Extreme events and climate change. How did wildfires and other stress events affect the social and policy aspects of the energy transition? A machine learning mass media article analysis.

Panagiotis Varelas[a], Francesco Contino[b] and Alessandro Parente[c]

[a] ULB, Brussels, Belgium, panagiotis.varelas@ulb.be, CA
[b] UCLouvain, Louvain-la-Neuve, Belgium, francesco.contino@uclouvain.be, CA,
[c] Institution, City, Country, e-mail, CA

Abstract:

Extreme events that unfolded in 2021 because of the intense weather conditions around the globe are a strong reminder that climate change is happening now. Wildfires in south Europe and California floods in west Europe, and hurricane Ida, are only a glimpse of our near future. According to the latest pledges from COP26 in Glasgow, the optimistic scenario is to keep the temperature increase of the planet around 2.1°C degrees, far from Paris Agreement and any other international agreement goals. Besides the environmental impacts, these stress events could potentially have economical and societal consequences. How are citizens and their acceptance of alternative technologies affected by them? What is the reaction from the mass media? How can uncertainty arising from these events potentially affect investments in renewable energy? Analyzing articles from mass media by applying web-scrapping and Natural Language Processing (NLP), we searched for a possible association between disasters and acceptance of alternative technologies. Based on our findings, stress events have a positive relation to the acceptance of new technologies, such as wildfires in southern Europe and floods in Germany and Belgium. Our results can serve as a guideline to policymakers for better and more accurate decision-making, to identify when and how new policies should be introduced to the public. We anticipate further extending our methods with additional machine learning algorithms and quantifying the acceptance of specific technologies. Finally, additional stress events not related to weather conditions can be included such as elections, ratification of policy acts, and international meeting agreements.

Keywords:

Climate Change; Machine Learning; NLP; Energy Transition; Media; Classification.

1. Introduction

Climate change is happening now, and the severe consequences can be witnessed by millions of people around the globe. Annual emissions are still rising, and mankind produces more than 50 billion tons of greenhouse gases into the atmosphere on an annual basis [1]. International agreements such as Paris Agreement [2] and the Glasgow Pact [3], supported by local and regional policy acts, pledged to keep the temperature increase of the planet well below 2, preferably to 1.5 degrees Celsius, compared to pre-industrial levels.

Currently according to the Climate Action Tracker and considering the latest news (November 2021) the optimistic scenario which assumes full implementation of all announced targets gives a temperature increase of 1.8 °C degrees by 2030 [4]. To achieve those goals, we should change many aspects of our everyday life, consuming less, travel less, and most importantly learn to live with the consequences. The effects of climate change are everywhere from the Mediterranean Sea, California, and Amazon rainforests with extreme wildfires to Louisiana, Germany, and Belgium with floods. Besides the environmental impact, such disasters could potentially release societal and economic problems to the local populations, such as reduction in purchasing power and loss of land value, loss of earnings and services, and loss of growing and pre-harvest crops.

Economic consequences are associated with the drop or increase in stock prices or the installation cost of technology. For example, the COVID-19 pandemic dramatically affected the stock prices of different companies in the energy sector [5]. Wildfires and Floods can also affect the economy by changing the real estate market and the unemployment rate in a specific region. The uncertainty of public acceptance and media awareness and how we can effectively quantify it is a key factor that we should evaluate after such disasters.

Policy Uncertainty [6] and Climate Policy Uncertainty [7] are two key indexes to measure the effectiveness and acceptance of Policies and Climate Policies respectively in each period. Finding, possible relations with acceptance and different kinds of events such as presidential elections, global strikes, and new legislation is also an additional goal of these indexes. On the other hand, hype and therefore media coverage can either have a positive or negative impact on different technologies. For instance, levels of government funding tend to increase the hype on specific technologies [8]. In, [9] a detailed analysis concerning the impact of wildfires and other extreme events on different psychological and societal factors is presented. Nevertheless, it is an important part of the energy transition and media support and/or opposition towards specific technologies should be excessively evaluated. To our knowledge, a thorough analysis of extreme weather conditions and their relationship with energy transition and social acceptance has not been conducted.

