Using Generative Models to Create a Visual Description of Climate Change

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Abstract

Scientific denialism refers to the discrepancy between information and its effective communication. In this project, our objective is to delve into the field of knowledge visualization by integrating the latest advancements in AI generative models. We aim to create a visually compelling and deterministic representation based on satellite data of Rio de Janeiro's climate over the next 100 years, elucidating its interaction with climate change. While we have achieved promising results in image generation, we still face challenges in constructing a cohesive video that maintains temporal coherence, semantic consistency and realism.

1 Introduction

In a survey conducted by Yale in 2021, 47% of Americans said they do not believe that global warming will harm them personally [22]. This exemplifies the significant gap between the dissemination of information and the acceptance among the general population, despite scientific advancements that highlight and substantiate ongoing climate changes..

In 2015, the World Economic Forum published an article based on the book "Made to Stick" [21], introducing the SUCCES acronym to combat scientific denialism. According to this framework, it is crucial to present information in a **simple**, **unexpected**, **credible** manner, presenting the data in a **concrete** way, connecting with the **emotional** aspects of the audience using analogies and metaphors and shaping scientific knowledge into compelling **stories** [12].

Thus, it can be inferred that when it comes to climate change and the perception of the general population, creating literal visual representations of abstract information becomes essential in fostering a stronger connection and raising awareness of the magnitude of this issue.

Therefore, this paper aims to present the construction of a cultural product, i.e., an audiovisual work that has the purpose of large-scale consumption [5], intended for Brazilian high school students and recent college students in order to generate awareness and

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discussion about climate change and the direct consequences for their personal life. Thus, data and scientific statements will be provided in a concrete way but with strong emotional appeal aiming to enhance acceptability and engagement among the audience.

Based on the analysis of meteorological data from the past 140 years, available from satellites GOES16 [2] and NOAA [4], regression models will be employed to comprehend the behavior of key climate factors that contribute to our understanding of climate changes and predict their patterns for the next 100 years. To present these findings, the data will be visualized within a unified pictorial landscape based on Guanabara Bay, Rio de Janeiro, allowing viewers to envision a possible future under new climatic conditions.

This study aligns with the field of Knowledge Visualization (KV), a relatively young discipline defined as "all (interactive) graphic means that can be used to develop or convey insights, experiences, methods, or skills" [15, 16, 17].

Historically, the evolution of infographics can be traced from the Middle Ages to contemporary computer-based visualization [32]. In recent months, there has been rapid and significant progress in the availability of generative AI models to the public. Prominent examples include DALL-E [31], Mid Journey [26], and Stable Diffusion [34], which are capable of generating complex synthetic images based on descriptive prompts.

Combining the synthesis capabilities of these algorithms with a systematic data-driven approach, novel visualizations can be created to offer alternative means of abstract information representation, promoting a new way of interacting with data in a pictorial format that may be more comprehensive for the audience.

In light of these considerations, we aim to address the following research questions:

Q1: Is it possible to utilize generative models to create data-driven knowledge visualizations?

Q2: How to guide the next generation to use AI as a tool for good?

Our contributions are as follows:

- Providing a novel pipeline to create more appealing scientific information presentations.
- Developing a strategy for the systematic and data-driven utilization of generative models as tools for innovative information visualization.
- Amplify the engagement and discussion around the climate change with high school and undergraduate students

2 Literature Review

In this study, we conducted desk research in the field of information visualization and examined the work of other artists who are creating with the goal of addressing climate change, in order to understand what has already been developed.

Regarding art created using generative models, some artists have been creating visual representations of landscapes, such as visualizations of coral reefs and observations of changes in glaciers [8, 20].

In the context of knowledge visualization, it is emphasized that it should provide assistance for reasoning, reflection, and the exploration of connections in new ways, in order to facilitate new discoveries based on shared insights [15]. It is also understood that pictorial representations reveal significant aspects of the history of visual culture and knowledge, and that familiar theories and methods from art history are used for their analysis [14].

The use of computers to generate creative works is an area that has been studied and validated in academia [27]. However, the use of AI for artistic creation still faces challenges in terms of public acceptance, as indicated by research that suggests that regardless of the technical quality, knowing that a production was created by computers leads to a decline in the evaluation given to the artwork [6].

