

Evaluating the impact of floods on gender equality from social media evidence

Research in Progress

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Abstract

Climate change is one of the major challenges of our times. As a matter of fact, one of the 17 Sustainable Development Goals established by the United Nations in 2015, Goal 13 (SDG 13), is about climate action. It aims to “take urgent action to combat climate change and its impact”. It is widely recognized that climate change does not affect people equally and often women are more vulnerable to climate change than men. As an aspect of using IS to combat climate change and other environmental threats, this paper aims at investigating whether relevant information related to the relationship between climate change (SDG 13) and gender equality (SDG 5) could be extracted from social media, in particular from Twitter, by exploiting image recognition technologies and crowdsourcing techniques.

Keywords: citizen science, SDG indicators, social media image analysis, floods, gender equality

Introduction

It is widely recognized that climate change does not affect people equally and often, women are more vulnerable to climate change than men (Nellemann et al. 2011, Sorensen et al. 2018). The related disasters and impacts often intensify existing inequalities, vulnerabilities, economic poverty and unequal power relations. For these reasons, the measurement of progress on SDG 13 needs also to assess how climate change affects women and whether climate change responses are properly taking into account the existing inequalities. A synthetic representation of the evaluation of the progress of SDGs and gender equality is shown in (Equal measures 2021). It is also clear that gender-related SDG data are still very limited and in particular in climate-related data (Encarnacion and Maskey 2021) and only recently there has been a focus in collecting them in systematic initiatives Grantham 2020, therefore new directions need to be found to collect relevant data from different and new sources. Social media represents nowadays a powerful tool to extract information that, if properly aggregated and analyzed can provide relevant insights and indicators. The urgent need to assess whether and how climate change affects women, requires a shift from readily available data to more ‘difficult-to-measure’ indicators. The goal of this paper is to present a methodological approach in which both AI and crowdsourcing have been used to process images from Twitter posts with the goal of getting insights from visual evidence on the factors related to the gender differentiated impacts

of these type of climate-related disasters. The paper provides the first results derived from the ongoing analyses.

In the following sections, first we discuss the state of the art, then we describe the approach and methodology followed to extract flood images from Twitter and we illustrate the results from crowdsourcing information from the resulting dataset, finally we discuss the possible limitations of our work and future research.

Related work

Several issues have been identified as keys in understanding why women prove to be more vulnerable to climate-related disasters (floods in particular) than men (Grantham et al. 2020, Nellemann et al. 2011, Sorensen et al. 2018):

Poverty: women face higher risk in situations brought by climate changes because they make up the majority of the world's economically poor. 70% of the world's poor are indeed women.

Inequities in labor division: Women play a critical role in agricultural and pastoral livelihoods, often bearing significant responsibility for managing critical productive resources such as land, water, livestock, biodiversity, fodder, fuel, and food. They are often responsible for gathering and producing food, collecting water and sourcing fuel for heating and cooking. With climate change, these tasks are becoming more difficult as distances travelled by women to access natural resources (such as water, fuel wood, fodder, food, pastures, medicinal plants, fuel, and crops) increase. Climate change-induced flooding is over time likely to increase women's workloads in domestic fuel and water collection in some regions. As a result, their time available for childcare, education and participation in public life is reduced. They also carry out a disproportionate amount of daily labor compared to men in household and community spheres, such as cooking, cleaning, child care, care of older or sick family members. Unequal gender division of labor is further skewed by climate change, as often, when livelihoods are destroyed and productive assets are eroded, men tend to migrate out in search of income generating opportunities.

Violence: Not only do women constitute the majority of victims of floods and experience the greatest difficulty in recovering from a disaster, but they are also more likely to be subject to sexual violence in the aftermath of disasters. Numerous reports have documented an increase in such violence against women following environmental disasters. In addition, inadequate temporary accommodation in post-disaster situations renders women vulnerable to sexual and gender-based violence.

Other critical gender inequalities: As previously stated, women are disproportionately vulnerable to climate change, but this is not because there is something inherently vulnerable about women, but because of socio-cultural structures that deprive women of access to resources, decision-making, information, education, etc. In countries where gender inequality is more severe, death rates for women in climate-related disasters are significantly higher. Just to mention few examples: in cultures that restrict women from leaving their houses unaccompanied or from learning to swim or to climb trees, women may suffer greater injury and fatality in some kinds of climate change-induced natural disasters; women in more unequal societies do not tend to move about in public spaces, which means they will not hear warnings, and are unable to get out fast enough; lastly, women are more likely to have dependents, such as children and elderly or sick relatives, which affects their ability to leave the damaged area.

