal)

The portrayal of events in the images is coded according to the types and impacts of extreme weather events as described in the IPCC policy document. The codes are defined as follows:

- 0 Not Applicable:** The image does not depict any recognisable weather-related event.
- 1 Temperature Extremes:** Images depicting unusually hot or cold temperatures, differing significantly from regional historical averages.
- 2 Heavy Precipitation and Pluvial Floods:** Images showing intense rainfall leading to rapid urban and pluvial flooding.
- 3 River Floods:** Images of excessive river and stream levels causing adjacent land inundation.
- 4 Droughts:** Images depicting prolonged low precipitation causing water scarcity and impacting ecosystems or agriculture.
- 5 Extreme Storms and Tropical Cyclones:** Images showing severe weather with strong winds and heavy rain, including tropical cyclones.
- 6 Compound Events:** Images illustrating concurrent or sequential extreme events, such as combined heatwaves and droughts or heavy rains with storm surges.

- 7 **Other:** Images that portray other types of extreme weather events not explicitly listed but relevant to the context of climate change.

Each image will be coded based on the primary weather event it represents, with the option to select 'Other' for images that depict extreme weather events not covered by the specific categories listed.

ENVIRO (Environmental Setting)

Environmental Setting reflects the location and setting of the event.

- 0 **Not Applicable:** The image does not convey a clear environmental context.
- 1 **Urban:** Cityscapes, towns, or built-up areas.
- 2 **Rural:** Countryside, farmlands, or sparsely populated areas.
- 3 **Industrial:** Factories, energy plants or regions indicative of industrial human labour.
- 4 **Polar Regions:** Icebergs, arctic landscapes, or antarctic expanses.
- 5 **Forests:** Woodlands, rainforests, or jungle settings.
- 6 **Water Bodies:** Oceans, lakes, or rivers.
- 7 **Coastal Regions:** Beaches, coastlines, or others areas potentially affected by sea-level rise
- 8 **Other:** Environmental settings not covered above.

GEOIMPACT (Geographical Impact)

This category focuses on identifying the geographical region depicted in the images as affected by climate change and extreme weather events. It aims to emphasise the regional differences in the impact of these phenomena³.

- 0 Not Applicable:** The image does not specify or imply a particular geographic region.
- 1 Global North:** Depictions mainly associated with regions of the Global North (e.g. North America, Europe). Look for landmarks or architectural styles etc. that are typical of these areas. Example: Images of flooding in a city with European architecture.
- 2 Global South:** Images indicating regions in the Global South (e.g., Africa, Latin America, parts of Asia). Key indicators could include tropical landscapes, traditional rural settings, or recognisable landmarks from these regions. Example: Depictions of droughts in African savannas.
- 3 Small Island Developing States (SIDS):** Scenes that specifically depict the particular challenges of small island developing states. Look for images of island states with characteristics such as low-lying coastal areas, tropical cyclones or the effects of sea level rise. Example: Coastal erosion on the Pacific islands.
- 5 Other:** For images that depict geographic impacts not covered by the above categories. This could include unique or less commonly represented regions in

³I'm not sure yet if this is applicable, but thought it would be interesting to analyse this in line with chapter 2.2.2

the context of climate change. Example: Melting glaciers in regions not typically associated with such phenomena.

Specific Countries or Regions: When an image clearly refers to a specific country or region. Identifiers can be national symbols (such as flags), certain geographical features or context-specific codes, then code according to the above categories.

Each image will be coded based on the primary environmental setting it represents, with the option to select 'Other' for images that depict environments not covered by the specific categories listed.

Each image will be evaluated based on the primary weather event it appears to represent, with the option to select 'Other' for images that depict extreme weather events not covered by the specific categories listed.

ELEREP (Elemental Representation)

Elemental Representation categorises the primary elements or subjects featured in the image.

- 0 Not Applicable:** No single element dominates the image.
- 1 Natural Landscape:** Natural environments like forests, oceans, or mountains.
- 2 Urban/Architectural:** Man-made structures, cities, or built environments.
- 3 Animal Life:** Prominent depiction of animals, wildlife, or fauna.
- 4 Energy Sources:** Focus on energy elements like solar panels, wind turbines, fossil fuels, coal plants etc.
- 5 Human Activity:** Human figures or activities.
- 6 Other:** Elements not specifically categorised above.

