SoA on prevention and preparedness DRR actions

Deliverable D4.1

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1.1. Document history

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3. IoT and citizen science joint initiatives for developing EWS to cope with weather-induced risks

3.1. Foreword

Deliverable 4.1 has the aim of summarizing the desk review activity carried out in the framework of Task 4.1 “Overview of existing knowledge”. The ambition was that of providing an overview of tools already available or under development for prevention and preparedness DRR actions. However, covering in a proper and credible way the entire State of the Art results not feasible given the constantly growing number of investigations addressing the different technological and scientific innovations aimed at mitigating weather-induced risks. Furthermore, it could probably lead to reinvent the wheel given the several already published seminal reviews on different scientific and technological innovations aimed at coping with the impacts of climate extremes. Under such premises, the overview has been targeted to cover a specific topic, up to now, not sufficiently investigated in the scientific literature: how the synergic adoption of IoT technologies and citizen science initiatives could support the implementation of impact-based forecasting frameworks. The topic could result highly interesting and in line with The HuT “philosophy”; indeed, the two innovations are planned to be implemented in different Demonstrators. Furthermore, they link in an innovative way the human and technological domains overcoming the “silos rationale” that usually prevent the development of effective integrated approaches.

3.2. Introduction

In Europe, in the period 1980-2019, weather extreme events have caused economic losses amounting to about EUR 446 billion corresponding to 81% of the total losses caused by natural hazard (EEA 2021). Although all impacts of natural hazards on people, economies and environment cannot be completely avoided, they can be substantially reduced implementing specific early warning systems (EWS).

By exploiting the Risk-informed Early Action Partnership (REAP) glossary (2022), EWS can be defined as “an integrated system of hazard monitoring, forecasting and prediction, disaster risk assessment, communication and preparedness activities systems and processes that enables individuals, communities, governments, businesses and others to take timely action to reduce disaster risks in advance of hazardous events”.

EWS nurture learning and understanding of natural hazards, provide us with warning information and give time to take early action, so as to avoid unnecessary consequences (Trogrlić 2022). The United Nations Sendai framework for disaster reduction recommends increasing availability and access to multi-hazard early warning systems by 2030. In 2020, only 23 out of 195 of the UN countries has a working multi-hazard national EW system. In these countries, 94% of the population exposed to natural disasters was successfully protected through evacuation following the early warning, showing the great effectiveness of these systems (Esposito 2022). The World

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Meteorological Organitation (WMO) recently released its Executive Action Plan (2023-2027) which summarizes the initial actions required to achieve the goal of ensuring every person on Earth is protected by early warning systems within five years and sets out the pathway to implementation. It calls for an estimated new targeted investments of 3.1 billion of dollars over the five years to advance the four multi-hazard early warning system (MHEWS) pillars from a scientific, technical, policy and financial perspective.

Recently, technologies such as the Internet of Things solutions have been integrated into alert systems to provide an effective method to gather environmental data and produce alerts (Esposito et al. 2022). The Internet of Things (IoT) consists of infrastructures interconnecting connected objects and allowing their management, data mining and the access to the data they generate (Dorsemaine et al. 2015). In the context of disaster management and Early Warning systems, the IoT provides the means for widespread environmental monitoring from different data sources, low latency communications and real-time data processing, which enable the generation of accurate and timely warnings in the case of disaster occurrence or forecasting (Esposito et al. 2022). More specifically, IoT sensors may be used in several fields: collecting meteorological data for the detection of forest and agriculture fire (e.g., Benzekri et al. 2020; Sharma et al. 2021); gathering information of soil condition for predicting landslides events (e.g., Oguz et al. 2019; Singh et al. 2019; Abraham et al. 2020); monitoring water levels in order to alert from floods (e.g., Al Qundus et al. 2020; D. Purkovic et al. 2019).