This study according to the state of the art and the existing knowledge around the topic is addressing the major problem of extreme events and their relationship with acceptance and trust towards different technologies. More specifically we are dealing with the Wildfires and the Floods that took place in Europe during the summer of 2021. These catastrophic events drew a lot of attention in the European most popular media. We analyze articles from top European media, using Natural Language Processing (NLP) and classification algorithms. The training dataset has been manually labeled by the authors of each news article.

First, in section 2, we start with an introduction to the state of the art concerning the impact of wildfires, floods, and other extreme weather conditions on the media and the local populations. In section 3 we give an in-depth description of all methods that we used during our research. We outline the main assumptions of our case study. In section 4, we answer the main question on whether wildfires and floods had a positive or negative impact on the acceptance of different technologies. Finally, in section 5, we present the conclusions and the future steps of our research.

2. Literature Review

Mass media coverage is a broadly used method to measure social awareness and hype for a short- period since media coverage changes fast daily [10]. Nevertheless, mass-media influence public opinion and their study is essential [11]. Nowadays, the internet becomes the main source of information for millions of people worldwide and since we depend on online media, their impact should be taken into consideration. To achieve our short-term goals and a sustainable future, media, and their influence on public opinion are of high importance. It is necessary to find the time window to run campaigns and inform the public while the levels of awareness and hype are still high [8]. Especially, after extreme events, we assume in this paper that public coverage is higher, and the hype is increased. Journalism and public concerns have shaped decisions in climate science and policy, just as climate science and policy have shaped media reporting and public understanding [12].

Machine learning is a promising tool to solve classification problems [13]. Newspaper articles Classification has been broadly used in literature to distribute articles and documents according to different policy topics [14]. Additionally, the combination of the different methods that we are using in this paper, NLP, and classification can have great accuracy of 91% when classifying articles, including techniques such as Support Vector Machines, Naïve Bayes, and k-Nearest Neighbors [15]. To date, an approach using ML and NLP to classify articles and find a relation between extreme events and media support for climate change and energy transition has not been conducted.

Energy modeling is one of the main tools available to explore energy systems. There are plenty of available energy models in the literature [16,17] and most of them are scenario-based. These scenarios are varying from changing core parameters of an energy system such as the renewable share, the storage availability, the acceptance or not of nuclear energy as a low emitting resource of energy, etc. [1]. Another classification of these models is whether or not are taking into consideration all different sectors including heating, mobility, industry, and not just the electricity sector [18]. There are plenty of existing energy models in the literature, with similarities and differences among them, currently, there is a lack of an external tool that would be adjustable to any existing model and able to measure the impact of the energy and climate policies on the energy systems and energy modeling, whether is a matter of simulation or optimization problem

Existing models are not considering the effect of extreme events on the energy systems. Traditionally these models are scenario-oriented. According to their input parameters such as demand, consumption, and available technologies, they can suggest a couple of different scenarios to the policymakers. Modern societies are rapidly changing by the decisions of political institutions. Recent major events in Europe and United States proved that energy transition is a dynamic condition affected by a plethora of different parameters that should be considered. Designing energy models needs to be a vice versa task proposing the optimal scenarios to the policy makers, considering at the same time the impact of such events.

3. Methodology

Our source of data is four major European media: The Guardian, France24, Deutsche Welle, and Euractive. To collect our data, we applied NLP [18] and Web-Scrapping [19]. We then used classification algorithms to extract energy-related articles.

3.1 Web-Scrapping and NLP

To get the articles we had to create a different web-scrapper for every webpage that we included in our case study. Every webpage has a unique HTML code and a variety of different HTML tags. The first part was to create a database for every webpage and collect the URLs from all opinion articles for 2021 and keep only the text. By applying NLP, we can simplify our articles and reduce both the size and processing time. First, we grouped words with similar meanings in the English language, such as better-good, bad-worse, tall-taller, etc., this process is called lemmatization and significantly decreases the size of each document [20]. Second, all the stop words were removed from our dataset, e.g., a, an, do, does, did. These words do not affect the meaning of the article and they further reduce the size of our data. Finally, we change all the remaining words into lower case. The final dataset consists of 7632 articles in their simplified version (Table 1).

