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Conceptions of Artificial Intelligence

How Image Generation Models Envision Extreme Weather Events

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Visual Communication of Climate Change

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1 Introduction

In recent years, the discourse surrounding climate change has evolved from abstract predictions to an urgent reality marked by real-time observable impacts. Among the most visible and alarming manifestations of this global phenomenon is the increase in extreme weather events. These events, growing more frequent and severe (IPCC, 2023j), are altering ecosystems, impacting lives, and affecting economies globally (IPCC, 2023d, p. 2460). The Intergovernmental Panel on Climate Change (IPCC) has identified these changes as a direct consequence of climate change, highlighting the need for effective communication strategies to foster public understanding and engagement (IPCC, 2023b).

In the realm of climate change communication, visual representations play a crucial role. Research indicates that images not only shape emotions but also influence behaviours towards climate change (Leiserowitz, 2006). Images enable a more rapid understanding of complex environmental risks (Epstein, 1994; Joffe, 2008) and catalyse the shift from passive observations to active participation (Keib et al., 2018). Furthermore, images help to retain information better than text-only information (Coleman, 2010; Graber, 1990), and provided readers have the same cultural references, images can overcome linguistic or geographical barriers when conveying information to an audience (Armfield et al., 2013).

Given this understanding of the power of visual media, the advent of advanced text-to-image generation models like *OpenAI*'s *DALL-E* or *Midjourney* introduces new opportunities and challenges in the field of climate communication. Text-to-image generation tools harness machine-learning algorithms to transform textual prompts into detailed visual representations (Zhang et al., 2023). There are two sides to this: on the one hand, these tools offer novel means of representation and image extraction, and thus an innovative way of presenting nuanced impacts and imagined scenarios of climate change; on the other hand, they raise questions about the authenticity and reliability of visual media.

Recent examples of AI-generated content being used in journalism signify a broader trend in the media industry where the lines between AI-generated and human-generated content are becoming increasingly blurred (Henrich, 2023; Kim, 2023). This trend is emphasised by an emerging discourse about the urgent need for comprehensive guidelines to navigate this new terrain (Council of Europe, 2023; Swiss Press Council, 2023).

Building on these developments, this paper delves into the emergent field of AI-augmented visual climate communication, particularly focusing on the depiction of extreme weather events. While the existing literature has largely focused on the impact of textual AI models like *ChatGPT*, the role of AI in generating visual content, especially within the domain of scientific and climate communication, so far, has not been researched much. This paper explores this field by focussing on an analysis of outputs of extreme weather event imagery from the *DALL-E 3* and *Midjourney* models.

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). It is important to note that whilst many people associate AI with "thinking" computers that are able to imitate human thought and behaviour, this understanding is not correct (Thomas & Thomson, 2023).

As Broussard et al. (2019, pp. 673 – 677) explain:

> To most people, the phrase [artificial intelligence] suggests that there is a synthetic brain inside the computer. This could not be further from the truth. Rather, AI more narrowly refers to a branch of computer science focused on simulating human intelligence (...) Machine learning at its heart is computational statistics. The AI we have today is merely complex and beautiful mathematics.

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, there has been a notable increase in the use and improvement of text-to-image models in artificial intelligence, including *OpenAI*'s *DALL-E* and *Midjourney* (Gozalo-Brizuela & Garrido-Merchan, 2023). These models are a subset of generative models in machine learning (Bie et al., 2023) capable of translating text into images. *DALL-E* leverages a transformer-based architecture rooted in natural language processing for text-to-image generation (Awan, 2023). *Midjourney*, while its specific architectural details are less clear, also forms part of this wave of AI models capable of transforming textual input into visual output.