However, the Executive Action Plan of WMO also highlights the need for a people-centred approach to effectively disseminate and communicate warnings as well as to support the early warning systems (e.g., to fill any gaps by contributing local data, etc.). The engaging of citizen through a participatory approach has a positive effect on community knowledge and attitudes for risk reduction (Aghaei et al. 2018). Moreover, the citizen involvement can provide valuable contributions to all parts of the warning value chain defined by Golding et al., 2019 (that includes observations, weather forecasting, hazard forecasting, impact prediction, warning generation, and decision making), especially through citizen science projects and activities (Tan et al. 2022). Citizen science is defined as a “type of science in which the general public contributes to the production of scientific knowledge, either alone, or more often in collaboration with professional scientists and scientific institutions” (Strasser and Haklay, 2018). Citizen science may also be known under different names, such as community science, participatory assessment, community-based monitoring, volunteer monitoring, and others (Shirk et al., 2012). More specifically, according to the framework proposed by Haklay (2012) there are different levels of participation in citizen science approach: “crowdsourcing” (citizen as sensors), “distributed intelligence” (citizen as basic interpreters), “participatory science” (participation in problem definition and data collection), “extreme citizen science” (citizen are involved from problem definition to the dissemination of results). In the largest part of initiatives, the citizens are involved in data collection (crowdsourcing). In general, citizen may send information about the presence of fire, flood, landslide and other natural hazard through specific mobile applications or upload photographs and/or video using social media (i.e., Twitter, Facebook etc.) (e.g., De Longueville et al. 2009; De Longueville et al. 2010; Degrossi et al. 2014; Le Coz 2016; Bielski et al. 2017, Kempf et al. 2021).

Although the synergic adoption of IoT sensor and the citizen science approach represents a promising direction in the provision of real-time and extensive information for early warning and risk management (Paul et al. 2017), this integrated approach has not yet been sufficiently covered by scientific investigations. By exploring the State-of-the-Art, the study tries addressing this gap by asking: “How the nexus between sensors and citizen science can represent an added value in the design and implementation of early warning systems to cope with weather-induced risks”?

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The document first provides a brief background on the adoption of IoT sensors and citizen science approach in the early warning system. In Section 3, the methodology used to compile the review paper is explained and the results obtained from the bibliographic research are reported and discussed. Section 4 outlines the strengths and limitations of the integrated use of IoT sensors and a participatory approach in the different early warning phases.

3.2.1. Background

Internet of Things

The Internet of things refers to a type of network to connect anything with the Internet based on stipulated protocols through information sensing equipments to conduct information exchange and communications in order to achieve smart recognitions, positioning, tracing, monitoring, and administration (Patel et al. 2016). A basic and generic IoT architecture includes three levels: (i) the local environment, containing smart objects or sensors that communicate with each other and interact or sense data from the environment; (ii) a transport layer that allows end-nodes from the first layer to communicate with higher layers and infrastructures; and (iii) a storage, data mining, and processing layer, usually implemented in the cloud, and possibly with systems and interfaces to let users access and visualize the data (Esposito et al. 2022). The IoT application covers different fields such as transportation, agriculture, healthcare, environmental monitoring as well as alert systems for disaster risk reduction. More specifically, Esposito et al. 2022 reviewed the literature regarding Internet of Things solutions in the field of Early Warning (EW) for different natural disasters: floods, earthquakes, tsunamis, and landslides.

Regarding the floods, prediction methods in Early Warning IoT systems can rely on hydro-geological models or statistical and Machine Learning models that collect data in real time from Wireless Sensors Networks (WSNs), send them to a remote server for processing and then display results or generate alarms (Esposito et al., 2022). For example, Sood et al. 2018 propose an intelligent architecture for monitoring and forecast floods. All relevant attributes of interest for flood prevention are detected using IoT devices and elaborated by High Performance Computing (HPC) processing. Moreover, IoT sensors can use to monitor the water level in order to prevent river flood, flash flood and coastal flood (e.g., Jayashree et al. 2017, Purkovic et al. 2019, Ragnoli et al. 2020, Mitra et al. 2016). When a threshold value is exceeded, an alarm is sent to the reference server. Ibarrache et al. 2020 implemented the Emergency Water Information Network (EWIN) that offers a solution permitting to send notifications and to real-time monitoring flash floods. Purkovic et al. 2019 proposes the use of ultrasound sensors to monitor the river water level in a Japanese city and detect floods early. Furquim et al. 2018 describe the results achieved by SENDI (System for dEtecting and forecasting Natural Disasters based on IoT), a system based on IoT and Wireless Sensor Networks (WMS) for the detection and forecasting of natural disasters and the issuing of alerts. The system was modeled by data collected by a real-world WSN installed in the town of São Carlos - Brazil, which carries out the data collection from rivers in the region. Al Qundus et al. 2022 propose a wireless sensor network decision model for the detection of flood disasters by observing changes in weather conditions compared to historical information at a given location. The data is sent to a cloud server in a monitoring room, where a decision can be made regarding response to a possible flood disaster. Thekkil et al. 2017 presents a real time Wireless sensor network based early flood detection and control monitoring system designed with a function of real time monitoring, guaranteeing connectivity in low cost. This system collects data in the form of images which are transmitted to the remote monitoring centre. The remote center processes the data by analyzing it and provide the necessary alerts. In many cases IoT sensors are coupled with machine learning techniques to predict the probability of flooding of a river basin (e.g. Sabbatini et al. 2021).

