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beAWARE

Enhancing decision support and management services in extreme weather climate events

700475

D3.1

Crisis Classification

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Abstract

This deliverable presents the Crisis Classification component of beAWARE platform. The objectives of Crisis Classification are to tailor methodologies and technological solutions able to provide timely and accurate warnings to authorities for a forthcoming extreme weather event, as well as to enhance decision support process during the crisis. The main aspects of the architectural schema of the Crisis Classification component along with the internal and external interactions and the data acquisition processes are exhibited in this document. Furthermore, the implementation of each component of the Crisis Classification system will be described as well as their integration stage of the operational beAWARE platform as a

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whole. Finally, novelty methodologies and techniques that will be used in the crisis modelling and classification task in terms of the crisis' hazard are analysed.
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Executive Summary

This document constitutes the **Deliverable 3.1 "Crisis Classification"** and encompasses 18 months efforts to define requirements, design the architecture and methodology and finally launch the implementation of the **Crisis Classification (CRCL)** component of the beAWARE platform.

The objectives of **Crisis Classification** component is to integrate and deploy the necessary technological solutions that will allow beAWARE framework to provide:

- **Early warning** to notify the stakeholders (authorities, first responders, citizens) regarding the upcoming extreme event, such as flood, fire and heatwave
- **Decision support** and real-time monitoring of the ongoing crisis providing risk assessment facilities to the stakeholders via the PSAP (*Public Safety Answering Points*) component.

To achieve these goals, Crisis Classification component consists of two main modules:

a) The ***Early Warning*** module which encompasses methodologies to fuse forecasts from sensors aiming to predict an extreme natural event, estimate the forthcoming crisis level and alert the stakeholders
b) The ***Real-Time Monitoring & Risk Assessment*** module which integrates fusion methodologies in a multilevel approach aiming to monitor the evolvement of a crisis event as well as estimate its severity in real-time. In the information/data fusion phase, the ***Sensor Fusion*** module utilises methodologies to combine sensory real-time data. In decision fusion phase the ***Decision Fusion*** module combines information obtained from sensors along with other resources, such as images/videos, audio messages and messages from social networks etc. in order to assess the crisis risk.

The Crisis Classification component interacts with other beAWARE components via the Knowledge Base Service (KBS) of beAWARE platform, as well as with other external resources to acquire the appropriate input data. Furthermore, it encapsulates innovative solutions that will allow to beAWARE platform to provide early warnings and assist authorities to risk assessment and decision support processes by providing to Public Safety Answering Point (PSAP) all the necessary information via a series of meaningful messages.

Generally, according to the Cambridge dictionary[1] the term "crisis" defines as "*a situation that has reached an extremely difficult or dangerous point; a time of great disagreement, uncertainty or suffering*". The unpredictability, the low probability of occurring and the requirement of a quick response in order to minimize its impact are three of the important aspects of crisis. Thus, **crisis management** involves the stages of prevention, mitigation,

[1] https://dictionary.cambridge.org/dictionary/english/crisis

preparedness, response and recovery and which are considered as the basic principles that any Decision Support System should have in order to face the crisis effectively ((Kamel, 2000); (Schanze, 2006); (Sànchez-Marrè, et al., 2008); (Prelipcean & Boscoianu, 2011)). beAWARE framework aims to incorporate state-of-the-art technologies in order to support stakeholders during all the stages of crisis management. Specifically, the Crisis Classification component will encapsulate forecasting methodologies in order to prevent a forthcoming crisis event and alert the end-users as well as it will be able to estimate the severity of the event. During the emergency phase, the Crisis Classification component will be able to real-time monitor the progress of an ongoing crisis event, fuse the heterogeneous information and assess possible decisions related to the severity level of the crisis and provide an overall risk assessment to authorities and decision makers.

In the following sections of this deliverable the designed architecture and methodological framework for Crisis Classification has been presented analytical. It is worth to note, that some of the modules of the system were already implemented in the content of first prototype of the system. So, the Early Warning component for all use cases has been deployed and is currently under evaluation and in the enhancement phase. Similar, a first version of a *Sensor Fusion* unit for *Real-Time Monitoring and Risk Assessment* module for the flood scenario is in the evaluation and refinement phase. The improvements as well as the development of the rest of the methodological framework are expected to be implemented and evaluated untill the 30th month of the project’s lifetime.

Abbreviations and Acronyms

AAWA	Alto Adriatico Water Authority
AHP	AUTO-HAZARD PRO
API	Application Programming Interface
ASR	Automatic Speech Recognition
ASR	Automatic Speech Recognition
BUI	Buildup Index
CRCL	CRisis CLassification
DC	Drought Code
DI	Discomfort Index
DMC	Duff Moisture Code
EFFIS	European Forest Fire information System
EMS	Emergency Management Services
FFMC	Fine Fuel Moisture Code
FL	Flood
FR	Fire
FRAPP	First Responders mobile application
FWI	Fire Weather Index
GIS	Geographical Information System
GML	Geography Markup Language
HEWS	Heatwave Early Warning System
HIRLAM	High Resolution Limited Area Model
.htm	Hypertext Markup Language (HTML)
HW	HeatWave
IMGAN	Image Analytics
IoT	Internet of Things
ISI	Initial Spread Index
KBS	Knowledge Base Service
Lat	Latitude
Long	Longitude
MTA	Multilingual Text Analysis
OCCI	Overall Crisis Classification Index
OGC	Open Geospatial Consortium
PFLCL	Predicted FLood Crisis Level
PFRCL	Predicted Fire Crisis Level
PHWCL	Predicted HeatWave Crisis Level
PSAP	Public Safety Answering Point
RS	River Section
S2S	sub-seasonal-to-seasonal
SCAPP	Citizen mobile application
SENSAN	Sensors Analytics
SMA	Social Media Analytics
VIDAN	Video Analytics

WL	Water Level
WS	Weather Station

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1 Introduction

Climate change refers to a change in the state of the climate that can be identified (e.g. by using statistical tests) and that persists for an extended period, typically for at least a few decades or longer (IPCC, 2013). Climate change can be caused by natural external forcings (e.g. modulations of the solar cycles and volcanic activity) and by anthropogenic forcings (e.g. changes in the composition of the atmosphere or in land use). There is strong evidence that currently observed changes in many climate variables, including extremes, can be attributed to anthropogenic climate change ((Hegerl & Zwiers, 2011); (Bindoff, et al., 2013); (Trenberth, Fasullo, & Shepherd, 2015); (Stott, et al., 2016)).