(Fritz et al. 2019) discussed the use of Citizen Science for collecting information relevant for SDGs. Among the possible sources of information in this context social media and crowdsourcing are being considered. One of the challenges of Citizen Science is the quality of extracted information, in particular due to the variety of the background of the contributors and possibly open and anonymous contributions. (Lukyanenko et al. 2020) considered strategies for improving the information quality, such as selecting contributors with a given background, or training the contributors, are illustrated, and also human factors.

Social media analysis in emergencies, and in particular in floods and earthquakes, has been discussed (Havas et al. 2017). The paper describes the challenge of selecting the relevant posts and defines several

technologies, such as crowdsourcing and automatic annotations of posts with ML trained models, for improving the quality of the results.

(Auteliano et al. 2019) handled the difficulty of retrieving relevant posts by using an approach to automatically improving the search keywords during an emergency event is proposed, and (Barozzi et al. 2019) provided a selection of good quality posts and images for crowdsourcing, filtering the posts on the basis of the characteristics of the images.

(Oliver et al. 2021) discusses social media analysis based on Twitter towards understanding the societal impact of hydrometeorological events. The analysis focuses on analyzing the text of the tweets, for understanding their intention and the source of the post. In particular, most of the tweets are descriptive or informative. The study also puts forward the difficulty in the analysis of datasets about such events, with the need of a manual annotation of all the tweets to identify the relevant ones.

In the VisualCit approach (Negri et al. 2021), the focus is on analyzing images from tweets automatically selecting the relevant tweets with ML classifiers, filtering out images which are not photos, selecting images in public places, and automatically geolocating them. Crowdsourcing to gather additional information for tweets annotation is performed only on the selected tweets, significantly reducing the number of tweets to be examined. The potential of deriving statistical indicators from the collected knowledge is also discussed based on a case study.

In the present paper we show how to develop the analysis of images from social media to collect posts about floods and identify gender-related problems, and we discuss the ability of identifying critical issues in this way.

Building a dataset on floods and gender equality

In this paper, we discuss the construction of a dataset for analyzing the impact of floods on gender equality. The goal is to be able to gather visual evidence on critical issues from images in tweets.

Methodology

The following requirements and constraints have been defined: i) the dataset should be based on images extracted from social media (in particular Twitter is considered in the study); ii) crowdsourcing by citizen scientists should be used for evaluating both the context of the post and the relevance to the research question. The size and the composition of the available crowd has proven one of the challenges in previous social media analysis with crowdsourcing projects. Therefore a requirement is iii) to collect an initial dataset to be analyzed by the crowd mainly composed of relevant posts, limiting the number of posts sent to crowdsourcing.

As discussed in related work, one of the challenges is to select the search keywords for initial selection of posts and to define the questions to be asked to the crowd, in order to gather evidence from the collected images.

Tool environment

In this work, we crawled Twitter to extract images related to floods and we applied a set of filtering components, to retain only non-duplicate images which are photos in public places, and safe for work during the crowdsourcing phase. Two components were specifically designed for collecting data about gender equality during floods for the purpose of this project. First, as we are focusing on getting evidence from the field during a flood, we developed a flood classifier to retain only images related to flooded areas (see Subsection Flood classifier), then we designed a crowdsourcing project to investigate about inequalities in this context, as described in Subsection Crowdsourcing.

Flood classifier

As previously stated, for the purpose of this work, it has been decided to focus on floods and therefore a flood classifier module has been developed and added to the pipeline described above. To perform image classification we used Deep Learning techniques and in particular Convolutional Neural Networks that are the de facto standard techniques for solving image classification tasks. We tried different models such as ResNet50, MobileNet, and Xception all having similar performances. Xception (Chollet et al. 2017) was the model selected for the classifier. We started from the pre-trained network on ImageNet and we applied fine tuning using the dataset we created. In particular we started from public datasets such as the eu-flood¹ (Barz et al. 2018) and other sources² (Sazara 2021). For the non-flood images we extracted some images from the COCO dataset and we crawled some random images. The validation accuracy was around 0.96% but after testing it with external source images we found out that it was not working as expected. Specifically, we noticed that the model did not recognize images from rural areas (that are the most common in Africa and in underdeveloped countries). The reason lies in the fact that the dataset was composed mostly of European flood images. Therefore, we added African floods images extracted from Google.