Concerning landslide events, IoT sensors, often combined with artificial intelligence, are used to monitor in real-time parameters such as ground movements, groundwater level measurements, meteorological data in order to precociously alert population in dangerous situation by means of a warning system (Debauche et al. 2021, Gamperl et al. 2021, Elmoulat et al. 2020; Thirugnanam et al. 2020; Joshi et al. 2019). Gian et al. 2017 propose and implement a rain-induced landslide early warning and monitoring system named as EWMRIL with a case study at the Nam Dan landslide (northern Vietnam). The proposed system consists of six sensor nodes and a rainfall station which are used to detect large amounts of real-time data such as soil moisture, pore water pressure, motion status and rainfall. Using a wireless communication system, the collected data is sent to the computer station for the analysis and prediction of the landslide instability, proposing three levels of alert: early, intermediate and imminent. Piciullo et al. 2022 propose a four-phase approach to set up a local landslide early warning system (Lo-LEWS, Piciullo et al. 2018) at slope scale with the support of Internet of Things (IoT) technologies. This methodology is applied to a monitored unsaturated steep slope in Norway threating a double railway line in Eidsvoll municipality. The IoT sensors are used for monitoring several parameters such as volumetric water content (VWC) and pore-water pressure (PWP) in order to back-calculate and validate a hydrological model. In Abraham et al. 2021, micro-electro-mechanical systems (MEMS)-based tilt sensors and volumetric water content sensors are used to monitor the active slopes in Chibo, in the Darjeeling Himalayas and to improve the alert systems. Aggarwal et al. 2018 propose a landslide monitoring system based on IoT using images from video cameras. It performs real-time analysis of the specific area, based on the video stream acquired by the camera and applies computer vision algorithms to detect landslide and notify them to the stakeholders via a mobile app. El Moulat et al. 2018 outline a new monitoring approach to detect hillslopes prone to be affected by landslides. It reports also continuous information from up-to-the-minute or real-time monitoring, providing prompt notification of landslide activities, advances understanding of landslide behaviors, and more effective engineering and planning efforts.

In addition to the risk of flooding and landslides, IoT sensors are also used in fire risk prevention. Benzekri et al. 2020 propose an early forest fire detection system based on collecting environmental wireless sensor network data in the forest to predict the occurrence of a forest fire using artificial intelligence. On the other hand, Sharma et al. 2021 define an IoT and deep learning-inspired multi-model system for detection, dissemination, and monitoring of active fire locations in agricultural activities.

Citizen science

Citizen Science can be defined as the voluntary, conscious and informed participation of various citizens, who generate, analyze large amounts of data, share their knowledge and results with scientists and other individuals with a purpose of social utility (Bernardo et al. 2020). Nowadays, the area of citizen science is increased due to the increasing availability of powerful and low-cost devices and sensors connected to the Internet. The starting point for citizen science was largely based on environmental data collection by volunteers (Paul et al. 2018). With time, the focus has broadened, shifting from acquiring data to other phases of the scientific process, including problem statement, analysis, and interpretation. In fact, the key framework defined by Haklay et al. (2012) identifies four different levels of participation and engagement in citizen science projects: In the simplest form of involvement (crowdsourcing) the participation is limited