Initially, these models are trained on large datasets of images paired with descriptive texts. The training involves understanding and correlating features in the text with visual elements in the images (Bie et al., 2023). For instance, 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 *Midjourney* and *DALL-E* are user-friendly and don't require technical expertise, democratising their usage. This has led to a substantial increase in users and outputs from these and similar platforms (Thomas & Thomson, 2023, p. 5)

Further explaining these models, Thomas and Thomson (2023, p. 5) describe the image generation process as iterative. The user can modify the command - known as "prompt engineering" (Liu & Chilton, 2022) - and obtain a subtle or significantly different result. *Midjourney*'s user interface even supports this by allowing users to "scale up" for accuracy or "remix" for variations without changing the text prompt.

2.1.2 The Data Behind

The efficacy and accuracy of text-to-image models are intrinsically linked to the data they are trained on as the datasets used for training directly influence the range and nature of images that these models generate.

Consequently, if the training data is skewed towards certain perspectives, geographies, or cultural contexts, the AI-generated images may mirror these biases, leading to a lack of diversity or inadvertent reinforcement of stereotypes (Mehrabi et al., 2021). For instance, a model trained primarily on a particular newspaper might generate images that reflect the stylistic and content patterns of that publication.

This reliance on pre-existing data for new image creation poses further ethical and legal challenges. Notably, in December 2023, *OpenAI* and *The New York Times* made headlines when the newspaper sued the software company for using its articles as part of the training data for its AI models without permission (Bradshaw & Miller, 2023). This case raises not only copyright issues, but also concerns about how AI models can recombine elements of copyrighted material to create new content, raising 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 for this paper, only two studies were found that investigate the output of such models:

García-Ull and Melero-Lázaro (2023) analysed gender stereotyping in images generated by *DALL-E 2*. This study revealed 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", discovering the images often portrayed journalists in ways that reflect societal biases in terms of gender, ethnicity, and age, neglecting the 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.

2.1.4 Implications for Journalism

So far, researchers have mainly focused on the impact of the use of generative AI (not specifically image generation) in journalism (Broussard et al., 2019). Pavlik (2023, p. 87) in collaboration with *ChatGPT* argues: "Generative AI can be relevant to journalism and mass media in several ways. For example, it can be used to generate news stories or articles, freeing up journalists to focus on other aspects of their work".

In general, some recent examples of AI-generated content in journalism indicate a broader trend towards such technologies being used in the journalistic workflow (Henrich, 2023; Kim, 2023). This shift is also supported by a study by Deloitte AG (2023) which, while not focusing exclusively on journalists, shows that 61% of Swiss professionals working with a computer now use generative AI technologies. This development emphasises how important it is for researchers to examine the results of generative AI more closely in order to further investigate the accuracy of the results and thus the justifiability of using such technologies in journalism.

2.2 Climate Change and Extreme Weather Events

Following the introduction of models for image generation, this subchapter briefly discusses the topic of analysis: climate change and extreme weather events.

2.2.1 Climate Change

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).

2.2.2 Extreme Weather Events

An "extreme weather event" is an occurrence that is rare at a particular place and time of year (IPCC, 2023h, p. 2908). Extreme weather events cover a wide range of 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, in which case they may be classified as extreme climate events. 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 as global warming continues.

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)

2.2.3 Impacts of Climate Change and Extreme Weather

Climate change and extreme weather events have far-reaching impacts on various regions and communities, affecting people's health, livelihoods, and overall well-being. These events can cause deaths, injuries, and damage to ecosystems or critical infrastructure (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 those in marginalised communities, are most at risk. They often face displacement, loss of income, 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).

According 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 Soudan, Niger and Bolivia. Generally, the impacts of climate change and extreme weather events are disproportionately felt in the Global South (IPCC, 2023f, p. 1180).

2.3 Visual Communication of Climate Change

Visual communication can be defined as the utilisation of visual elements, such as signs, typography, images, drawings, illustrations etc. 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 critically 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 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 to connect climate action with consumer behaviour. These images are designed to engage consumers to evoke a sense of personal responsibility towards climate action, influencing them to purchase their products. In each instance, the chosen frame and narrative is used to advance 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 aims to explore the narratives constructed by these models, focusing on key aspects such as characters depicted in the images, the types of consequences illustrated, 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. These visual attributes are highly effective in influencing audiences (Garber & Hyatt, 2003).