Each image will be coded based on the primary element it represents, with the option to select 'Other' for images that depict elements not covered by the specific categories listed.

PERSO (Personification)

Does the image personify climate change or its impacts? Personification in this context involves attributing human characteristics, emotions, or actions to non-human elements or abstract concepts related to climate change or its impacts. This includes scenarios where human figures or groups are central in the depiction of climate change, actively contributing to the image's meaning, such as portraying human emotions in response to climate phenomena or politicians discussing climate change.

0 No.

1 Yes.

SOLUT (Solution Visualisation)

Are solutions or adaptations to the problem depicted? This includes portrayals of actions taken to mitigate or adapt to climate change, such as renewable energy sources (solar panels, wind turbines), reforestation, sustainable practices, or community initiatives. It also covers depictions of scientific or technological advancements aimed at addressing climate issues.

0 No

1 Yes

CHARA (Character Focus)

Character Focus identifies the primary subjects represented in the image. This includes human figures, groups, or symbolic entities that are central to the depiction of the event or its impacts. The focus is on understanding the types of characters used to personify or depict the narrative of the image, whether they are directly impacted by the event, representing a response to it, or symbolising broader concepts related to climate change.

- 0 Not Applicable:** No discernible character focus.
- 1 Politicians:** Political figures or representations of governance.
- 2 Victims:** Individuals or groups suffering or in distress.
- 3 Activists:** Individuals or groups actively engaged in advocacy.
- 4 General Public:** Everyday people, crowds, or community members.
- 5 Scientists/ Experts:** Individuals portrayed as researchers or authorities on climate.
- 6 Health Professionals:** Individuals portrayed professionals from the health care industry.
- 7 Symbolic Figures:** Characters representing concepts like Mother Nature or future generations.
- 8 Other:** Any character focus not covered above.

Each image will be coded based on the primary character it represents, with the option to select 'Other' for images that depict elements not covered by the specific categories listed.

ENTIT (Affected Entities)

This category focuses on identifying and classifying the entities that are depicted as being negatively affected in the AI-generated images. It seeks to understand the range and types of entities (e.g., humans, nature, infrastructure) that are impacted by the scenarios presented.

- 0 Not Applicable:** This category is used when there are no entities affected or represented in the image.
- 1 Human Impact:** Depicts impacts on individuals or communities.
- 2 Natural Impact:** Images showing the effects on natural elements like flora, fauna, landscapes, and ecosystems.
- 3 Infrastructural Impact:** Depictions of the impact on built environments, such as buildings, roads, bridges, etc.
- 4 Economic Impact:** Images portraying effects on economic aspects, including industries, markets, employment, and overall economic conditions.⁴
- 5 Other:** For images that depict impacts on entities not covered by the above categories or where the impact is of a different nature.

Each image will be coded based on the primary entities it appears to affect, with the option to select 'Other' for images that depict entities not covered by the specific categories listed.

⁴Within this category, 'Economic Impact' specifically refers to negative effects on various economic elements. This encompasses images that depict downturns in industries or markets, job losses or negative labour dynamics, challenges in commercial sectors, financial crises, and adverse effects on global trade. The emphasis is on scenarios that visually represent economic struggles, recessions, or other detrimental effects on economic stability and growth

IMPACT (Impacts of Extreme Weather Events)

This category assesses the specific consequences and nature of impacts caused by extreme weather events as depicted in the images. It aims to understand the varied and multi-dimensional effects these events have on different aspects of life and the environment.

- 0 Not Applicable:** This category is used when there is no impact shown in the image.
- 1 Health & Well-being:** Focuses on the direct impact on human health, including physical injuries, fatalities, and mental health issues.
- 2 Home & Livelihoods:** Addresses the socio-economic impacts such as homelessness, loss of income and displacement. Focuses on the challenges faced by individuals and communities in maintaining their standard of living and securing their basic needs after extreme weather events.
- 3 Environmental Damage:** Illustrates impacts on the natural environment, including pollution, landscape change and loss of biodiversity. This category emphasises the detrimental effects on ecosystems, wildlife habitats and the overall integrity of natural landscapes.
- 4 Infrastructural Breakdown:** Indicates the destruction or failure of critical infrastructure such as buildings, roads and bridges. This also includes the failure of important services and supply facilities, which impairs the normal functioning of the affected areas.
- 5 Economic Strain:** Examines the broader economic impact, such as financial hardship for individuals, market instability and challenges for different sectors.