This study is supported by the GaiaSenses initiative, a project developed at Centro de Tecnologia da Informação Renato Archer (CTI) which creates automated audiovisual artworks by accessing planetary databases [28].

3 Methodology

With the aim of developing a solid idea based on a novel approach to generative models, the project execution was divided into concept and product phases, based on the Design Thinking Double Diamond.

3.1 Concept

Based on the collection of analyzed information, the project, now named Watchman, referring to the workers responsible for residential security, is based on the idea that providing understandable and easy access to data can help people be more aware of climate changes [33].

Observing the engagement in discussions about climate change on social media, 56% of users from Generation Z (born after 1996) stated that they interacted with this topic in the past week, compared to 44% of users from other generations, namely Millennials (born between 1981-1996), Gen X (born between 1965-1980), Boomers (born between 1946-1964), and older [36]. Therefore, it is interesting to develop a project that provides foundation and tools for Generation Z individuals to express their opinions and viewpoints [18].

According to Jeffrey Stuart, professor in the field of Knowledge Visualization, "the 'aura' of the digital object is fundamental to how it is received by its audiences" [23]. Therefore, to create a product that is relevant to our audience, we decided to utilize the entrepreneurship frameworks of Business Model Canvas, Empathy Maps, and Persona Canvas [30], contributing to the construction of a cultural product.

As expressed in Seth Godin's book, Tribes, "people are easier to lead to where they wanted to go in the first place" [19]. 69% of Gen Z social media users stated that climate change content made them feel anxious about the future, with one of the causes being the dissatisfaction with the insufficient amount of current actions being taken [36].

Thus, by observing how the existence of this sentiment can drive action in favor of the environment, we will provide a visual tool that collaborates with the viewpoint of these users, allowing them to express their concerns to others beyond their generation. Additionally, we will combine technological trends such as the creation of art and virtual experiences by AI, along with advancements in the sci-fi field, that enabling us to imagine scenarios and offering a sense of wonder and escape [9].

3.2 Product

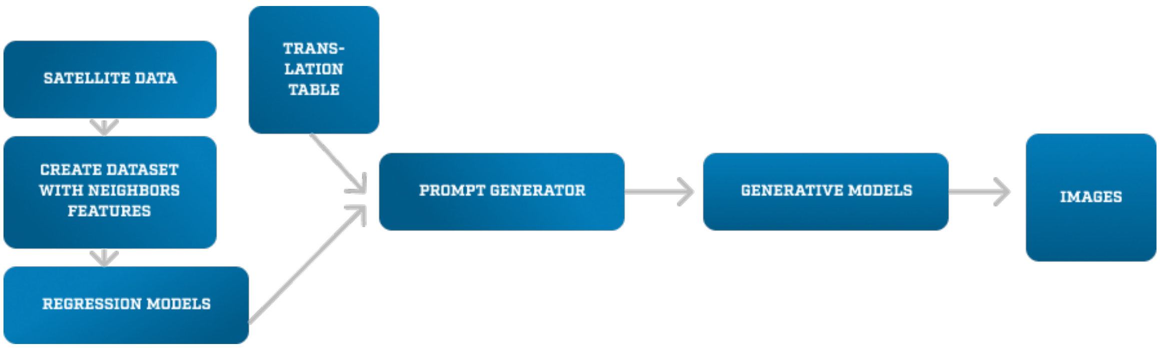

Figure 1: Pipeline to create images based on satellite data.

With the concept defined, a literature search was conducted to identify technologies and applications that could contribute to the project implementation. An overview of the pipeline applied at the project can be seen at figure 1. According to the Global Climate Observing System (GCOS), there are essential climate variables that help us understand the behavior of climate change. Through the GOES16 and NOAA satellites, we have access primarily to Surface Atmosphere-related information. Thus, for our analysis, we utilized variables such as precipitation rate, pressure, skin temperature, and downward solar radiation flux [10].

Through NOAA, due to the limitations of the provided locations, data from 1836 to 2015 were collected using the geographic coordinates -23, -42, corresponding to the city of Arraial do Cabo, Rio de Janeiro, Brazil. Each climate variable generated a dataset (Table 1) containing the collection period and the abstraction criterion of the variable (highest value, lowest value, or average), which was defined based on the distribution assumed by the data (Figure 2).

Table 1: Climate variable information.