Table 1. Initial Dataset

Attributes	Description
Articles	7,632 in total
Total Number of Words	3,472,468
Mean Size of Article	456
Standard Deviation	336
Standard Deviation (removing outliers)	115
Title	The title of each article
Text	The main body of the article
Date	Range between 01/01/2021 and 31/12/2021
Category	75 initial categories
Binary Category	Energy or Non-Energy related category

3.2 Machine Learning Classification Problem

A classification problem is a Machine Learning (ML) supervised problem and refers to the ability of the algorithm to classify something into a distinct set of classes or categories [13]. A classifier should be able for example to recognize whether a photo belongs to a pet or a vehicle, can distribute photos between men and women, to recognize whether a photo shows a healthy or cancerous cell. In this example, we modeled a classifier that distributes articles into two categories as mentioned already non-energy related and energy related. To train our model we split the initial dataset into two sub-datasets: a) the training dataset which we used to train our model with articles that we label with their category 0 for non-energy and 1 for energy-related articles. The training dataset (Table 2) contains 6613 articles in total where 5430 falls in the non-energy related category and the rest 1183 fall in the energy related category (Table 3)

Table 2. Initial, Training and Validation Dataset

Dataset	Description
Initial Dataset	7613
Training Dataset	6613
Validation Dataset	1000

The articles have a title and the main body. The reference year is 2021 and the range is between 01/01/2021 and 31/12/2021. To create our classifier, we had first to decide on several categories the categories have been decided by human auditing and according to the author's personal beliefs and biases. Some of the categories were: external policies, digital, environment, energy, agriculture, economy, etc. As described already in this paper we would like to measure the mass media awareness around energy transition and climate change therefore a binary category classifier is enough to give answers and results to our hypothesis. The binary category was 0 for non-energy-related articles and 1 for energy-related articles.

Table 3. Training Dataset

Training Dataset	Number of Articles
Total	6613
Non-energy related	5430
Energy related	1183

Before diving into the different algorithms and their performances. We would like to explain the decision between the different categories. NLP library offers the ability to analyze our data based on the appearances of specific keywords or groups of keywords. According to these appearances, the classifier decided whether an article belongs or not to a specific category. In Tables 7-8 we represent the most frequent words and set of words for energy and environment-related category. Initially, the number of categories that we did process was 72. The reason that we decided to create a binary category is the fact that this paper is addressing the attention related to energy and the environment, meaning that it includes all articles with a topic related to different technologies, climate change, and energy policies. Binary classification is important to highlight all these articles and quantify the real attention in media. Furthermore, a classification problem with that many classes could lead to low performance and accuracy. Thus, we decided in this case study to use a simple version of our model to achieve higher accuracy and the same time deliver a clear message to the media's attention throughout 2021.

Table 5. Most Frequent Words in the Non-Energy and Non-Environmental Category

Most Frequent Words	Occurrences
EU	20377
european	17502
commission	6753
minister	5869
government	5271
us	5033
president	4809
people	4451
countries	4346
health	4140
member	4061
digital	3907
europe	3896
states	3878
data	3792

Table 6. Most Frequent Bigrams in the Non-Energy and Non-Environmental Category

Most Frequent Bigrams	Occurrences
european commission	3600
member states	2838
prime minister	2462
european union	2140
european parliament	1999
united states	1566
human rights	1231
can not	1088
der leyen	955

von der	925
eu countries	908
last year	901
foreign minister	814
data protection	783
northern ireland	733

Table 7. Most Frequent Words in the Energy and Environmental Category

Most Frequent Words	Occurrences
energy	6118
EU	5374
climate	5229
european	4611
gas	3114
carbon	2877
commission	2281
green	2234
emissions	2227
renewable	1587
countries	1546
hydrogen	1477
power	1414
fossil	1273
coal	1204