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 in Climate 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.

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Appendix

A Prompts

To explore the representation of extreme weather events by text-to-image models *DALL-E* and *Midjourney*, a series of prompts have been formulated. The process begins with a broad, open-ended prompt to allow the text-to-image models to freely interpret and depict what they perceive as an extreme weather event. This overarching prompt serves as a foundation for more detailed prompts focusing on specific types of weather events as identified by the IPCC

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 2.2.3).

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.*

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 14: *Depict recovery efforts following extreme weather events.*

Prompt 15: *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 16: *Depict the reasons contributing to extreme weather events.*

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

Prompt 18: *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 19: *"Depict weather patterns in a world where average global temperatures have risen by 2 degrees Celsius."*

Prompt 20: *"Illustrate the changes in spring weather patterns due to global warming."*

- **Prompt 20b:** *"Illustrate the changes in summer weather patterns due to global warming"*
- **Prompt 20c:** *"Illustrate the changes in autumn weather patterns due to global warming"*
- **Prompt 20d:** *"Illustrate the changes in winter weather patterns due to global warming"*

Prompt 21: *"Showcase the impact of sea-level rise in a coastal city in the future."*

Prompt 22: *"Depict the future state of polar regions (if current warming trends continue)."*

Prompt 23: *"Visualise future agricultural landscapes affected by changing climate conditions."*

Prompt 24: *"Illustrate the transformation of urban areas in response to future extreme weather events."*

Prompt 25: *"Depict human life adaptation in a future with frequent extreme weather events."*

Prompt 26: *"Visualise 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 3* 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 3* 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 3* and *Midjourney* 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, for example, `1_DALL-E`, signifying the first image created by *DALL-E 3*.

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 can be derived from the image's filename, for example, `19_Midjourney`, signifying the 19th image created by Midjourney.

1	*DALL-E 3*
2	*Midjourney*

PROMPT

The specific text prompt used for generating each image.

DATE

The date on which the image was generated.

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 considers how these events are visually represented in terms of catastrophe, challenge, or opportunity.

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.

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.[1]
- **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.

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.

[1] Within 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

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 3* 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.

```python
import requests
import os

api_key = 'given-api-key-here'

def download_image(url, save_path, file_name):
    """
    Downloads an image from the specified URL and saves it to a local directory.
    """
    # Send a GET request to the URL
    response = requests.get(url)
    if response.status_code == 200:
        # Create the save directory if it doesn't exist
        os.makedirs(save_path, exist_ok=True)
        # Create the full path for the new file
        file_path = os.path.join(save_path, file_name)
        # Open the file and write the image content to it
        with open(file_path, 'wb') as file:
            file.write(response.content)
        print(f"Image downloaded successfully: {file_path}")
        return file_path
    else:
        # Raise an exception if there's an error in downloading
        raise Exception(f"Error downloading image: {response.status_code}")

def generate_image(prompt, model="dall-e-3", size="1024x1024", quality="standard", n
    =1, api_key = api_key):
    """
    Generates an image based on a text prompt using the DALL-E API.
    """
    # Set up the headers for the API request
    headers = {
```

```
        "Authorization": f"Bearer {api_key}",
        "Content-Type": "application/json"
    }

    # Define the data payload for the POST request
    data = {
        "model": model,
        "prompt": prompt,
        "size": size,
        "quality": quality,
        "n": n
    }

    # Make the POST request to the DALL-E API
    response = requests.post("https://api.openai.com/v1/images/generations", json=
    data, headers=headers)
    if response.status_code == 200:
        # Return the URL of the generated image
        return response.json()['data'][0]['url']
    else:
        # Raise an exception if there's an error in the API call
        raise Exception(f"Error in API call: {response.status_code} {response.text}"
    )

def generate_and_download_image(prompt, save_path, file_name):
    """
    Combines the functions of generating an image and downloading it.
    """
    # Generate the image and retrieve the URL
    image_url = generate_image(prompt)
    # Download the image from the URL
    return download_image(image_url, save_path, file_name)

# Example usage
prompt = "a photorealistic image of a tsunami"
save_path = "downloads"
file_name = "tsunami.jpg"
generate_and_download_image(prompt, save_path, file_name)
```

C.2 *ImagineAPI.dev Midjourney* API Image Generation

Given the absence of an official *Midjourney* API, third-party services such as *ImagineAPI.dev* offer an alternative means of accessing *Midjourney*'s image generation model.