Variable	Acronym	Criterion	Data Quantity
Precipitation Rate	prate	max	65379
Pressure	pres	mean	65744
Skin Temperature	skt	max	65744
Downward Solar Radiation Flux	dswrf	max	65379

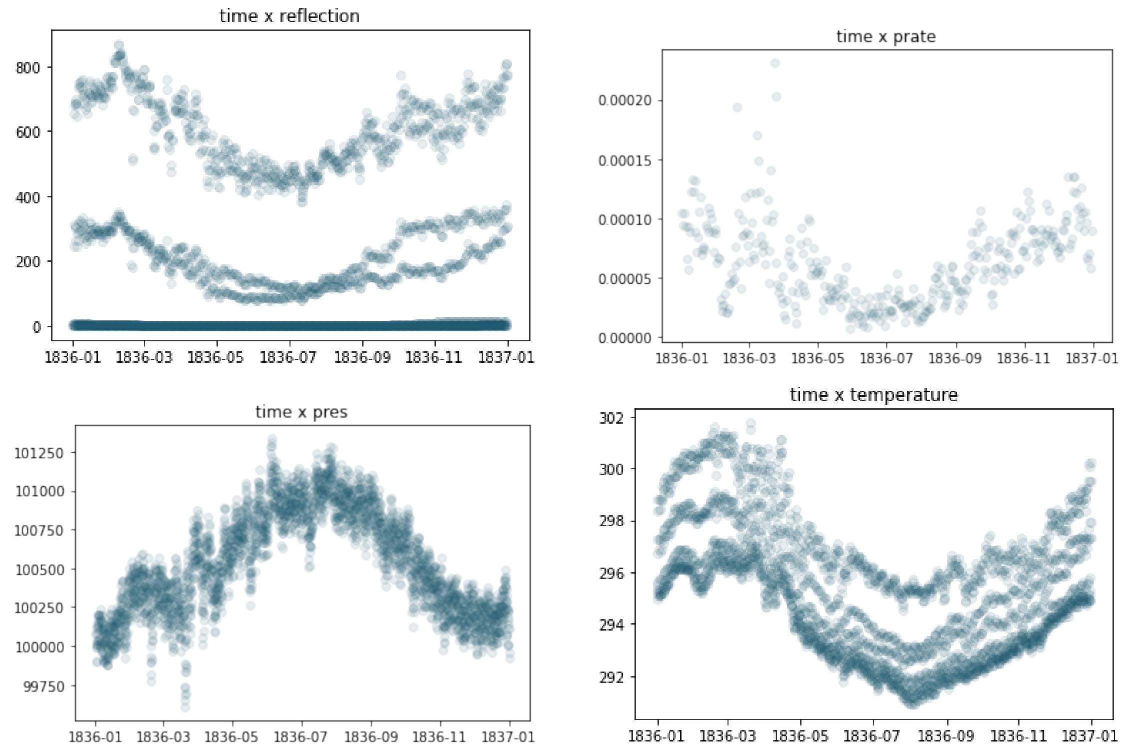

Figure 2: Downward Solar Radiation Flux, Precipitation Rate, Pressure and Skin Temperature distribution during a single year.

3.2.1 Regression Models

To predict the values of climate variables for the next 100 years, we group the averages by month and build a new dataset that combines the date the information was collected, the values of 5 months prior to the current month, and the values found for that same month in the 5 previous years.

Regression algorithms were used to create models applied to the data. Each dataset was individually divided into training and test sets, respecting the *75:25* ratio. Cross-validation with $n = 5$ was performed for each of the following models with their respective parameters:

- **Model A:** Linear Regression (fit_intercept = True, False)
- **Model B:** Decision Tree Regressor (max_depth = None, 5, 10)
- **Model C:** Random Forest Regressor (n_estimators = 15, 20, 50, criterion = squared_error, absolute_error, friedman_mse, poisson)
- **Model D:** Gradient Boosting Regressor (n_estimators = 20, 50)
- **Model E:** SVR (C = 1, 5)

The models were evaluated on the training set using the R2 metric, MSE (Mean Squared Error), and MAE (Mean Absolute Error). Once the best performance model was selected, it was evaluated on the test set using the same metrics adding the RMSE (Root Mean Squared Error).

The prediction process was conducted iteratively, whereby each subsequent value on the timeline was calculated and appended to the dataset, enabling the consideration of the next value. Data generation spanned from the year 2016 to 2123.