Table 8. Most Frequent Bigrams in the Energy and Environmental Category

Most Frequent Bigrams	Occurrences
european commission	1551
climate change	869
renewable energy	829
member states	796
European parliament	474
European union	451
greenhouse gas	440
fossil fuels	437
EU countries	408
green deal	408
natural gas	403
energy efficiency	323
nuclear power	323
gas emissions	311
climate neutrality	288

3.3 Machine Learning Algorithms and Performances

Machine Learning model accuracy is the measurement used to determine which model is best at identifying relationships and patterns between variables in a dataset based on the input, or training, data [21]. In other words, before deciding which algorithm works best for our problem, we should first evaluate and test a few of them. The test was based on the correct prediction rate in the pre-defined training dataset. Each article was labeled with a category which was 1 for environmental or/and energy-related articles and 0 for the rest. Then we run the model to give each article a new label based on its prediction. The more the correct predictions the higher the test accuracy. There is a plethora of different classification algorithms that can be effective for a classification problem. In this case study, we compare the most used in the literature [13] (Table 4).

Table 4. Machine Learning Model Performance

Model	Test Accuracy

Logistic Regression	95.46
Random Forest	93.04
Multinomial Naïve Bayes	93.55
Support Vector Classifier	94.15
Decision Tree Classifier	92.84
K Nearest Neighbour	89.47
Gaussian Naïve Bayes	90.22

According to our measurements, Logistic Regression is giving the best with an accuracy of 95.46%, and the rest of the models are giving also really promising results which can be used accordingly. In, these points we decided to further check our data validity and performance by testing them with our validation test. Keeping a part of the initial dataset for further validation has been broadly used in the literature [22]. Our validation test gives an accuracy of an average of 80% considering the above-mentioned models.

At this point, we would like to mention that the model could be further improved, since according to the literature 80% is considered an acceptable success rate, for a classification problem [22]. Nevertheless, overfitting might occur in some cases. Authors encourage further research, possibly with a larger initial dataset from more resources and with alternative ways to distribute the articles into categories.

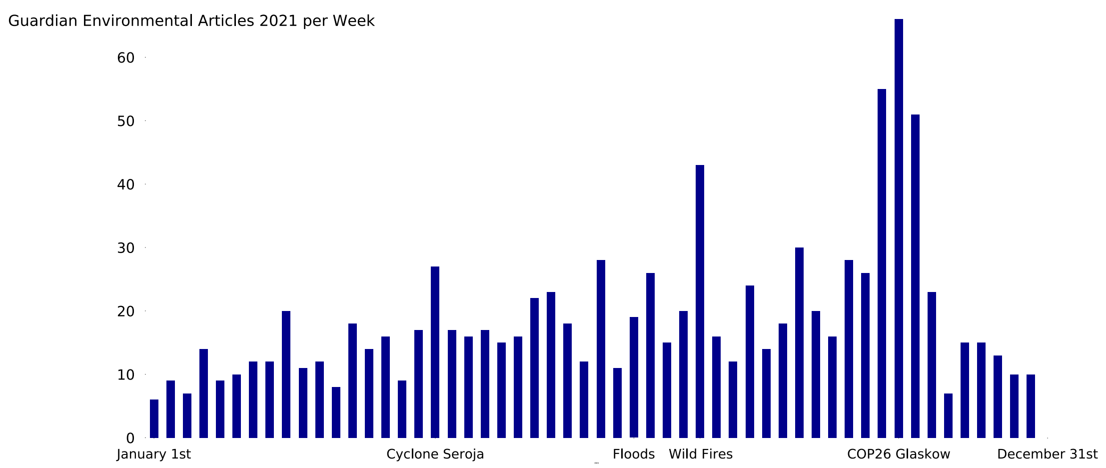
4. Results

Our main hypothesis is that media are affected by major events and that normally an increased hype is following for a short period. The purpose of this paper is to move a step forward and quantify that increased attention with a binary article classifier using machine learning. The influence of the media on public acceptance is significant [23] but this study cannot predict the population behavior towards climate change and energy transition. We would like to suggest possible tools to increase social acceptance while the attention is higher because of media coverage.