Is this a flood image?

YES NO

Are there people in it?

YES NO

Are there more women than men?

YES NO CANT TELL

Do they seem in danger?

YES NO CANT TELL

Are there shelters nearby? (Any place giving

The following link to the tweet might help in answering to the questions :

<http://twitter.com/anuuser/status/1391177986897022981>




Figure 1. Crowdsourcing interface (extract)

To further improve the classifier we decided to use a cyclic approach:

1. Use image extraction from Twitter and the flood filter to gather new flood images from a new crawling.
2. Manually label the predicted flood images retrieved from the previous step.
3. Add the manually labeled images to the dataset.
4. Train flood filter with the larger dataset.
5. Go back to step 1

We completed the training cycle when the precision of the classifier reached 0.95.

Crowdsourcing

The crowdsourcing application leverages the crowd in order to extract relevant information from the re-sulting pictures. We used the PyBossa-based Project Builder tool from Citizen Science Center Zurich³, in

¹ <https://github.com/cvjena/eu-flood-dataset>

² <https://www.dropbox.com/sh/grxeeep1k9aoyziq/AAByrZYB-jGOoTvboYp22fJFa>

³ <https://citizenscience.ch/en/>

which the selected images are shown to the crowd workers, together with questions regarding the depicted people, the activities they are doing and the environment they are in. Unique tasks are created for each tweet and tasks are considered completed once three different crowd workers analyze the tweet. Figure 1 shows the provided interface and some of the questions. The project can be accessed at <https://lab.citizenscience.ch/en/project/329>. The results of all the questions will be discussed in the next section.

Analysis of the results

Once an overall progress of 70% was reached (317 completed tasks over 452), the data were analyzed using matplotlib.pyplot. For the completed tasks (analyzed by at least three different crowd workers), the answers selected by the majority of the workers were considered for the analysis.

Some interesting results were obtained by analyzing pictures in which more women are present.

As shown in the histograms in Figures 2 and 3, those pictures are depicting mainly poor people and in the majority were taken in underdeveloped countries, according to almost all of the crowd workers' answers. Those results have a correlation with what has been stated above regarding poverty. Poverty and vulnerability are not uniformly correlated, but economically poor people and socially excluded groups tend to suffer disproportionately from vulnerability and the majority of the world's poor are, indeed, women.

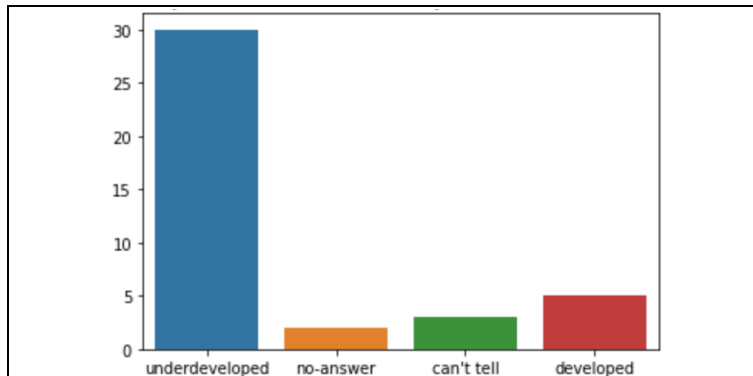


Figure 2. “Do you think the photo was taken in a developed or in an underdeveloped country?”