During recent decades Europe faced the increase in severity, duration and/or extent of many types of extreme weather- and climate-related events, and research indicates that under future climate change this trend will persist (Pachauri, R. K., Meyer, L. A., 2014); (EEA, 2017a); (EEA, 2017b). Particularly, global warming is projected to intensify the hydrological cycle and increase the occurrence and frequency of flood events (including pluvial floods and flash floods) in large parts of Europe; frequency, intensity, duration, and health impacts of heat waves will increase, especially in southern and south-eastern Europe; projected increases in heat waves, droughts, and dry spells will lead to expansion of the fire-prone areas and increase the duration and severity of fire seasons across Europe, mostly in southern Europe. According to the European Environment Agency, the total reported economic losses caused by weather- and climate-related extremes in the 33 EEA member states over the years 1980–2016 over EUR 450 billion (EEA, 2017b). The largest share of the economic impacts was caused by floods (approximately 40%), while heat waves were the deadliest, followed by flooding, landslides and forest fires.

The beAWARE project develops a decision-making support system for preventing and reducing the damages from floods, heatwaves and fires – key future risks in Europe caused by a changing climate, as defined in IPCC Fifth Assessment Report (Pachauri, R. K., Meyer, L. A., 2014). These risks of increased damages are already moderate (high confidence), and with an additional warming of 1°C will become high (medium confidence). Risks associated with extreme heat increase progressively with further warming (high confidence). The necessity of beAWARE is also evident from the two latest editions of Global Risks Reports (published by the World Economic Forum), where extreme weather events were ranked first among top 10 global risks in terms of likelihood and second in terms of impact, just behind weapons of mass destruction ((WEF, 2017); (WEF, 2018)). The beAWARE platform integrates state-of-the-art methodologies and technologies in order to obtain heterogeneous data from multiple resources, analyse and fuse them through intelligent reasoning mechanisms assisting the stakeholders (authorities, first responders, decision makers, etc.) alerting to a forthcoming extreme event (Early Warning phase), as well as managing the ongoing extreme crisis.

Among the other components of beAWARE platform, the **Crisis Classification** has conceived to encompass technologies in order to provide services into two directions: a) firstly, as an Early Warning System, it will notify the authorities and first responders to the upcoming extreme conditions such as the hazard of flood, fire or heatwave (pre-emergency phase); b) secondly, as a real-time monitoring and risk assessment system when a crisis is evolved, it will support local stakeholders, authorities and rescue teams to make accurate and timely decisions and actions.

The Crisis Classification system is designed to provide these two-folds functionalities in an innovative and beneficial manner. The proposed unified and holistic framework for crisis management encapsulates services and tools which cover the pre-emergency as well as the emergency phase providing important capabilities to stakeholders. Hence, the Early Warning module actively involve the communities at risk, facilitate and awareness of risk effectively disseminate alerts ensuring the preparedness. Furthermore, the Real-time Monitoring and Risk Assessment module enables to track and report constantly the evolvement of an ongoing extreme event classified its severity/risk. Another advantage is that the Crisis Classification system combines the fused heterogeneous information acquired from individual incidents or group of incidents. Finally, Crisis Classification is flexible to adapt and handle any type of crisis event, even a compound of extreme events in a multihazard scenario.

1.1 Outline

This document is structured as follows:

- Section 2. *Background and Related Work*: discusses the main concepts related to the Crisis Classification and briefly mentions the scientific achievements and state-of-the-art methodologies.
- Section 3. *User and Technical Requirements*: presents the requirements in technical as well as user layer of Crisis Classification system.
- Section 4. *Architecture*: exhibits the high-level architecture of the Crisis Classification system, the interactions with other internal and external modules of beAWARE framework and the integration approach.
- Section 5. *Methodological Framework*: presents analytical the methodological framework behind the Crisis Classification system and its modules.
- Section 6. *Conclusions and Future Plans:* outlines the main conclusions and presents briefly the future plans of the Crisis Classification system.

2 Background and Related Work

Before, we proceed with the analysis of the Crisis Classification architecture and methodological framework; it will be useful to present briefly the relevant background notions, approaches and methods that have been proposed in the field of decision support systems for crisis risk assessment focusing on the three use cases, namely the flood, fire and heatwave.

2.1 Decision Support Systems for Crisis Management

Crisis management is a dynamic, complex and multi-disciplinary process, consisting of consecutive sets of activities to collect information, analyse heterogeneous data, formulate alternatives, decision-making processes, implementation, and monitoring (Ezzeldin, 2014); (Prelipcean & Boscoianu, 2011). As authors state, an integrated framework for extreme risk analysis should include the following four steps (Prelipcean & Boscoianu, 2011):

1) ***Scenario formulation*** in which the collection and analysis of data related to hazards in terms of their possible origins, pathways, and mitigation are defined;
2) ***Extreme risk assessment*** in which the list of potential extreme events together with their exposure or vulnerability is formulated;
3) ***Extreme risk management*** in which the development of mitigation measures and procedures based on the output from the risk characterization should be carried out;
4) ***Communication*** by using a dedicated platform to enable a better understanding of the rationale behind the categories of risk assessment.