4.1 Articles Prediction Category

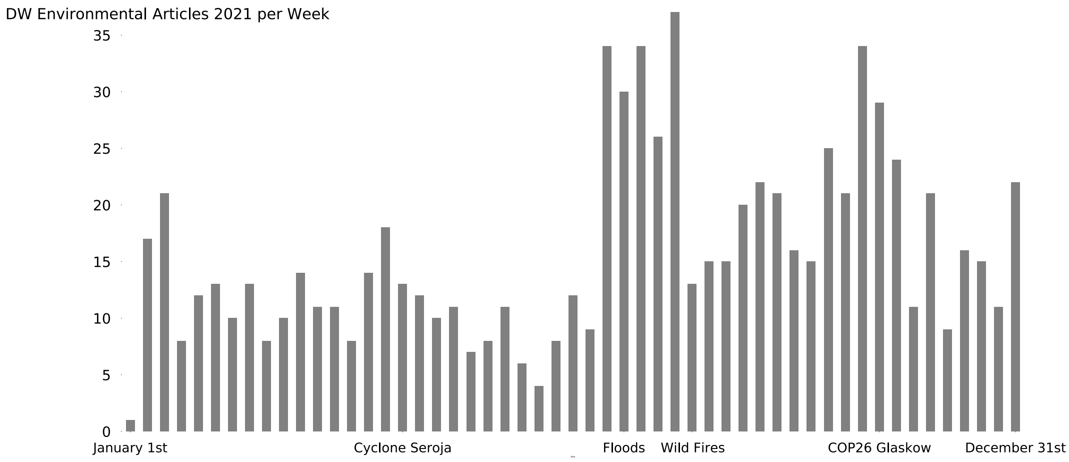
To better understand and overview the reference year 2021, we present the number of energy-related articles per week and media. That is allowing us to interpret our data in a way to see how different stress events have or do not have an immediate impact on the attention. Additionally, in that way, we do comprehend the time window that potentially could be used to introduce new energy and climate policies and crusade campaigns to raise the awareness of civil society. In the long run, consumers and local societies are a crucial part of the equation of energy transition [24].

Fig. 3: "The Guardian": Articles of Energy and Environmental Interest for 2021 per week.



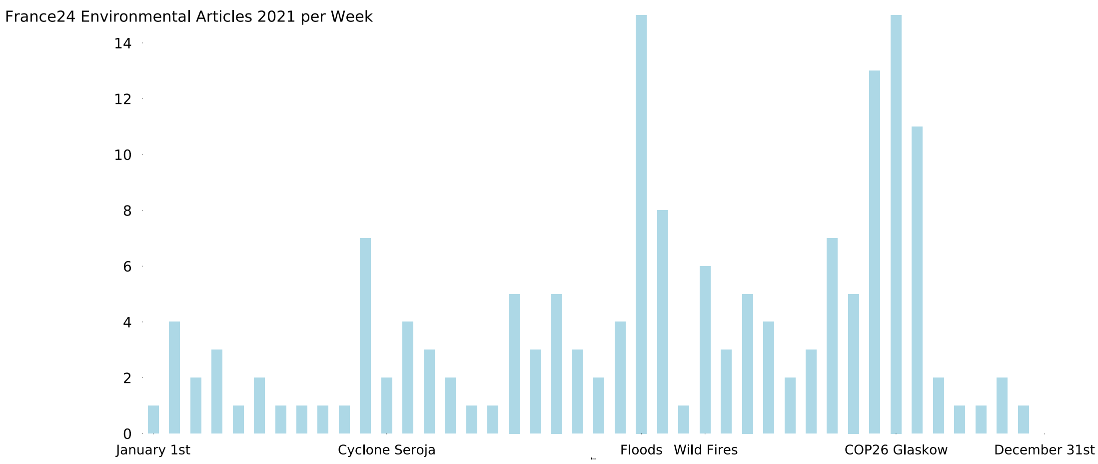
In the UK, The Guardian is one of the leading media both online and on paper. The United Kingdom is a world leader in the energy transition [25]. It has reduced more than 40% of its CO2 emissions since 1990 and it significantly reduced electricity generation from non-renewable energy resources such as coal and oil [25]. Therefore, it is important to have a representative liberal media from the United Kingdom. As we can see in Fig 3. Extreme events followed by increased attention, we highlight 4 major events for 2021 and we encourage the reader to further explore this relationship with more extreme events that are not presented in this study. These events include 3 weather-related extreme events: 1) Cyclone Seroja 2) Central Europe July Floods and 3) South Europe Wildfires. Additionally, COP26 United Nations Conference that was held in Glasgow between October 31st and November 12th, 2021, has been included in the study due to its high importance. According to Fig 3, we observe that there was indeed an increased hype after Cyclone Seroja and Wildfires and the highest during COP26. The thin red dotted line represents the mean average for the entire year.