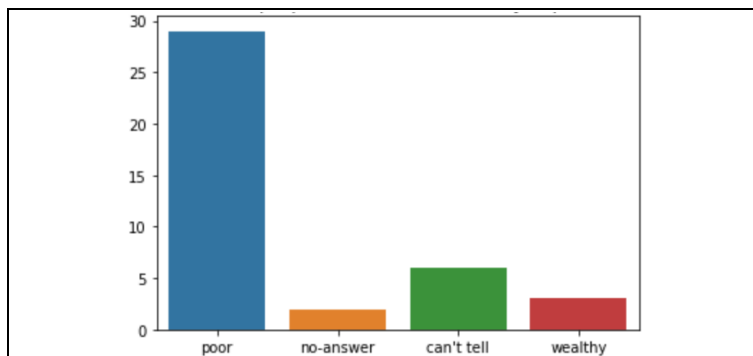
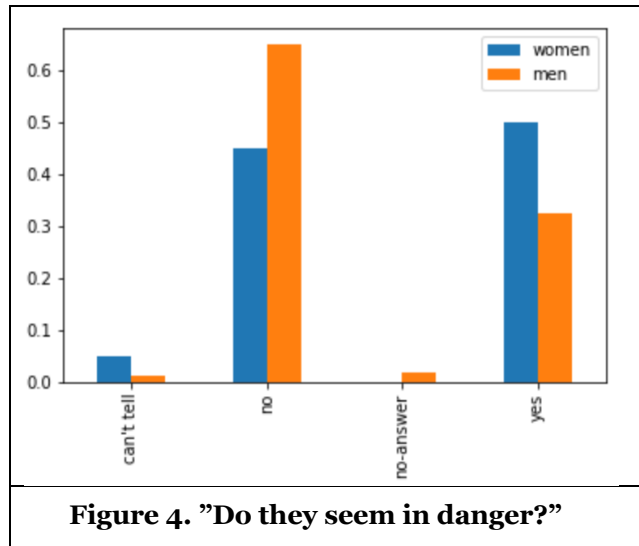
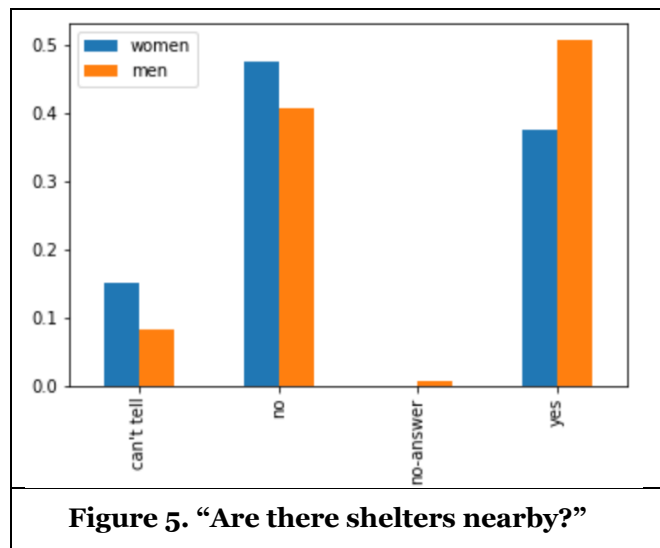


Figure 3. “Do the people involved seem wealthy or poor?”

Furthermore, the histograms in Figure 4 show a comparison between the answers to the question “Do they seem in danger?” associated with pictures in which more men are depicted and the answers to the same question associated with pictures with more women. Interestingly enough, men are apparently exposed to less danger in flood situations with respect to women.

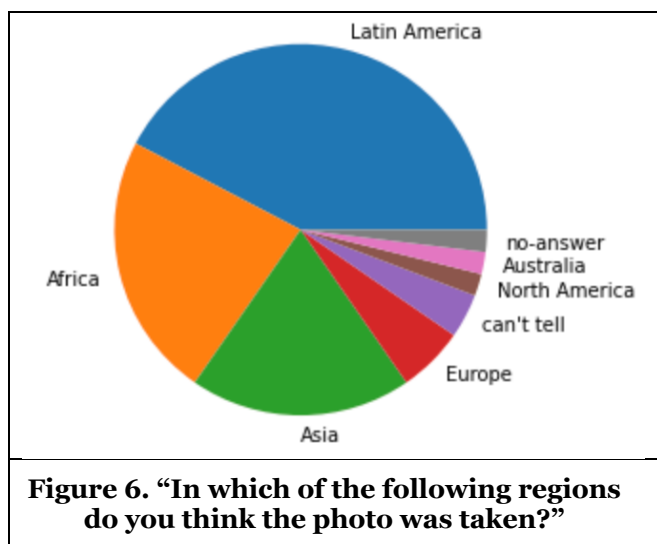


Similar results were obtained by analyzing the data related to shelters: as shown in Figure 5, the percentage of pictures showing shelters (any place giving temporary protection from bad weather) and in which mostly women are present is lower with respect to the percentage of pictures showing shelters and in which mostly men are present.