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to the provision of resources. For example, the participants are asked to share the information about occurred events, carry sensors around and bring them back to the experiment organizers (citizen as sensors, volunteered computing). The second level is 'distributed intelligence' in which the participants are asked to take some basic training and then collect data or carry out a simple interpretation activity (citizen as basic interpreters; volunteered thinking). The third level "participatory science" is a level of participation in which the problem definition is set by the participants, and in consultation with scientists and experts, a data collection method is devised. The participants are then engaged in data collection but require the assistance of the experts in analyzing and interpreting the results. The fourth and highest level of Haklay's framework is "extreme citizen science" in which the citizen are involved from problem definition to the dissemination of results. This mode of science requires that scientists act as facilitators, in addition to their role as experts.

Citizen science contributed to various scientific disciplines such as ecological monitoring of mammals (Parsons et al., 2018), ecology and conservation (Kobori et al., 2016; Harebottle et al., 2020), drinking water research (Brouwer et al., 2018) observations of the earth in general (Fritz et al., 2017; Rubio-Iglesias et al., 2020) as well as in natural hazards and disaster research (Marchezini et al., 2018; Hicks et al., 2019; Vinnell et al., 2021). More specifically, Tan et al. (2022) explore how citizen science contribute to the warning value chain defined by Golding et al. 2019 for high impact weather- induced events. Each part of the chain, such as hazard monitoring, modeling and forecasting, risk assessment, communication and preparedness activities, is typically associated with an experts community that delivers that function. Citizens can provide information exploiting web Portals or mobile applications such as WarnWetter app in Germany (https://www.warnwetterapp.de/) collecting around 660,000 observations from July to November 2020 (Kempf, 2021), WeatherX App in Australia (https://weathex.app/), I REACT app permitting to provide real time information in case of forest fire through their mobile personal devices (Bielski et al. 2017). Another example is OpenStreetMap, a popular online platform for the general public and researchers to record and map observation, monitor hazards and share early warnings (Hicks et al. 2019). Various platforms have been developed to deal with flood risk: FCO (Flood Citizen Observatory), a crowdsourcing platform which is used by volunteers (considered as human sensors) to upload important parameters for flood risk management in Brazil (Degrossi et al. 2014); Flood Patrol (Philippines), an Android mobile phone application developed for allowing people send flood reports to NOAH (Nationwide Operational Assessment of Hazards) for mapping; SIGNALERT (France), a smartphone application to report various situations of natural hazards including floods (http://www.signalert.eu/.); mPING (Meteorological Phenomena Identification Near the Ground, NOAA, USA), a free mobile phone application used to collect public weather reports, including flooding across the USA as contributions to the Flood Observations – Citizens As Scientists using Technology Project (FLOCAST7) launched in 2013 (http://www.nssl.noaa.gov/projects/ping/) (Le Coz et al. 2016).

Citizen science projects can also involve high schools to build weather stations and collect weather data and study related impacts such as urban heat waves (Kox et al. 2021; Lam et al. 2021) or involve volunteers in weather and climatic modeling experiments using their home computer (Sparrow et al. 2021). But citizens also use information from other parts of the value chain, not just the warning. For example, weather enthusiasts take their weather readings and share them with national weather services and volunteer networks (Gharesifard et al., 2017; Krennert et al., 2018) in order to improve forecast for decision making (Phan et al. 2018). Furthermore, citizens can also involve in the discussion and recognition of natural hazards both in person (Abunyewah et al., 2020) and through online channels and social media (Kankanamge et al.,

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2020). For example, Pennington et al. 2022 develop a system based on artificial intelligence capable of recognizing and classifying landslides from photos posted by citizens on Twitter platform. This helps improving risk awareness and community preparedness to natural disasters.

In order to have a visual inspection, the papers related to the IoT sensors and citizen science approach are classified according the different stages of warning value chain proposed by Golding et al. 2019. Figure 1 shows two different levels. The first one concerns papers in which only IoT sensors are used for early warning system, in the second level there are articles where a citizen science approach is implemented. Moreover, the various papers have been differentiated with different colors according to the hazard considered (blue for floods, red for fires, brown for landslides, black for multihazards).