Fig. 4: "Deutsche Welle": Articles of Energy and Environmental Interest for 2021 per week.



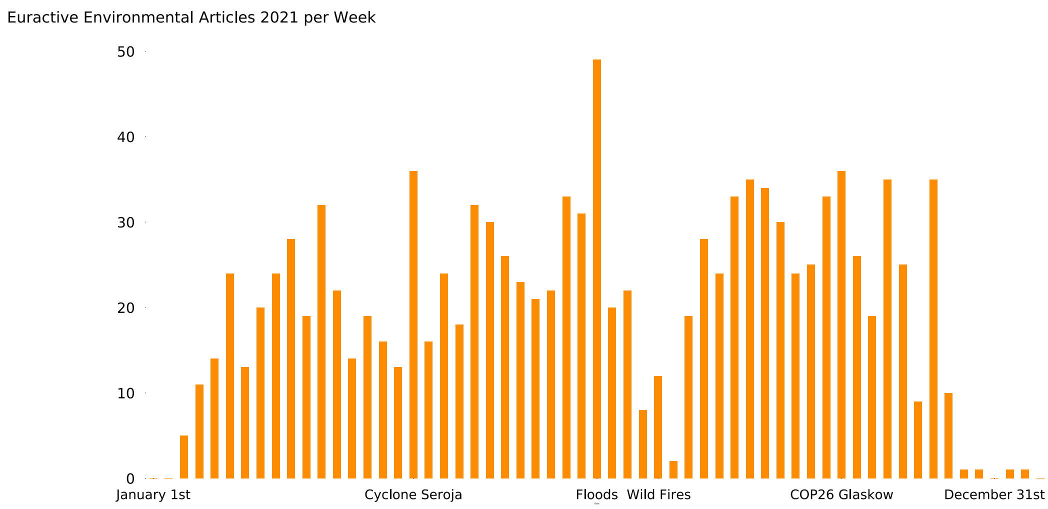
Deutsche Welle (Fig. 4) is one of Germany's leading newspapers with thousands of articles per year and a huge influence on the German population. In addition, Germany's government's decision [26] to phase out nuclear power, which is a major debate currently in the literature on whether nuclear power is a part of the solution to meet our pledges [27], makes Germany a country that we should take into consideration in this case study.

Fig. 5: "France24": Articles of Energy and Environmental Interest for 2021 per week.



France24 represents France in this case study (Fig. 5). France is one of the few countries in Europe that is highly dependent on nuclear power [28]. In this sense, it is important to include France in our case study, in addition, France is one of the major economies in the European Union and an important international player in the Energy Sector. Finally, is a neighboring country, and France is one of the main energy partners to Belgium thus it is of high importance to us to include France in our study.

Fig. 6: "Euractive": Articles of Energy and Environmental Interest for 2021 per week.



Last, we extracted data from Euractive (Fig. 6) an important major media located in Belgium. Euractive is focusing on European's Union news and policies. We also used our dataset mainly from this webpage due to the high number of different categories that it contains. Belgium is the country of our main interest since we are in Brussels and other cities of Belgium.