Below is an example of how to use their API in Python to generate and download the images.

```python
import http.client
import json
import time
import os
import requests

def send_request(method, path, api_key, body=None):
    """Establishes a connection and sends a request to the server."""
    conn = http.client.HTTPSConnection("demo.imagineapi.dev")
    headers = {
        'Authorization': f'Bearer {api_key}',  # Authorisation header with API key
        'Content-Type': 'application/json'
    }
    conn.request(method, path, body=json.dumps(body) if body else None, headers=
    headers)
    response = conn.getresponse()
    data = json.loads(response.read().decode())
    conn.close()
    return data

def generate_image(prompt, api_key):
    """Generates an image based on the prompt and returns the image ID."""
    data = {"prompt": prompt}
    response_data = send_request('POST', '/items/images/', api_key, data)
    return response_data['data']['id']

def get_image_status(image_id, api_key):
    """Retrieves the status of the image generation."""
    response_data = send_request('GET', f"/items/images/{image_id}", api_key)
    return response_data['data']

def wait_for_image(image_id, api_key):
    """Waits for the image to be generated, checking the status every 5 seconds."""
    while True:
        image_data = get_image_status(image_id, api_key)
        if image_data['status'] in ['completed', 'failed']:
            return image_data
```

```
        else:
            print(f"Image generation in progress. Status: {image_data['status']}")
            time.sleep(5)

def download_images(image_data, download_path):
    """Downloads the images to the specified path."""
    if not image_data or 'upscaled_urls' not in image_data:
        print("No image data provided for download.")
        return

    urls = image_data['upscaled_urls']
    os.makedirs(download_path, exist_ok=True)

    for url in urls:
        file_name = url.split('/')[-1]
        file_path = os.path.join(download_path, file_name)

        response = requests.get(url)
        if response.status_code == 200:
            with open(file_path, 'wb') as file:
                file.write(response.content)
            print(f"Image downloaded successfully: {file_path}")
        else:
            print(f"Error downloading image from {url}: {response.status_code}")


# Example usage
api_key = 'given-api-key-here'
prompt = "a photorealistic image of a tsunami"

image_id = generate_image(prompt, api_key)
image_data = wait_for_image(image_id, api_key)

download_path = "downloads"
selection_path = "selection"
download_images(image_data, download_path, selection_path)
```

C.3 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.

```python
import matplotlib.pyplot as plt
import numpy as np
import cv2

# Function to analyse an image and extract its visual attributes
def analyse_image(image_path):
    # Read the image in BGR format
    image = cv2.imread(image_path)

    # Convert the image to RGB format
    image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

    # Convert the image to HSV format for brightness and saturation analysis
    image_hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)

    # Calculate the average color (in RGB)
    average_colour = np.mean(image_rgb, axis=(0, 1))

    # Round the average color values and convert to integer
    rounded_average_colour = np.round(average_colour).astype(int)

    # Calculate the overall average intensity of RGB
    average_rgb_intensity = np.mean(rounded_average_colour)

    # Calculate the average brightness (V channel of HSV)
    average_brightness = np.mean(image_hsv[:, :, 2])

    # Calculate the average saturation (S channel of HSV)
    average_saturation = np.mean(image_hsv[:, :, 1])

    # Display the image
    plt.imshow(image_rgb)
    plt.axis('off')
    plt.title('Analysed Image')
```

```
    plt.show()

    # Return the computed visual attributes
    return rounded_average_colour, average_rgb_intensity, average_brightness,
    average_saturation
```

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).