3.2.2 Generative Models: Prompt Engineering

The challenge of generating synthetic images with deterministic meaning arises from the inherent randomness in the image creation process. It is difficult to create images that represent the same location but with specific variations in certain conditions, such as climate in our case. Additionally, generating images in a temporal aspect presents the challenge of maintaining a visually coherent sequence while accurately depicting the imposed changes.

To generate images with desired climatic characteristics, we explore a recent area described in the literature as prompt engineering. Although generative models are primarily developed for natural language understanding, the achievement of the desired results relies on the individual's ability to accurately describe the object [29, 25].

Several guidelines are proposed for the methodological production of high-quality images, as the following template [29]:

[Medium] [Subject] [Artist(s)] [Details] [Image repository support]

To incorporate a deterministic bias, the creation of prompts used by the models should be guided by metrics obtained through satellite data.

Based on the descriptive language used by meteorological services, numerical values were translated into corresponding English words that represent human perception of climatic factors. For more complex situations involving the analysis of multiple elements, such as the correlation between average temperature increase and tidal levels, translations were based on scenario analysis described by researchers in a general context, rather than directly abstracted from collected data.

Thus, the subject field was manipulated to translate climatic factors into natural language, creating specific environments and conditions for each combination of factors (Figure 3).

Moreover, due to our utilization of the English language for data transcription, the information originates primarily from North American and European countries, leading to a bias towards climatic conditions specific to those regions. In addition, generative models tend to have a greater emphasis on landscapes found in these countries, resulting in a bias towards depicting ecosystems other than that of Brazil.

With respect to the artistic objectives already described, the remaining prompt engineering criteria were employed based on the most commonly used keywords to describe visual aspects of the image. Our poetic proposal involves seeking a realistic image of a late afternoon, conveying the tranquility and melancholy of the end of the day, reflecting the uncertainty of the future. The prompts used depend on the input data and are variations of Table 2.

Figure 3: Prompt modifications to generate image: (Figure 1) clear sky, lush vegetation, few boats in the water, calm sea; (Figure 2 and 3) cloudy sky, destroyed vegetation, drown boats in the water, lightning, stormy sea; (Figure 4) clear sky, vegetation covered in snow, frozen water, sunset lights, calm sea.

3.2.3 Generative Models: Temporal Connection

Once the method for generating high-quality images that visually represented the data was established, it was necessary to develop a model that could create images while considering the temporal aspect to present the prediction as a video, maintaining the connection between subsequent frames.

Applications such as Deforum [1] and Kaiber.ai [3] enable the creation of videos by concatenating multiple images from generative models. However, they do not provide complete control over the image production process. In this study, both of these tools were experimented, along with the creation of custom videos using a time-lapse approach, where each individually generated image was compiled using the stable diffusion v1.5 API, configured at a frame rate of 24 frames per second where each frame represents a single month.

Three strategies were employed for the continuous generation of images:

- Image-to-image by varying the image_strength parameter between values of 0.6, 0.7,

Table 2: Keywords to create prompt variations [11, 35].

Medium	**Subject**	**Artist**	**Details**	**Image Repository Support**
A photograph of	{place = Guanabara Bay}	VSCO, Pinterest	figurative style = renaissance style, hyperrealism	Quality Booster = 4k, award-winning photograph
	{sky_condition = clear sky, fog, high clouds, mid-level clouds, very cloudy, light showers, light rain, rain, rain shower 75%, rain shower, storm with few clouds, storm}		"colors = {sky_light = sunset lights, golden hour, overcast, melancholic atmosphere, darker atmosphere, lightning, thunderclouds, lightning, darkness}, pastel colors, natural"	90s
	{vegetation_condition = lush, dense, beautiful, wind, destroyed} vegetation			
	{human_ocuppation = boats in the water, few boats in the water, drown boats, chaos}			
	{sea_level = calm sea, light chop, moderate sea, rough sea, stormy sea, low tide, high tide, floods, deluge}			

0.75, and 0.8 while also using random seed.

- Image-to-image with a single seed.
- Text-to-image with a single seed.

4 Results

The experimental results obtained in this work are presented in the following sections.