Furthermore, they conclude that in the modern literature a lot of applications are presented, procedures and activities capable to anticipate, prepare for, prevent and reduce different types of risks/losses associated to different type of crises, but there are only few integrated frameworks to deal directly with these extreme events. In this case, the decision maker needs technical assistance to support the decision making process before, during, and after extreme events (Prelipcean & Boscoianu, 2011). Moreover, towards in the direction to cover this gap, Ezzeldin proposed a conceptual framework for the information elements that should be included in any effective decision support system in crisis management unit (Ezzeldin, 2014). This framework, which contains five parts, can be a basis for understanding the nature of the decision support system in a crisis situation, as claimed by authors.

Generally, the concept of **risk** refers to the combination of the probability of a certain hazard to occur and of its potential negative impacts ((European, 2007); (FLOODsite, 2009); (UNISDR, 2009); (Prelipcean & Boscoianu, 2011))

$$\boldsymbol{R} = \boldsymbol{f}(\boldsymbol{H} \times \boldsymbol{V} \times \boldsymbol{E}) \quad (1)$$

where

- H denotes the hazard

- V denotes the Vulnerability
- E denotes the Exposure

Hazard (H): The hazard is the occurrence of the physical event, which can happen with a certain probability and intensity. The difference between the hazard and the disaster is that a hazard may not cause any negative impact (EEA, 2010).

Vulnerability (V): Vulnerability is defined as the susceptibility or predisposition for loss and damage to human beings and their livelihoods, as well as their physical, social, and economic support systems when affected by hazardous physical events. Vulnerability includes the characteristics of a person or group and its situation that influences its capacity to anticipate, cope with, resist, respond to, and recover from the impact of a physical event ((Schneider, et al., 2007); (Cardona, 2011) ; (Gaillard, 2010)).

Exposure (E): Exposure is defined in this report as the presence of people, livelihoods, environmental services and resources, infrastructure, and economic, social, and cultural assets in areas or places that are subject to the occurrence of physical events and that thereby are subject to potential future negative impacts ((UNISDR, 2009); (Gasper, 2010)).

The first two elements, hazard and vulnerability, are characterized by probability distributions, while the latter, exposure is measured in money. The result of R is an expected value measured in a monetary unit.

2.2 DSS for Flood Crisis Management

In the context of a natural disaster, the emergence of numerous Early Warning systems and specialised Decision Support Systems (DSS) plays an important role in assisting to reduce the risks resulting from the interaction of human societies and their natural environments. Especially floods can be classified among the most disastrous natural phenomena, since they can cause fatalities, severe damages to the environment and the economic development of the affected areas. Recognizing these negative aspects of flood crises the EU introduced the European Flood Directive 2007/60/EU which demands for the preparation of Flood Hazard and Risk Maps and finally Flood Risk Management Plans at the level of the river basin district from all Member States ((European, 2007); (Papathanasiou, Safiolea, Makropoulos, & Mimikou, 2009)).

By motivating this, remarkable scientific/research efforts have been made to develop Decision Support Systems dedicated to flood risk management, serving various aspects of decision options for prevention, mitigation, preparation, response and recovery from flood impacts ((Castellet, et al., 2006); (Albrecht, Jaap, & Frederiek, 2010); (Fotopoulos, Makropoulos, & Mimikou, 2010); (Demir & Krajewski, 2013); (Zhanming, et al., 2014); (Artinyan, et al., 2016); (Kauffeldta, Wetterhallb, Pappenbergerb, Salamonc, & Thielenc, 2016); (Muste & Firoozfar, 2016); (Linyao, Zhiqiang, Qing, & Yida, 2017)). In (Linyao, Zhiqiang, Qing, & Yida, 2017) a classification of these systems according to their functional roles has been proposed.

Currently, the majority of these emerged tools are not capable to provide an integrated and generalised framework for formulating decision options for crisis level estimation and risk assessment. Furthermore, the advances to the Internet of Things (IoT) as well as the increasing volume of heterogeneous data from multiple resources (mobile phones and Apps, sensing data, drones etc.) generate new capabilities and opportunities to timely alerting and tackling effectively an extreme weather or natural phenomenon. The authorities and decision makers should confront new challenges in flood risk management by operating in a holistic and interoperable framework combining data from multiple resources. Few efforts toward this direction have been made by proposing generalised platforms combining the flood risk management relevant science, such as Iowa Flood Information System – IFIS (Demir & Krajewski, 2013), FLOODSS (Muste & Firoozfar, 2016), Flood Disaster Management System - FDMS (Linyao, Zhiqiang, Qing, & Yida, 2017).