This includes both immediate economic losses and longer-term financial impacts.

- 6 Other:** Impacts not specifically covered above, or unique representations of the effects of extreme weather events.

ACTION (Action Depiction)

Action Depiction categorises the types of activities or actions within the image that are related to the event.

- 0 No Action Shown:** The image is static with no movement or activity depicted. It may be a landscape or a scene without any characters or dynamic elements.
- 1 Suffering:** Visual elements such as facial expressions, body language, or context suggest pain, distress, or hardship. This may include scenes showing the aftermath of a disaster or individuals in a state of despair.
- 2 Recovery Efforts:** Depicts individuals or groups actively engaging in reconstruction, medical aid, or providing assistance. Signs of activity include construction, medical care, or distribution of resources.
- 3 Prevention Measures:** Activities clearly aimed at preventing or lessening the impact of an event are shown. This could include barriers against floods, fire-fighting efforts, or vaccination campaigns.
- 4 Adaptation Strategies:** Strategies or technologies that suggest adjustments to living with the event's consequences. Examples could be houses built on stilts in flood-prone areas or use of renewable energy sources.

- 5** **Other:** Includes any actions that do not fit into the above categories or are not immediately clear, such as abstract or symbolic representations of activity.

ENERG (Energy-Sources Visualisation)

Are energy sources depicted in this image? If so which?

- 0** No
- 1** **Renewable Energy:** Depictions focusing on sustainable energy sources such as solar panels, wind turbines, hydroelectric power.
- 2** **Non-Renewable Energy:** Imagery emphasising traditional energy sources like fossil fuels, coal plants, oil rigs.
- 3** Both

EVEREP (Event Representation)

Event Representation categorises how the image depicts the event, focusing on its visual portrayal and implied implications

- 0** **Not Applicable:** Used for images without reference to a specific event, depicting generic or static scenes.
- 1** **Destructive:** Indicates images emphasising destruction, chaos, or harm, including visible damage and human distress.
- 2** **Manageable:** Suggests the event is under control, evidenced by emergency services, relief efforts, or resilient infrastructure.

- 3 **Neutral:** For images presenting the event without a clear positive or negative perspective, often showing the event in progress.
- 4 **Opportunistic:** Implies the event as a catalyst for positive developments, like community solidarity or environmental rejuvenation.
- 5 **Other:** For images not covered in the above categories.

Each image will be coded based on the primary event it represents.

B.5 Visual Composition

The following variables pertain to the visual attributes of images produced by AI text-to-image models. These attributes are computed using a designated python script to provide a standardised quantitative assessment of the visual attributes present in each image in the dataset.

COLOR (Average Colour (RGB))

This variable quantifies the average colour in the image, represented as RGB (Red, Green, Blue) values. Each component is measured on a scale from 0 to 255, where 0 denotes no colour presence and 255 signifies maximum intensity. To determine the average colour, the individual values of R, G, and B are summed and then divided by 3, providing a single number that reflects the combined intensity of all three colours.

- 1 Low: The mean of RGB values is significantly lower than the mid-point (0 - 85).
The distribution of values suggests muted or subdued colours.
- 2 Medium: The mean of RGB values is around the mid-point (86 - 170). This range indicates a balanced level of colour intensity.

- 3** High: The mean of RGB values is significantly higher than the mid-point (171 - 255). This end of the spectrum represents vivid and intense colours.

BRIGHT (Average Brightness)

This variable measures the overall brightness of the image. It is computed as the mean value of the 'Value' channel in the HSV (Hue, Saturation, Value) representation of the image. The scale ranges from 0 (complete darkness) to 255 (maximum brightness).

- 1** Low: Value channel average is significantly lower than the mid-point (0 - 127). This typically corresponds to a darker image.
- 2** Medium: Value channel average is around the mid-point (128 - 191). This level of brightness is considered moderate.
- 3** High: Value channel average is significantly higher than the mid-point (192 - 255). Such values suggest a very bright image.

SAT (Average Saturation)

Saturation is the intensity of colour in the image. This variable captures the average saturation level, with 0 representing a lack of colour (grayscale) and 255 indicating the most vivid colour intensity possible.