4.0.1 Regression Models

Time series regression models pose significant challenges in their application. Although in some cases the R-squared (R2) values are not unfavorable, the models fail to predict variations over a long period considering only close neighbors (Table 3). This results in a tendency to stabilize, as observed by the continuous lines in Figure 4. In this case, the data is not normalized, thus the mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) metrics may yield high values.

As observed in the graphs, the increasing trend in average temperature, coupled with higher levels of precipitation, creates a conducive environment for flooding and landslides [7, 24]. The rise in solar radiation and atmospheric pressure further exacerbates urban heat islands. The possibility of abrupt pressure changes also leads to an increase in the occurrence of storms in the region [13].

Table 3: Regression model performance.

Feature	**Model**	**Hyperparameters**	**R2**	**MSE**	**RMSE**	**MAE**
dswrf	Random Forest Regressor	100, absolute_error	0.67659	3775.47692	61.44490	41.58604
prate	Gradient Boosting Regressor	n_estimators = 50	0.74398	1.26E+06	3.55E+10	2.33E+05
pres	Linear Regression	fit_intercept = True	0.88376	9430.83746	97.11249	73.25006
skt	Linear Regression	fit_intercept = True	0.73151	1.43912	1.19963	0.89668

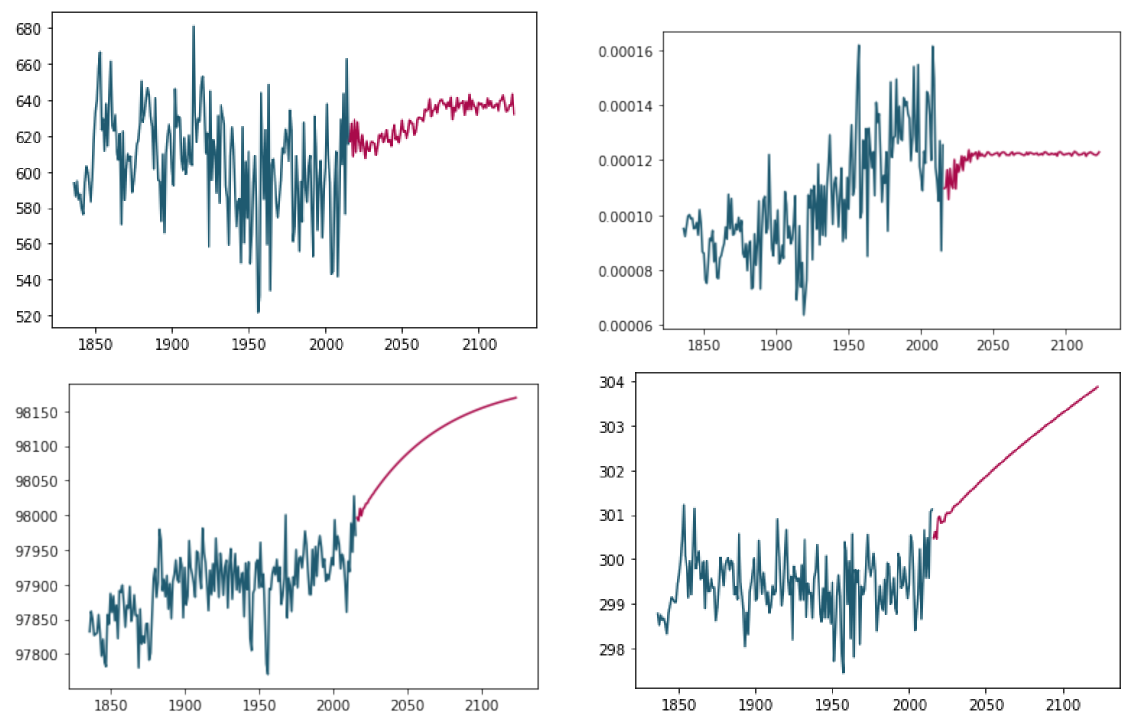

Figure 4: Downward Solar Radiation Flux, Precipitation Rate, Pressure and Skin Temperature predicted values until 2123.

4.0.2 Generative Models

From the composition of different parameters using the chosen generative models, it can be observed that for the image_strength parameter with values above 0.75, the changes in the image are more subtle. However, after multiple iterations, the image becomes distorted by the generation of noise, as observed in Figures 7 and 8.