2.3 DSS for Fire Crisis Management

In the framework of fire, noteworthy efforts have been made towards to create Early Warnings and Decision Support Systems for fire crisis management. Specifically, a number of decision support GIS platforms have been developed which support wildfire prevention and/or control activities focusing on fire detection, fire weather, fire risk analysis and fire behaviour modelling ((Lee, et al., 2002); (Chuvieco, 2004); (Taylor & Alexander, 2006); (Fiorucci, Gaetani, & Minciardi, 2008); (Davies, Ilavajhala, Wong, & Justice, 2009); (Barber, et al., 2010)). The acquired knowledge from these systems enables fire protection agencies to spatially define and identify forecasted high risk areas and plan the necessary preventive and control actions (Taylor & Alexander, 2006). The Firementor system primarily focuses on the provision of services for decision and operational support in fire suppression (Markatos, Vescoukis, Kiranoudis, & Balatsos, 2007). AUTO-HAZARD PRO (AHP) is a decision support system for prevention planning and emergency management of forest fire events. The system encompasses functionalities for weather data management, geographical data viewer, a priori danger forecasting and fire propagation modelling, automatic fire detection, and optimal resource dispatching (Kalabokis, et al., 2012). The major limitation of the Firementor and AHP DSS is that they are not web-based applications. Opposing, WFDSS (Pence & Zimmerman, 2011) and European Forest Fire Information System - EFFIS (San-Miguel-Ayanz, Schulte, & Schmuck, 2012) operate through the web. WFDSS provides comprehensive, risk-informed decision making and implementation planning, while EFFIS aims to provide up-to-date, reliable, and harmonized information on forest fires during both pre- and post-fire phases at a European and Mediterranean level. Virtual Fire is a web-based platform which integrates advanced technologies, tools and protocols into a state-of-the-art web-based GIS application, to assist on early fire warning, fire control and coordination of firefighting forces (Kostas, Nikolaos, Fabrizio, & Fotis, 2013).

2.3.1 Fire Weather Indices

One of the main characteristic of the above DSS for fire risk management systems relies on the utilisation of indices that enable to estimate the fire danger. Here, a synopsis of the Canadian Forest Fire Weather Index, which is one of the most popular indices, is given:

Canadian Forest Fire Weather Index (FWI)

The Canadian Forest Fire Weather Index (Van Wagner, 1987) comprises six standard components. The first three are fuel moisture codes that follow daily changes in the moisture contents of three classes of forest fuel with different drying rates. The last three components are fire behaviour indexes representing rate of spread, fuel weight consumed, and fire intensity. The system depends solely on weather readings taken each day at noon local standard time (LST): temperature, relative humidity, wind speed, and rain during the previous 24 hours. A brief description of the six components is presented below (Lawson & Armitage, 2008):

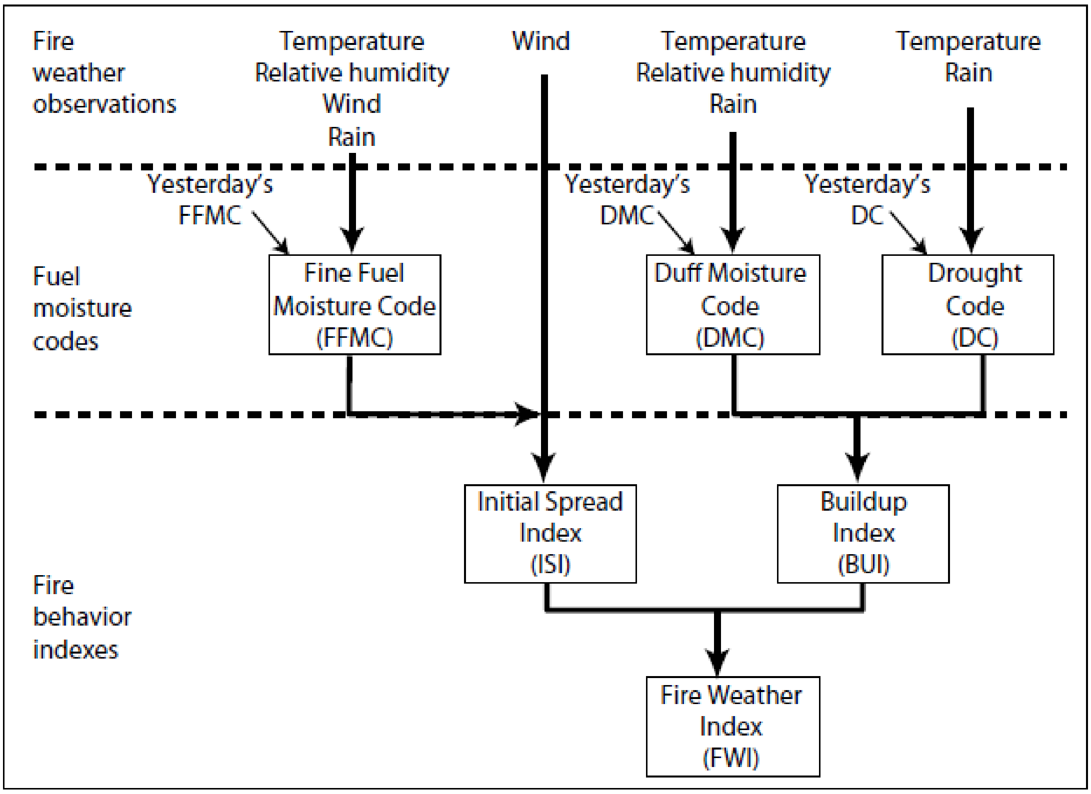

Figure 1: Structure of the Canadian Forest Fire Weather Index System

- The Fine Fuel Moisture Code (FFMC) is a numeric rating of the moisture content of litter and other cured fine fuels. The FFMC is an indicator of the relative ease of ignition and flammability of fine fuels.
- The Duff Moisture Code (DMC) is a numeric rating of the moisture content of loosely compacted organic (duff) layers of moderate depth. The DMC is an indicator of fuel consumption in moderate duff layers and medium-sized downed woody material.
- The Drought Code (DC) is a numeric rating of the moisture content of deep, compact organic layers. The DC is an indicator of seasonal drought effects on forest fuels and the amount of smoldering in deep duff layers and large logs.

The two intermediate fire behaviour indexes represent fire spread rate and amount of available fuel:

- The Initial Spread Index (ISI) is a numeric rating of the expected rate of fire spread, which combines the effects of wind and FFMC on rate of spread without the influence of variable quantities of fuel.
- The Buildup Index (BUI) is a numeric rating of the total amount of fuel available for combustion, which combines DMC and DC.