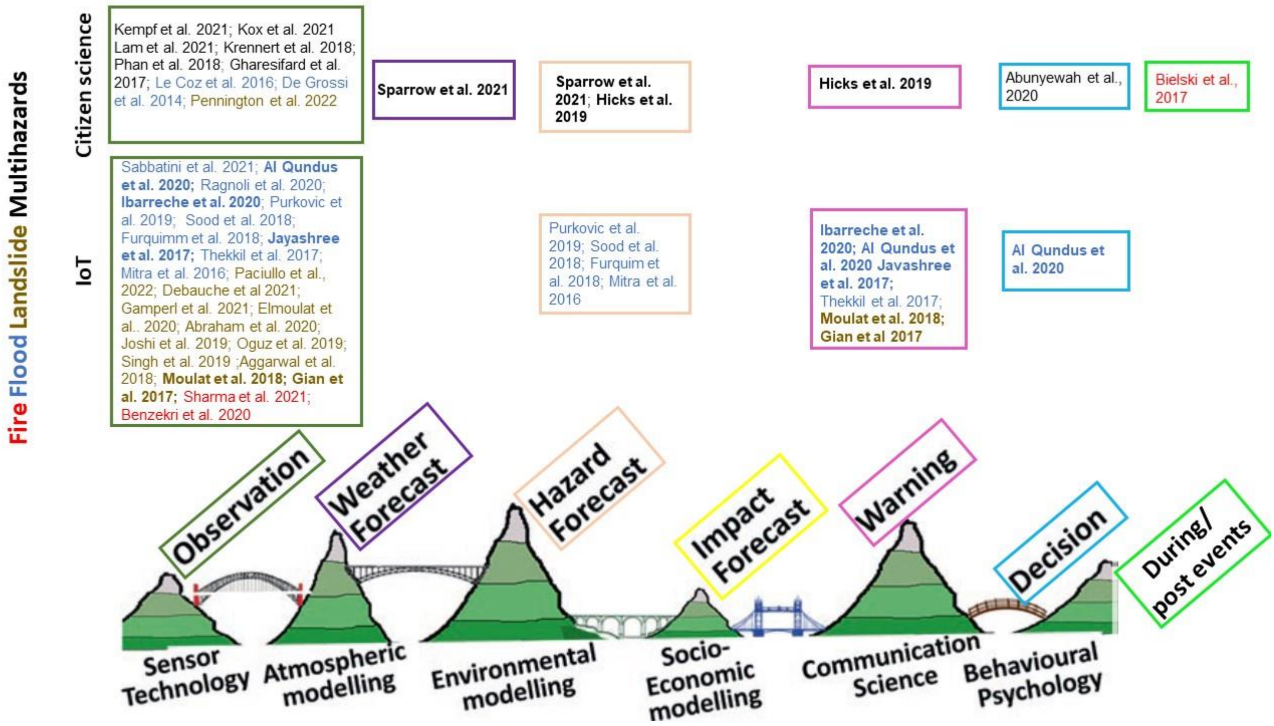

Figure 1: Articles placed in the warning value chain proposed by Golding et al. 2019.

3.3. Materials and Methods

To identify the main peer-reviewed works investigating approaches or displaying case studies where IoT monitoring and citizen science approaches are jointly used for warning purposes (associated with weather-induced risks), Scopus and Google Scholar search engines have been used.. The search is focused on title, abstract, and key words and search themes are combined using the Boolean operator “AND”:

- Citizen science AND Internet of Things (145 documents)

- Crowdsourcing AND Internet of Things (418 documents)

- Citizen Science AND IoT (107 documents)

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- Crowdsourcing AND IoT (419 documents)

The papers are further visually inspected to detect those suitable for the scopes of the investigation. Moreover, the search is complemented by exploiting Google Scholar. Finally, bibliography in the review studies is checked identify other studies that meet the inclusion criteria.

3.4. Results and discussions

After the selection, ten main articles are selected. More specifically, 7 articles concern floods, one floods and landslides (multihazards), one concern forest fires and one related to the heat waves in urban settlements. Table 1 shows all the details relating to the technological approach used, citizen participation and the reference study area.

Table 1: Descriptive papers analysis for the systematic review of literature.