In all figures and media that we are presenting in this case study, we can observe some repeated patterns. The number of energy or environmental-related articles is increased and is above the annual average after extreme events. We highlighted 3 extreme events and one international conference. The highest number of articles for Euractive, France24, and Deutsche Welle was during the July floods where all these countries Belgium, France, and Germany were affected seriously. July flood's impact was both economic and environmental, additionally, more than 200 people lost their lives. It is important to prevent such disasters in the future but is also important to interpret and analyze them to understand the societal aspects. Media as we stated already affects a lot of public opinions and therefore this kind of study is essential for the energy transition and our carbon neutral future.

In Table 5. and Table 6. we would like to provide the reader with an annual comparison between the 4 different media that we selected in this case study. These two figures are giving us an overview to realize the level of awareness of each media. From these figures, we can see that Euractive is by far the most "environmentally friendly" media of the 4 since the ratio between Non-Environmental and Environmental articles is the highest with almost 22% of the total number of articles having an environmental interest. The least environmentally friendly is France24 with less than two 2% of its articles (Table 5).

Table 5. Media Environmental Friendliness

Media	Percentage of Environmental Articles in 2021
Deutsche Welle	6,1%
France24	1,4%
The Guardian	7%
Euractive	21,7%

Table 6. Annual Comparison between different media

Media	Number of Non-Environmental Articles	Number of Environmental Articles
Deutsche Welle	13648	835
France24	11419	164
The Guardian	14818	1018
Euractive	5430	1183

4.2 Guidelines for the Policy Makers

The main goal of this paper is to highlight the importance of climate change and to suggest possible guidelines to policymakers. To tackle climate change, a multi-discipline approach is necessary combing different scientific fields. Computer science with modern computers is powerful enough for the technical part which in this study, is the binary article classifier. In this section, we would like to propose how this classifier could potentially become a useful tool for policymakers and improve the decision-making process. We firmly believe that is important to know how different events like those tested, can affect the media attention and subsequently social attention. Social acceptance [29] is a key parameter for a successful energy transition and therefore we decided to study the media's reaction. It is necessary to study each country separately with more data and more resources. As a first suggestion, we propose that while this attention is higher it is easier to inform citizens and run campaigns in favor of climate change. Such disasters, which we should avoid in the future might be the driver to inform and raise the awareness of the public. The problem is, as we can see from the figures above that the hype falls dramatically a few or in some cases just one week after the incident. This is the moment that governments and political parties could keep the level of attention in higher levels. Policymakers should visit affected areas inform and talk with civil society. In case of new projects in the area after the disaster citizens should be a core part of the decision-making process. Additionally, governments should subsidize any affected household. Finally, new environmental laws following the disasters should be available to everyone in a public consultation.

5. Conclusions

The path towards carbon-neutrality probably is one of the hardest [1] coordinated projects that ever existed. Different countries should collaborate and take mutual decisions to achieve a sustainable future. Many scientists in different fields should cooperate including engineers, biologists, environmentalists, and others. Literature offers, a huge variety of different methods and models to predict and create different future energy scenarios. These powerful tools are facing several constraints and uncertainties. The way that different extreme events caused by climate change affected the existing energy models should be further studied. Recent extreme events like the COVID-19 pandemic and the War in Ukraine clearly show the huge impact of such events on the energy system. Those disruptions may change dramatically the existing energy national plans and it is necessary to consider them. This study is dealing with the social impact and more specifically the media attention.

Our method is a powerful tool to measure social aspects of the energy transition. We foresee expanding our method to a classifier with more categories. Given the fact that such events may occur more frequently, it is essential to measure the attention of every different technology separately. What are the energy trends following an extreme event? Is there higher attention towards wind or solar power? Such questions should be answered to have a successful energy transition.

Finally, we highlight, that policymakers should not make their decisions based on these events, but they should be able to track them and be aware of the different consequences that these phenomena might have.

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