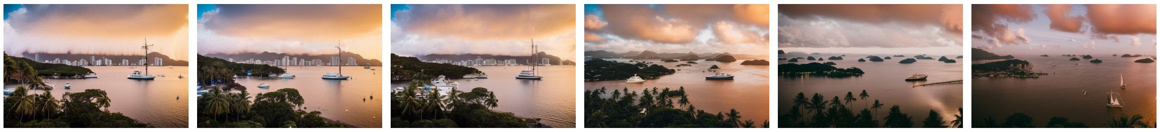

Figure 5: Stable Diffusion, image-to-image, image strength = 0.6.

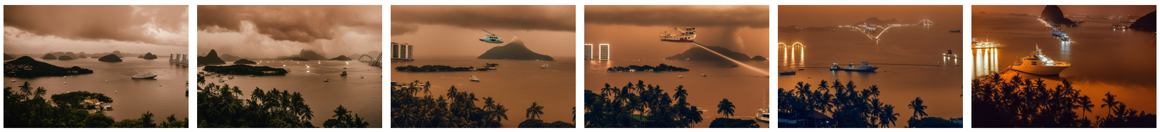

Figure 6: Stable Diffusion, image-to-image, image strength = 0.7.

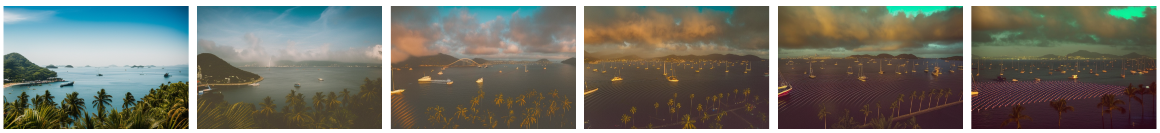

Figure 7: Stable Diffusion, image-to-image, image strength = 0.75.

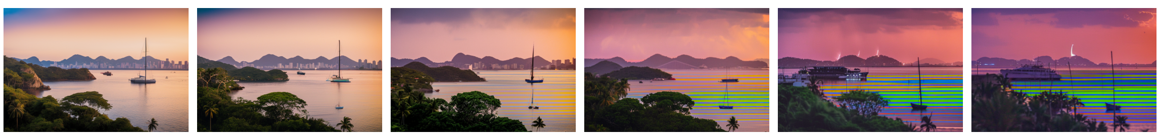

Figure 8: Stable Diffusion, image-to-image, image strength = 0.8.

Figure 9: Stable Diffusion, image-to-image, image strength = 0.8, seed = 903193145.

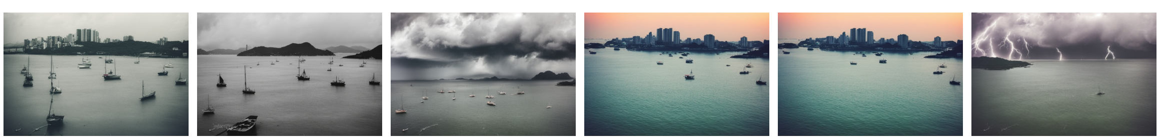

Figure 10: Stable Diffusion, text-to-image, seed = 2792954258.

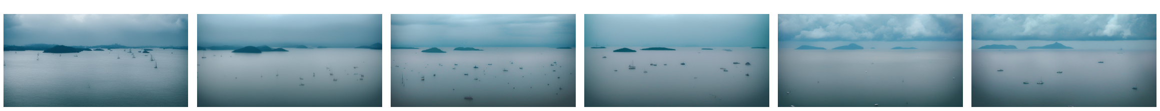

Figure 11: Deforum, text-to-image.

The distortion can be delayed by assigning random values to the seed generator, pushing the appearance of these results to the hundredth iteration. Conversely, when using a pre-established seed, the noise becomes evident in the first six generated images as observed in

Figure 12: Kaiber.ai, text-to-image.

Figure 9.

When the previous image is not used as a parameter, but the seed value is fixed, the generated images do not exhibit visual correlation among themselves when subtly altering the prompt. Conversely, when alternating between different prompts, consistently similar images are generated in accordance with the prompts used (Figure 10).

For lower values of the image_strength parameter, starting from 0.7 (Figure 5 and 6), a temporal correlation is established while the generated images assume the characteristics described by the prompt. However, with an increasing number of iterations, the model tends to "hallucinate", generating random elements that do not relate to the environment.