- 1** Low: Saturation average is significantly lower than the mid-point (0 - 127). This indicates a lack of colour intensity, leaning towards a grayscale image.
- 2** Medium: Saturation average is around the mid-point (128 - 191). Suggests moderate colour intensity.

- 3** High: Saturation average is significantly higher than the mid-point (192 - 255).
Represents highly saturated colours.

B.6 Visual Synecdoches and Iconic Representation

This subchapter explores how AI models like *DALL-E* and *Midjourney* use visual synecdoches and iconic imagery to represent extreme weather events. The analysis focuses on identifying and interpreting common visual metaphors and symbols that have emerged as iconic representations in climate change communication.

SYNEC (Visual Synecdoche Identification)

This category involves identifying the presence of specific visual synecdoches or symbols in the imagery. It seeks to capture the use of iconic images like polar bears on melting ice, smokestacks emitting pollution, or barren landscapes, which have become shorthand for broader climate change narratives.

- 0** **Not Applicable:** The image does not contain any recognised visual synecdoches
- 1** **Polar Imagery:** Includes images of polar bears, melting ice caps, or other arctic symbols.
- 2** **Industrial Pollution:** Depictions of smokestacks, factories, or other industrial pollution symbols.
- 3** **Renewable Energy:** Imagery of wind turbines, solar panels, or other symbols of sustainable energy.
- 4** **Deforestation:** Images showing clear-cut forests or barren land.

- 5 Storms and Hurricanes:** Images showcasing hurricanes, cyclones, or severe storms, representing turbulent and destructive weather patterns.
- 6 Fire-Related Events:** Imagery of wildfires, forest fires, or burning landscapes, heat.

C Code Scripts

C.1 DALL-E 3 API for Image Generation

DALL-E is now accessible through an API by *OpenAI*, allowing developers to integrate its capabilities directly into their applications.

Below is an example of how to use the *DALL-E* API in Python to generate and download an image. This code snippet demonstrates how to programmatically request *DALL-E* to create an image based on a specified prompt and then download the generated image to a local directory.

```
1 import requests
2
3
4 api_key = 'given-api-key-here'
5
6 def download_image(url, save_path, file_name):
7
8     """
9         Downloads an image from the specified URL and saves it to a local
10        directory.
11
12    """
13
14    # Send a GET request to the URL
15
16    response = requests.get(url)
17
18    if response.status_code == 200:
19
20        # Create the save directory if it doesn't exist
21
22        os.makedirs(save_path, exist_ok=True)
23
24        # Create the full path for the new file
25
26        file_path = os.path.join(save_path, file_name)
27
28        # Open the file and write the image content to it
29
30        with open(file_path, 'wb') as file:
```

```
19     file.write(response.content)

20     print(f"Image downloaded successfully: {file_path}")

21     return file_path

22 else:

23     # Raise an exception if there's an error in downloading

24     raise Exception(f"Error downloading image: {response.status_code}")

25

26 def generate_image(prompt, model="dall-e-3", size="1024x1024", quality="

27     standard", n=1, api_key = api_key):

28

29     """
30         Generates an image based on a text prompt using the DALL-E API.
31
32     """
33
34     # Set up the headers for the API request
35
36     headers = {
37
38         "Authorization": f"Bearer {api_key}",
39
40         "Content-Type": "application/json"
41
42     }
43
44
45     # Define the data payload for the POST request
46
47     data = {
48
49         "model": model,
50
51         "prompt": prompt,
52
53         "size": size,
54
55         "quality": quality,
56
57         "n": n
58
59     }
60
61
62     # Make the POST request to the DALL-E API
63
64     response = requests.post("https://api.openai.com/v1/images/generations"
```

```
        , json=data, headers=headers)

47 if response.status_code == 200:

48     # Return the URL of the generated image

49     return response.json()['data'][0]['url']

50 else:

51     # Raise an exception if there's an error in the API call

52     raise Exception(f"Error in API call: {response.status_code} {

53         response.text}")

54 def generate_and_download_image(prompt, save_path, file_name):

55     """
56     Combines the functions of generating an image and downloading it.
57     """

58     # Generate the image and retrieve the URL

59     image_url = generate_image(prompt)

60     # Download the image from the URL

61     return download_image(image_url, save_path, file_name)

62

63 # Example usage

64 prompt = "a photorealistic image of a tsunami"

65 save_path = "downloads"

66 file_name = "tsunami.jpg"

67 generate_and_download_image(prompt, save_path, file_name)
```

C.2 *Midjourney* Image Generation Using Default Interface

In this study, the images are generated using *Midjourney*'s standard interface, specifically version 6.0 of the model. This approach was chosen instead of using third-party APIs such as *ImagineAPI.dev* in order to comply with legal and ethical standards.