The final fire behaviour index, the Fire Weather Index (FWI), combines ISI and BUI to represent the intensity of a spreading fire as energy output rate per unit length of fire front.

EFFIS developed and utilised the FWI and categorised its value into 5 fire danger classes are defined with simple FWI thresholding, irrespectively of the fuel types (San-Miguel-Ayanz, Schulte, & Schmuck, 2012):

Table 1: FWI ranges defining the fire danger classes in EFFIS

FWI ranges	Fire Danger Class
< 5.2	Very Low
[5.2, 11.2)	Low
[11.2 – 21.3)	Moderate
[21.3, 38)	High
≥ 38	Very High

2.4 DSS for Heatwave Crisis Management

Heatwave Early Warning systems aim to reduce the human health consequences of heatwaves. These systems involve various functionalities including the forecasting the heatwave event, the prediction of possible health outcomes, the triggering of effective and timely response plans targeting vulnerable populations, the notification of heatwave events, the communication of messages and the evaluation and revision of systems ((Ebi, Teisberg, Kalkstein, Robinson, & Weiher, 2004); (Ebi, Kovats, & Menne, 2006); (Hajat, et al., 2010)). In Europe, the need to develop plans to effectively cope with extreme heatwaves events emerged after several devastating heatwave crisis events. Thus many countries implemented Heatwave Early Warning System (HEWS) as a risk reduction strategy aiming to reduce avoidable human health consequences of heatwaves through timely notification of prevention measures to vulnerable populations (Lowe, Ebi, & Fors, 2011). In (Lowe, et al., 2016) an Early Warning system exploiting the reliable sub-seasonal-to-seasonal (S2S) climate forecasts of extreme temperatures is proposed. The system aims to improve the exploitation of short-to-medium-term resource management and the incorporation into heat-health action plans aiming to protect vulnerable populations and ensuring access to preventive measures ahead of imminent heat wave events in Europe.

As heatwaves have significant impacts on both ecosystems and human beings, the scientific interest focuses on understanding the phenomenon including how heatwaves are measured; their driving mechanisms observed and projected changes, and quantifying the anthropogenic influence behind these changes. In review papers ((Zuo, Pullen, Palme, Bennetts, & Chileshe, 2015); (Perkins, 2015)) scientists attempt to present an overview of the advances that have been carried out to deal with these challenges.

3 User and Technical Requirements

The Crisis Classification system is designed and developed to serve the end users' needs and requirements as those have already been captured and extensively analysed in the deliverable D2.1[2]. Simultaneously, Crisis Classification system should obey and be aligned with the technological requirements of the beAWARE project which have been identified and outlined in the deliverable D6.2[3].

In the following tables (Table 2, Table 3, Table 4) a mapping between the technical and user requirements of Crisis Classification system per pilot are presented. Also, various colors present the degree of the readiness and maturity of the Crisis Classification system to meet these requirements. Thus, the yellow color indicates that the system is in basic/initial state to accomplish any requirement. On the other hand, the green color indicates that the CRCL is in mature condition to fulfill a specific requirement.

The first column lists the pilot following by the technical requirements number, name and description. The last two columns list the user requirement number and name.

[2] beAWARE deliverable *D2.1 Use Cases and Initial User Requirements*
[3] beAWARE deliverable *D6.2 Data-Source Integration Framework*

Table 2: Technical and User Requirements of CRCL in flood pilot

Pilot	TR#	TR name	TR description	UR#	UR name
Flood	TR_CRCL_01	Gather data from Weather Forecast Services	CRCL gathers meteorological data and forecasts from various resources.		
	TR_CRCL_02	Flood Forecasts	This TR provides reliable and trustful flood forecasts, potential dangerous situations and the forecasted level of risk to the authorities.	UR_102	Map of the AMICO Flood EWS results
				UR_116	Warning people approaching flood areas
				UR_118	River overtopping
	TR_CRCL_03	Estimation of river overtopping and generate warnings	Based on the forecast results automatic warnings on river levels overtopping some predefined alert thresholds will be generated and delivered to authorities.	UR_103	Flood warnings
				UR_116	Warning people approaching flood areas
				UR_118	River overtopping
	TR_CRCL_04	Forecast rainfall intensity and generate warnings	This TR enables authorities/citizens with the ability to know in real time if the rainfall intensity is overtopping predefined alert thresholds.	UR_122	Rainfall warnings
	TR_CRCL_05	Evaluation of the level of risk	The CRCL module evaluates the forecasted level of risks (based on all the available resources/dataset) and delivers appropriate messages to authorities.	UR_128	Evaluation of the level of risk

Table 3: Technical and User Requirements of CRCL in fire pilot

Pilot	TR#	TR name	TR description	UR#	UR name
Fire	TR_CRCL_06	Gather specific weather data	This TR aims to gather specific weather data of the Valencia place, as it has a specific microclimate that might be different from other places.	UR_206	Specific weather data
	TR_CRCL_07	Estimation of critical aspects and generate warnings	This TR is responsible to analyse the collected data (drought, air temperature and other weather aspects, fuel accumulation spots, crowds, etc.) in order to detect the following kind of situation, process, material or condition that can cause a wildfire or that could intensify its damaging impacts. The generated warnings will be forwarded to authorities/first responders.	UR_202	Detection of critical aspects
	TR_CRCL_08	Automatic detection system	The CRCL module will operate as an automatic detection system of the forest fire, which is able to analyse data based on all the available resources/datasets and provide predictions of the advancing fire.	UR_205	Analysis of advancing fire
				UR_218	Automatic detection system