Article	Hazard	Technology approach	Citizen approach	Study area	DOI
Kisters et al. 2022	Heat waves in urban settlements	IoT sensors collect the air temperature measures	Citizens collect the temperature measures (crowdsourcing)	Germany	https://doi.org/10.1007/978-3-031-23298-5_9
Bernardo et al. 2020	Forest fire	IoT sensors collect meteorological data	Citizens take photos, report fires, upload weather data, add records, on web application (crowdsourcing)	Portugal	https://doi.org/10.18502/keg.v5i6.7088
Ilukkumbure et al. 2022	Flooding	IoT Sensors collect the real-time meteorological conditions	Citizens take photos, report fires, upload weather data, add records, on web application (crowdsourcing)	Sri Lanka	10.1109/ICAC54203.2021.9671141
Nugroho et al. 2022	Flooding	IoT network collect rainfall data	Students collect meteorological data (participatory science)	Indonesia	10.1088/1755-1315/1109/1/012015
Escamilla Ambrosio et al. 2021	Flooding	IoT sensors collect meteorological data	Citizens collect and sharing meteorological information (crowdsourcing)	Spain	https://doi.org/10.1007/978-3-030-69136-3_10

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Donratanapat et al. 2020	Flooding	IoT network transmit river level data	Geotagged tweet (crowdsourcing)	USA	https://doi.org/10.1016/j.envsoft.2020.104828
Castro et al. 2019	Flooding	Sensors for collecting real time water level	Upload Pictures and individual perceptions of the severity of the flooding event (crowdsourcing)	Mexico	10.1109/ISC246665.2019.9071781
Loftis et al. 2018	Coastal Flooding	Low cost sensors for collecting water level	Visualization of flood model forecast with app (distributed intelligence)	USA	10.1109/SCOPE-GCTC.2018.00009
Loftis et al. 2017	Coastal Flooding	Low cost sensors for collecting water level	GPS data about extents flood (crowdsourcing)	USA	https://doi.org/10.1145/3063386.3063764

The papers are discriminated with different colors according to the hazard considered (blue for floods, red for fires, orange for heat waves, brown for landslides, black for multihazards) in the framework proposed by Golding et al. 2019 (Figure 2).

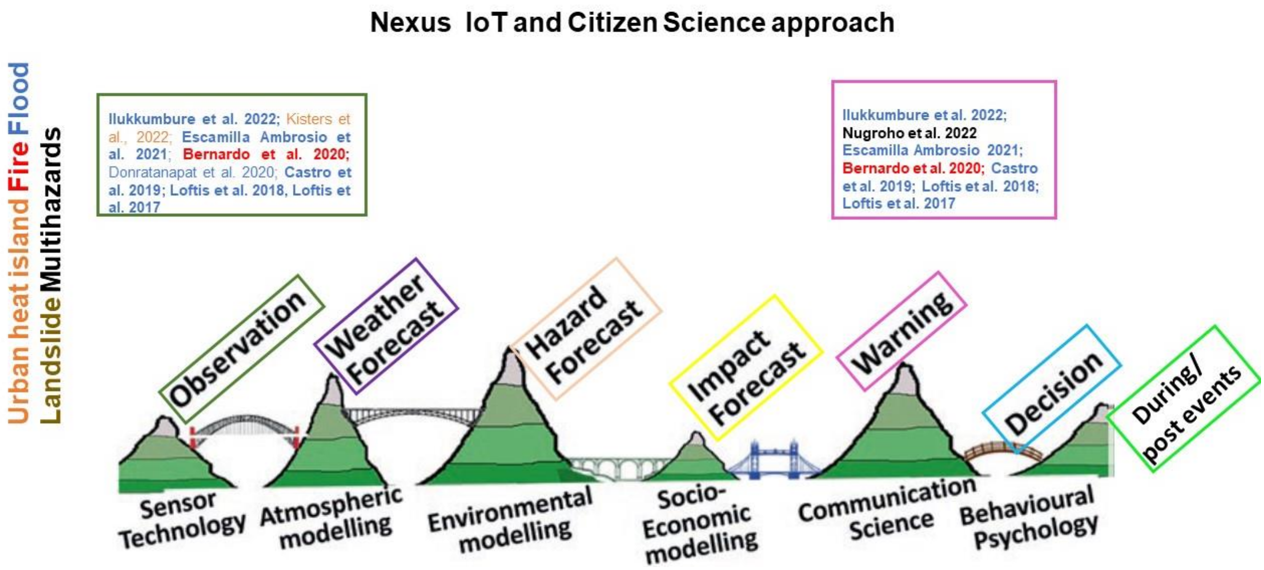

Figure 2: Articles with IoT and Citizen Science approach placed in the warning value chain proposed by Golding et al. 2019.