The process of generating images in *Midjourney* involves manually entering specific prompts directly into the *Midjourney* interface on *Discord*. An example of such a prompt is illustrated below:

```
/imagine prompt: a photorealistic image of a tsunami --v 6 --s 100
```

This example demonstrates the format and parameters used:

- **Prompt Command:** The `/imagine` command initiates the image generation process.
- **Prompt Content:** The actual prompt, in this case, "*a photorealistic image of a tsunami*" defines the subject of the generated image.
- **Version Parameter (`-v`):** The `-v 6` parameter specifies the use of *Midjourney* version 6.0.
- **Stylize Parameter (`-s`):** The `-s 100` parameter sets the level of stylisation. Low stylisation values produce images that are close to the prompt but less artistic. High stylisation values produce images that are very artistic but less in line with the prompt. The default value of `-stylize` is 100 while the parameter accepts integer values from 0-1000 when the current model is used.

C.3 Image Naming Convention and Organisation

A specific naming and storage convention will be used to systematically manage the generated images, where each image will be named according to the format `ImageID_PromptID_Model_Date_Pro`. This structure makes it easier to track and identify the images in the data set.

- `ImageID`: A unique identifier for each image.

- **PromptID:** The identifier of the prompt used, which links each image to its source prompt.
- **Model:** The AI model used for generation (*DALL-E* or *Midjourney*).
- **Date:** The date the image was created, which helps with chronological analysis.
- **PromptExcerpt:** An excerpt from the prompt for a quick context reference.

The images will be stored in a root directory, with individual subfolders for each prompt.

C.4 Visual Attribute Detection

This Python script is designed to analyse images and extract key visual attributes, specifically average colour, brightness, and saturation. The script performs the following steps:

1. **Reading the Image:** The image is read in BGR (Blue, Green, Red) format using OpenCV.
2. **Colour Conversion:** The image is then converted to RGB (Red, Green, Blue) format for colour analysis, and to HSV (Hue, Saturation, Value) format for brightness and saturation analysis.
3. **Calculating Averages:** It computes the average colour in the RGB format, and the average brightness and saturation from the HSV format.
4. **Output:** The script returns the calculated averages of colour, brightness, and saturation for further analysis.

```
1 import matplotlib.pyplot as plt  
2 import numpy as np  
3 import cv2  
4
```

```
5 # Function to analyse an image and extract its visual attributes
6 def analyse_image(image_path):
7     # Read the image in BGR format
8     image = cv2.imread(image_path)
9
10    # Convert the image to RGB format
11    image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
12
13    # Convert the image to HSV format for brightness and saturation
14    analysis
15
16    # Calculate the average color (in RGB)
17    average_colour = np.mean(image_rgb, axis=(0, 1))
18
19    # Round the average color values and convert to integer
20    rounded_average_colour = np.round(average_colour).astype(int)
21
22    # Calculate the overall average intensity of RGB
23    average_rgb_intensity = np.mean(rounded_average_colour)
24
25    # Calculate the average brightness (V channel of HSV)
26    average_brightness = np.mean(image_hsv[:, :, 2])
27
28    # Calculate the average saturation (S channel of HSV)
29    average_saturation = np.mean(image_hsv[:, :, 1])
30
31    # Display the image
32    plt.imshow(image_rgb)
```

```

33     plt.axis('off')
34
35     plt.title('Analysed Image')
36
37     # Return the computed visual attributes
38
39     return rounded_average_colour, average_rgb_intensity,
40
41     average_brightness, average_saturation

```

C.5 Intercoder- and Intracoder-Reliability

This Python script is designed to calculate Krippendorff's alpha for two given coding matrices.