Table 4: Technical and User Requirements of CRCL in heatwave pilot

Pilot	TR#	TR name	TR description	UR#	UR name
Heatwave	TR_CRCL_09	Heatwave forecasting and generate automatic warnings	CRCL module estimates the real time weather data providing to the authorities with forecasts regarding the progression of a heatwave phenomenon. The system will be able to predict the affected area in accuracy. Also, it is able to automatically generate and provide the authorities with an appropriate warning when an imminent heatwave phenomenon is forecasted.	UR_301	Real time weather forecast
				UR_302	Automatic warning
				UR_321	Affected area
	TR_CRCL_10	Risk assessment for a forest fire	CRCL assesses the fire risk of a forest based on weather forecast during or in the upcoming period after a heatwave. Also, it will generate the early warning messages to notify the authorities.	UR_303	Risk assessment for a forest fire
				UR_312	Warning citizens
				UR_338	Warnings
	TR_CRCL_11	Risk assessment for heatwave intensity	CRCL estimates the risk regarding the intensity of the imminent heatwave phenomenon in the city. The generated warnings will forward to the authorities automatically.	UR_304	Heatwave intensity
				UR_312	Warning citizens
				UR_338	Warnings

4 Architecture

In this section, a description regarding the position and role of the Crisis Classification component to the architectural schema of beAWARE platform is presented. The interoperability of Crisis Classification module with other beAWARE components, such as the SensorThings Server API, the Image/Video and Audio analysis component, the multilingual text analysis component, the social media component as well as the beAWARE mobile application is crucial for serving its goals. Furthermore, the interactivity aspects of the Crisis Classification module with external resources are exhibited.

4.1 Global View of Crisis Classification System

As extensively described in Deliverable D7.2[4] (Figure 2) consists of the four (4) layers: a) **Ingestion layer**, which contains the mechanisms and channels able to import data into the platform; b) **Internal services layer**, which is comprised of a set of technical capabilities which are consumed by different system components including services such as generic data repositories and communication services; c) **Business layer**, which contains the components that perform the actual platform-specific capabilities; d) **External facing layer**, which includes the end-users' applications and PSAP (Public-safety answering point) modules, interacting with people and entities outside the platform (end-users of the platform). The beAWARE platform will utilise innovative and state-of-the-art technological solutions in a cloud-based Service-Oriented Architecture (Wei & Blake, 2010; Petrenko, 2014). The components of the system are connected via Web Services to exchange data and messages via Message Bus.

The Business layer encompasses the components that empower the platform with specific analytical capabilities. A particular group of components in this layer tackles the analysis of different kinds of data flowing into the platform. A main aspect of the components in this category is the extraction of semantic information from various kinds of input data flowing into the platform from various different sources. Among this group we can find the following components:

- Social Media Analysis Services
- Image analysis
- Video analysis
- Automatic speech recognition - Audio analysis
- Sensor analysis

[4] *Delivarable 7.2* System requirements and architecture and D7.3 Integrated operational beAWARE platform, the architecture of beAWARE platform

These components help to determine the **Crisis Classification module** to drive the detection of crisis events generating early warnings and which leads in turn to meaningful decision support.

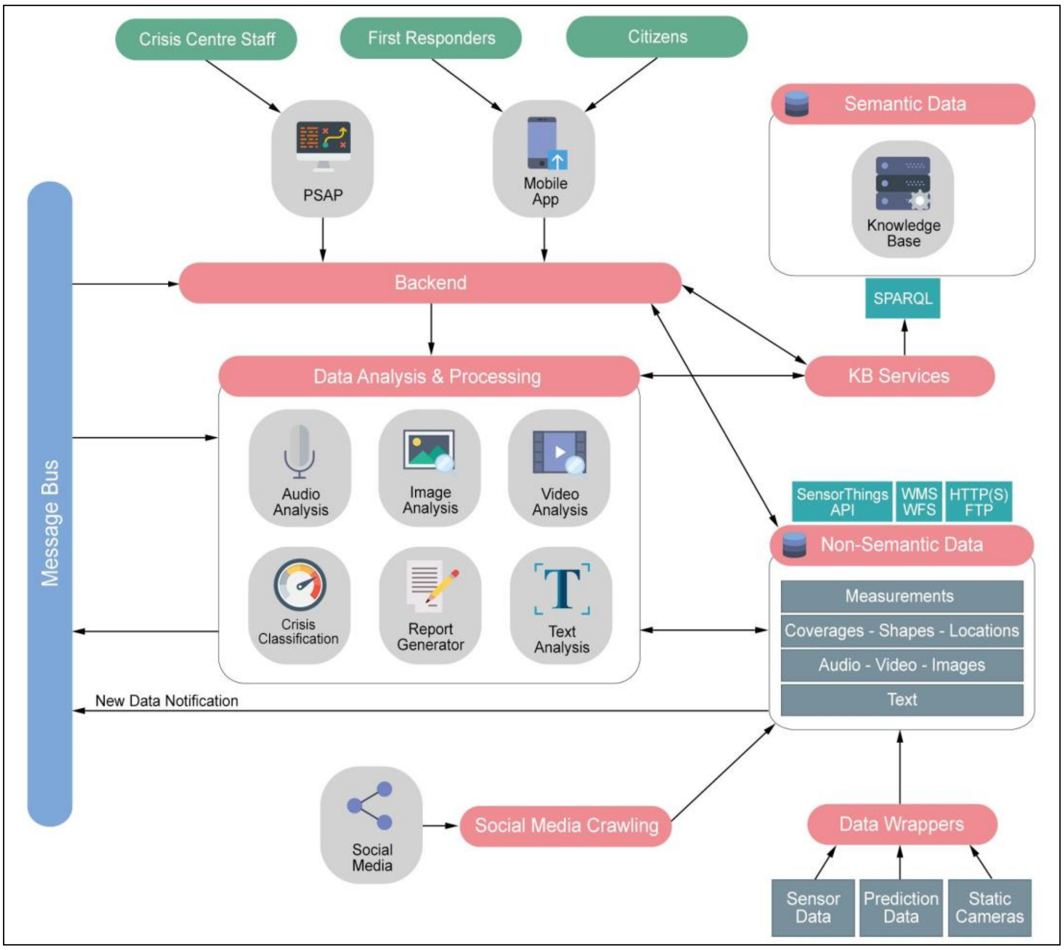

Figure 2: Architectural high-level view

The backbones components of the **Crisis Classification** system are (Figure 3):