This accumulation factor of images also presents both positive and negative aspects. Firstly, it enables the representation of subtle climate changes that occur over time, such as rising sea levels. However, it can accentuate certain aspects of the image that distort the environment. In one of the executions, the number of boats exponentially increased to the point of completely occupying the scene (Figure 13).

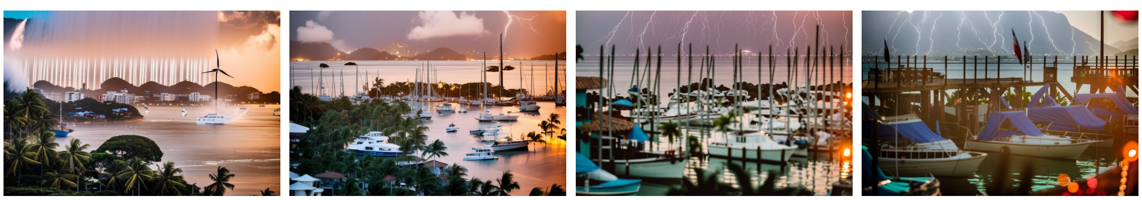

Figure 13: Stable Diffusion, Image-to-Image, image strength = 0.6.

5 Discussion

When comparing individually generated images that do not receive a previous image as a parameter, a closer resemblance to real landscapes, precisely evoking the visual description of the used data, can be found. However, when incorporating temporal connection, the precise description of the image is compromised.

In the video settings we used, each frame corresponds to the climatic state of a month, with insufficient space to justify transitions between different climates, such as from a sunny day with calm tides to a stormy day.

The temporal generation of images also requires continuous monitoring of transformations to achieve the desired results. With each iteration, the creations increasingly take on a Hollywoodesque character, deviating from the concept of faithfully portraying the scenery in a photograph (Figure 12). With each iteration, it is observed that the Atlantic Forest found in Rio de Janeiro is represented with palm trees and trees reminiscent of those found on the beaches of California, for example.

One possibility to maintain greater control over hallucination and temporal transition would be to work on the inversely proportional combination of the image_strength values, which represents the extent to which the initial image influences the creation, and cfg_scale, which represents how strictly the diffusion process should adhere to the prompt description.

Regarding the tested models, Stable Diffusion was the one that presented greater control over the creation process and visibly more interesting results. The Deforum tool generated a continuous sequence of images and also allows defining prompts for each frame, necessitating further exploration of the available parameters to achieve better creations (Figure 11).

Thus, we can discuss the raised research questions:

Q1: It is possible to utilize generative models to create data-driven knowledge visualizations, especially with isolated images. However, using the approach proposed in this research, a study needs to be conducted on the transcription of the data to natural language so that the model can understand the description. Consequently, the visual representation may be heavily biased by the author's interpretation of the obtained information.

Q2: Generative models can indeed be used as tools to manifest complex ideas and thoughts stemming from human creativity, going beyond mere reproduction of previously created works. Therefore, their value as art can be discussed from the perspective of the significance attributed to them, rather than solely based on the technical complexity of their development.

6 Conclusions and Future Work

The Watchmen project generated interesting results in observing the progression of climatic events in the city of Rio de Janeiro. However, due to the hallucinatory capacity of generative models, they are not yet completely faithful to reality to assume a deterministic nature. The future is not deterministic but semantic consistency and plausibility must be maintained for people to connect with what they see.

Despite the current results achieved in this work, it can continue to be developed in the two proposed fronts: concept and product. Regarding the cultural product objective, all concept research was conducted through desk research due to time constraints, necessitating field research to gain a deeper understanding of the audience, their concerns, and how we can work towards effective communication.

It is also interesting to evaluate the emotional impact of the created videos and modify the visualization to establish a stronger connection with the audience. On the technical side, exploring ways to have greater control over hallucination during image generation and achieving a smooth transition without necessarily resorting to time-lapse construction is necessary.

Developing the capability to alter specific parts of an image while simultaneously changing the context to maintain overall coherence is interesting for representing the same scenario with different weather conditions. For example, when transitioning from a sunny day to a windy day, elements of nature such as trees and the sea should visibly react to this condition. Lastly, training these models on specific image databases for each ecosystem to be represented is also highly beneficial for obtaining more realistic images.

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