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Concerning the investigation about heat wave in urban settlements, the identification of the most susceptible areas within cities generally rely on satellite images since existing sensor networks are not dense enough. Kisters et al. 2020 propose an alternative approach based on a citizen-owned distributed sensor network consisting of Smart Home and Internet of Things devices. These sensors can be connected to publicly available infrastructure such as buses, rental bicycles or electric scooters. These mobile measurements help gain momentary insight into areas that have not previously been well covered. With existing measurements from mobile sensor stations a regression model is trained to learn their dependencies with nearby fixed weather stations. to derive a fine-grained heat map. In this case IoT sensors are used in the observation phase as well as the citizen science approach (crowdsourcing, Figure 3).

Bernardo et al. 2020 integrate citizen science activities and IoT solutions to address forest fire risk. More specifically, IoT sensors are used to measure specific atmospheric parameters such as air temperature, wind direction and speed from forest in order to calculate the Fire Weather Index (FWI) (Van Wagner, 1974). On the other side, through a smartphone app, which may be associated with a low-cost data collection device, the volunteers are asked to share information about fire-prone areas and areas affected past and new occurrences. This data are used by experts to support decision making processes.

Ilukkumbure et al. 2022 explore the use of IoT sensors and crowdsourcing to provide insights into the development of the pre and post flood risk management. IoT devices track in real-time meteorological conditions and monitors continuously. Crowdsourcing is carried out through a Portal including pre-defined questionnaires to gather information from the affected communities and able to receive real-time updates, for monitoring floods and extreme weather conditions in nearby locations during the events. The data sets are analyzed and validated by using statistical analysis and used as inputs for forecast models exploiting machine learning and deep Learning approaches.

Escamilla Ambrosio et al. 2021 propose a framework according to which community members of a specific urban zone, prone to flooding, collaborate in sharing information about weather conditions using IoT techniques. The gathered information is sent to a cloud to be analysed together with information from weather forecast and a network of sensors and surveillance cameras installed in specific areas inside and surrounding the studied zone.

Nugroho et al. 2022 develop a “very early warning system” (VEWS) and community-based rainfall data management in a village of Indonesia to monitoring the occurrence and the impacts of floods and landslides. The rainfall is recorded manually by the students at elementary schools every day and transmitted using cellular telephones by the teacher to the village’s officer. The rainfall data are linked to the flow rate (monitored through IoT network) at each outlet in the catchment area of each rain gauge to obtain a threshold value of rainfall able to trigger precipitation-induced disasters.

Donratanapat et al. 2020 develop a *Flood Analytics Information System* (FAIS), a Python Web application (national scale prototype) to gather Big Data from multiple servers and analyze flooding impacts during historical and real-time events. The application is smartly designed to integrate crowd intelligence, machine learning and natural language processing of tweets to provide flood warning with the aim to improve situational awareness for flood risk management. More specifically, FAIS combines flood peak rates and river level information with geotagged tweets (crowdsourcing) to identify a dynamic set of at-risk locations to flooding. The pipeline uses IoTs-APIs (Application Programming Interface) and machine learning for transmitting, processing, and loading Big Data. The prototype was successfully tested in real-time during Hurricane Dorian flooding as well as for historical event (Hurricanes Florence) across the

Carolinas, USA where the storm induced extensive disruption to infrastructure and communities.