a) The **Early Warning** component which is responsible to generate timely notification alarms for an imminent crisis event and assess its Overall Crisis Level for the whole region or subregions based on the forecast hydrological, hydraulic and weather data.
b) The **Real-time Monitoring & Risk Assessment** component which is able to assist authorities and local stakeholders to monitor the evolution of the crisis event by estimating its overall crisis level and its severity in order to make efficient decisions and timely actions. This module interacts with SensorThings Server API to grab real-time observations from the sensors located in sensing stations in the area of interest. Moreover, it ingests the results of the analysis, which are generated from other

beAWARE components, such as multimedia and textual analysis components, the social media component and the mobile app component aiming to provide an overall estimation of the crisis severity.

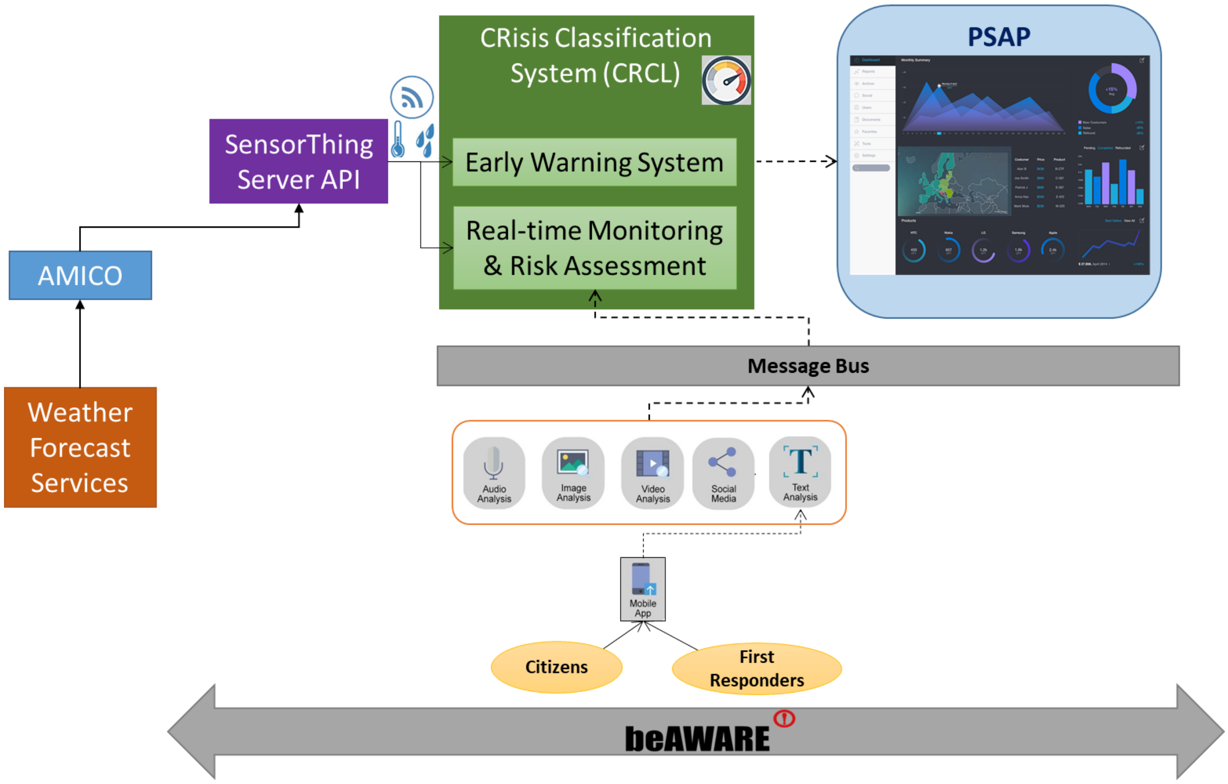

Figure 3: Architectural view of Crisis Classification component

The **Real-Time Monitoring and Risk Assessment** component consists of two modules:

a) *The **Sensor Fusion Module*** is responsible to collect sensing data and fuse them by employing information/data fusion methodologies. The input data are grabbed by sensors which measure various parameters such as water level, temperature, precipitation, humidity etc. Then the module combines the data in order to make inferences about the extreme crisis event and track its current situation. The outcome of this process is the *Observed Crisis Level* index enabling to assess real-time the severity level of the ongoing crisis event.

b) *The **Decision Fusion Module*** is enabled with functionalities to consolidate the information acquired from Sensor Fusion module (Observed Crisis Level) and from the analysis of others beAWARE modalities (Crisis Severity Level). Particularly, the estimated crisis severity levels from different modalities of beAWARE system are delivered to the current module which is empowered with state-of-the-art processes to fuse them and provide an overall crisis risk metric.

The reasoning behind this module is to employ all available information from heterogeneous resources, such as sensors, mobile phones and social media of citizens and first responders, in order to generate more accurate estimations regarding the crisis risk, supporting in this way the decision makers and other stakeholders.