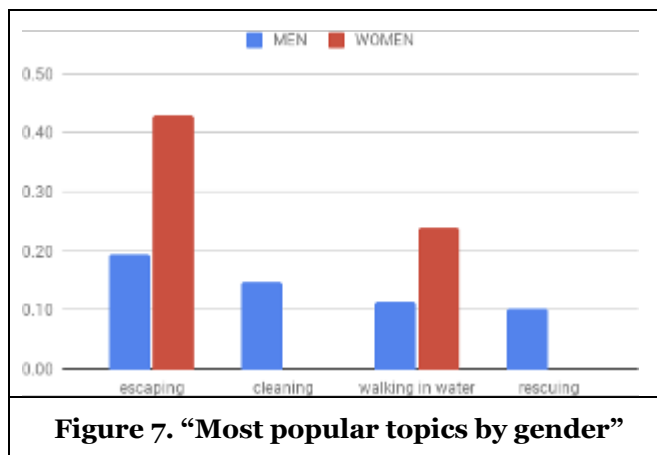


Finally, we analyzed the data related to the images' locations obtained through crowdsourcing, where the crowd workers could see the image and also access the tweet using the direct link to it to inspect the source as shown in Figure 1, and combined it with the OECD (Organization for Economic Cooperation and Development) "Gender, Institutions and Development" Database. As shown in Figure 6, Latin American and African countries seem to be the ones where the majority of the floods shown in the images hit in the period under consideration (beginning of April 2021). This type of result is strictly correlated to the outcome obtained analyzing the OECD Database⁴, which shows that legal frameworks do not protect women from violence in many of the most frequently hit countries.

⁴ <https://stats.oecd.org/viewhtml.aspx?datasetcode=GIDDB2019>



Lastly, we analyzed the labels collected through crowdsourcing to characterize the scene of the photo, we classified them manually by topic to visualize and compare the most recurrent topics present in the answers to the question regarding the activities that people in the images are doing. It is interesting to note that "escaping" and another topic associated with movement ("walking in water") are the most frequent in pictures in which more women are present. Topics such as "rescuing" and "cleaning" instead, which might come within the scope of "repairing the post-disaster situation", are only present in pictures in which mostly men are present (Figure 7).



Limitations and future work

This work focuses on contributing new tools for enhancing gender-based data collections in emergency scenarios. This work contributes to setting the basis for building information ecosystems which are collecting data from different sources, stating clearly possible biases and constraints, as advocated for instance in (Geisler et al. 2021).

However, it is important to remark that the results illustrated above present a number of limitations: limited number of available data, relatively few images depicting more women than men with respect to the ones depicting more men than women and, not exact knowledge of actual number of women and men in the images.

In addition, several possible biases can be introduced in the analysis process described in the previous sections. Let us consider some possible sources of biases. The initial source of information in this study is

Twitter. A first consideration is on Twitter users posting on social media. We analyzed a sample of 100 tweets from our dataset for evaluating a possible gender bias in this direction. In the collected set, as expected, the majority (45%) of the posts are coming from the news or organizations (rescuers, NGOs, public administrations). Additional 9% of the posts could not be associated with a gender. In the other posts there was a substantial gender balance, with 24% women and 22% men. This aspect should be further investigated in different areas of the world, to analyze in detail where such a bias could be more important.

Another possible source of bias could be from the crowd performing the crowdsourcing. The crowdsourcing performed in the paper was performed by a small community, mainly linked to the authors of the paper. While we did not perceive a possible bias in this direction, we have to say that the constraints on the crowdsourcing tool were not allowing us to have access to the crowd information, and therefore also some further investigation should be performed in this direction, making the crowd gender information visible in the analysis.

It is also clear that while new evidence can be extracted with a mix of social media analysis and crowdsourcing, the available size of the crowd poses limitations on the amount of information that can be processed on a single event. Further research is needed in this direction, to be able to further refine the selection of posts and limit the human analysis only to relevant posts, and to further automate some tasks, e.g., building ad hoc classifiers for specific questions. For instance, an automatic classification of locations of posted images can be performed using approaches such as (Middleton et al. 2014, Scalia et al. 2021), and further classifiers could be trained based on an initial crowdsourcing activity on a selected sample. In future research it will be important to associate to all information stored in the information system not only basic metadata, but also information about the information extraction process, including not only precision and accuracy information, but also information about sources and possible biases introduced by the analysis process.

Concluding remarks

The paper presents a case study in which evidence of gender inequality is obtained by analyzing posts from Twitter and using Machine Learning to reduce the number of irrelevant posts for the research, followed by crowdsourcing for extracting further information. The initial results show clear evidence that the number of women in danger is higher than that of men. The case study will be continued to increase the number of posts for increasing the gathered evidence and to analyze the differences emerging in different areas of the world.

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