The function will return a dictionary with Krippendorff's alpha scores for each column that is present in both dataframes.

```

1 import krippendorff
2
3
4 def calculate_krippendorff_alpha_for_all_columns(df1, df2):
5
6     alpha_scores = {}
7
8     # Iterate over columns that are present in both dataframes and are
9     # numeric
10
11    for col in df1.columns.intersection(df2.columns):
12
13        if pd.api.types.is_numeric_dtype(df1[col]) and pd.api.types.
14
15            is_numeric_dtype(df2[col]) and col != 'CU':
16
17            # Stack the two coders' ratings together for the current column
18
19            ratings = np.vstack([df1[col].values, df2[col].values])
20
21
22            # Calculate Krippendorff's alpha for the current column,
23            # handling NaN values

```

```
13     alpha = krippendorff.alpha(reliability_data=ratings,  
14         level_of_measurement='nominal')  
15  
15     alpha_scores[col] = alpha  
15  
15     return alpha_scores
```

D Glossary

A

AI (Artificial Intelligence)

A branch of computer science focused on creating systems capable of performing tasks that typically require human intelligence (Broussard et al., 2019).

API

Application Programming Interface: A set of rules and protocols for two or more software systems to communicate with each other, enabling the integration of their features and data. A documentation or standard that describes how such a connection or interface can be established or used is called an API specification.

Autonomous System

A network of computer-controlled operations or processes that perform tasks and make decisions without human intervention, using algorithms and often incorporating elements of artificial intelligence and machine learning. generative art, it refers to a computer program or algorithm that independently creates art based on predefined rules or parameters, with minimal human intervention.

C

Climate Change

Long-term changes in temperature and weather patterns, mainly caused by human activities like fossil fuel combustion, deforestation, and agriculture (United Nations, n.d.).

D**Data Bias**

The tendency of AI models to reflect biases present in their training data, leading to skewed or stereotypical outcomes (Mehrabi et al., 2021).

Generative Art

The practice of using autonomous systems, often including computers or digital technology, to create art or become the artwork itself (Galanter, 2019).

E**Extreme Weather Events**

Rare meteorological phenomena that significantly deviate from the historical averages of a particular place and time (IPCC, 2023i).

F**Framing**

The process of selecting and emphasising certain aspects of a topic while excluding others, thereby shaping the audience's perception (von Sikorski & Matthes, 2020).

I**Iconic Imagery**

Iconic imagery describes powerful, easily recognisable images that have become symbols or

representations of broader concepts, themes, or issues. These images are often so strongly associated with certain subjects that they can instantly evoke specific ideas, emotions, or contexts in the viewer's mind (O'Neill, 2019).

M

Machine Learning

A subset of AI that involves training computers to learn from and make decisions based on data (Broussard et al., 2019).

N

News Factor Theory/ News Value Theory

A theory in communication and media studies that identifies and analyses the elements making a story newsworthy. It suggests that certain characteristics, such as conflict, prominence, timeliness, proximity, and human interest, increase the likelihood of an event being reported as news.

The theory was first introduced by Galtung and Ruge (1965).

NGO

Non-Governmental Organisation: An independent organisation that operates outside of government control, often focused on addressing social, environmental, political, or human right issues. NGOs can range from small, local groups to large, international organisations.

P**Prompt Engineering**

The technique of crafting input prompts to guide AI models to produce desired outputs (Liu & Chilton, 2022).

S**Saturation**

Saturation refers to the intensity or purity of a colour. A highly saturated colour is vivid and rich, while a less saturated colour appears more muted and greyish.

T**Text-to-Image Models**

AI technologies that convert textual descriptions into visual imagery, like *OpenAI's DALL-E* and *Midjourney*.

Transformer-Based Architecture

A neural network design used primarily in natural language processing, known for its self-attention mechanism.

V**Visual Attributes/Visual Modalities**

The characteristics of visual elements in an image, such as colour, brightness, and saturation,

which can influence perception and emotional response (Kress & van Leeuwen, 2020).

Visual Communication

The conveyance of ideas and information through visual elements such as images, signs, and typography (Smith et al., 2004).

Visual Synecdoche

A visual representation that uses part of a whole to symbolise a larger concept or idea, often used in climate change communication (O'Neill, 2019).

E List of Figures

List of Figures		
1	Text-to-Image Models Google Search Trends	14
2	AI Model Image Variability	16

F List of Tables**List of Tables**

1 Types of Extreme Weather Events	7
---	---