Castro et al. 2019 proposed another prototype Flooding Alert System (FAS) which seamlessly integrates real-time data, crowdsourced data, historical data and provides timely and precise information to users so that they can make informed decisions during these events. More specifically, The FAS technical infrastructure is composed by Internet of Things sensors (equipped with an image processing algorithm) strategically placed across urban areas to collect real-time data about water levels. FAS includes a mobile application to provide residents with the ability of accessing or contributing with flooding data (crowdsourcing). The FAS App mobile application displays a feed of recent flooding events that includes an image, location, date-time, and the severity of the flooding. FAS will send notifications to users who are located nearby flooding events or have a route that covers a flooded area. Users will be provided with information about past incidents in nearby flooded areas to foster their responsive actions to ensure their safety.

Loftis et al. 2017 and Loftis et al. 2018 propose the StormSense tool (website at: http://www.stormsense.com), an IoT-enabled inundation forecasting research initiative to enhance flood preparedness in the smart cities of Hampton Roads USA), for flooding induced by storm surge, heavy rainfalls, and tides. More specifically, StormSense can detect, model, and communicate flood occurrence through the joined action of scientists (Virginia Institute of Marine Science, VIMS) supported by IoT water level sensors, hydrodynamic models, artificial intelligence, and voice-assisted technologies. StormSense's network employs a mix of ultrasonic sonar and radar remote sensing technologies to record water levels and develop autonomous alert messaging systems through the use of three separate cloud environments: one to manage the water level monitoring sensors and alert messaging, one to run the model and interface with the post-processed results, and one to geospatially present the flood results. Moreover, the "Sea Level Rise" citizen science app is used to validate the flood forecast model by using GPS-reported points of maximum flooding extents.

The desk review clearly displays how IoT sensors are generally used in the observation and alert phase (Figure 2). These sensors are often used by citizen to collect meteorological and environmental data (crowdsourcing). Furthermore, in most cases, citizens are involved above all in the first level of participation proposed by Haklay et al. 2012 (Figure 3).

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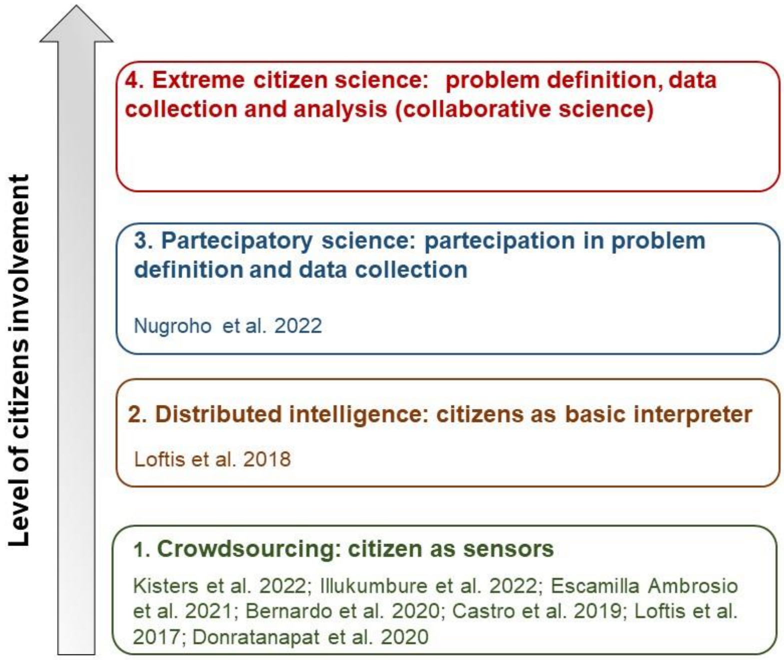

Figure 3: Classification of the articles according to level of citizen involvement proposed by Haklay et al. 2012.

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4. Brief conclusions

Desk review has the goal to provide an overview about recent experiences where the integrated adoption of IoT technologies and citizen science initiatives supported the warning stages to cope with weather-induced hazards. The first finding concerns the limited number of studies where the two "innovations" are adopted in a jointed way; mainly if compared with the steadily increasing number of researches where the two ones are used independently. The adoption of citizen science-driven approaches and the spreading of low cost IoT sensors can entail a significant increase of the actual temporal and spatial resolution for atmospheric and environmental data. Furthermore, it enables a full involvement of communities more aware about the significance of weather-induced risks and more willing to support DRR prevention activities.

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