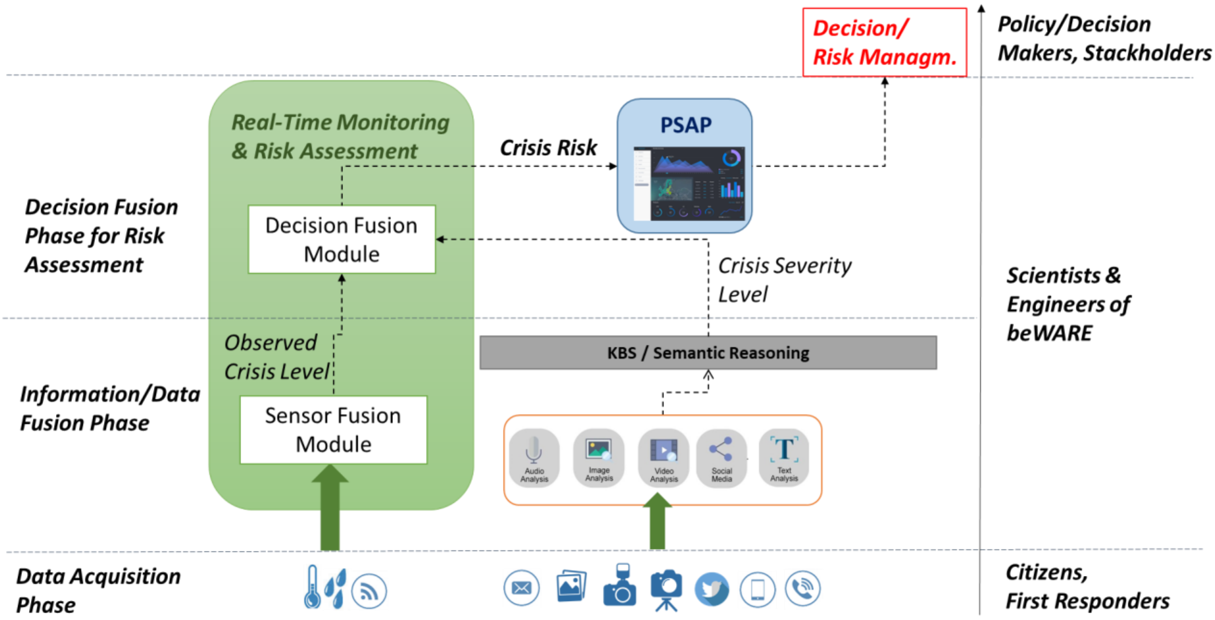

Figure 4: High-level architecture of Real-Time Monitoring and Risk Assessment component

In the following subsections a brief description of internal components of beAWARE which interact with Crisis Classification system is mentioned.

4.2 Internal Services

In this section, the internal components of beAWARE, which connect and interact with the Crisis Classification system will be mentioned briefly.

4.2.1 SensorThings Server API

Within the beAWARE platform, time-series of sensing quantities are accessed by using the OGC SensorThings API (Liang, Huang, & Khalafbeigi, 2016). This API defines a RESTful interface to access sensor data over HTTP in an on-demand fashion, with data encoded in the developer-friendly JSON format. It offers rich querying mechanisms to request relevant data, based on, for example, location of the feature of interest, time, type of sensor, and/or observed property.

The API offers explicit linking between entities, meaning that the JSON representation of an entity contains the (http) links to the related entities. This makes the API very developer friendly, since URLS are explicitly declared. A developer can point his web browser at the index of the server and get a list of all available entity types, with links where to find those entities. For instance:

https://beaware.server.de/SensorThingsService/v1.0/


```
{
  "value" : [ {
    "name" : "Datastreams",
    "url" : "https://beaware.server.de/SensorThingsService/v1.0/Datastreams"
  }, {
    "name" : "MultiDatastreams",
    "url" :
"https://beaware.server.de/SensorThingsService/v1.0/MultiDatastreams"
  }, {
    "name" : "FeaturesOfInterest",
    "url" :
"https://beaware.server.de/SensorThingsService/v1.0/FeaturesOfInterest"
  }, {
    <truncated for brevity>
  }, {
    "name" : "Sensors",
    "url" : "https://beaware.server.de/SensorThingsService/v1.0/Sensors"
  }, {
    "name" : "Things",
    "url" : "https://beaware.server.de/SensorThingsService/v1.0/Things"
  } ]
}
```


Following the link to Things will list all the “Things” available in the server: https://beaware.server.de/SensorThingsService/v1.0/Things

The data of each Thing links further to other entities. For instance, the Datastreams that are defined for a Thing can be found by following the link listed under “Datastreams@iot.navigationLink”. In turn, these Datastreams link further to the actual Observations. This linking principle makes it very easy to find out what data are offered by a server implementing the SensorThings API, without having to use special tools to query the service.

The data model of the OGC SensorThings API consists of 8 entities, with their properties and relations (see Figure 5). The entities are:

- **Thing**: A virtual or physical object. Depending on the use case this can be the object being observed, like a river section, or the sensor platform, such as a satellite.
- **Location**: The locations of Things. These can be geographic locations, encoded as points or areas, or symbolic locations, like a postal address.

- **HistoricalLocation**: the link between a Thing and a Location, with the time indicating when the Thing was in a certain Location.
- **Sensor**: A sensor that can generate data.
- **ObservedProperty**: A property of the feature of interest that is being observed by a sensor. For instance, the water level in a river, or the air temperature.
- **Datastream**: a collection of Observations of one ObservedProperty, made by one Sensor, and linked to one Thing.
- **Observation**: a measurement made by a Sensor.
- **FeatureOfInterest**: The geographic area or location for which an Observation was made. This can be the same as the Location of the Thing, which is often the case for in-situ sensing. In the case of remote sensing, the feature of interest can be different from the location of the Thing, depending on what is chosen as the Thing. The feature is a geographical point or a polygon encompassing an area or volume, usually encoded in GeoJSON.

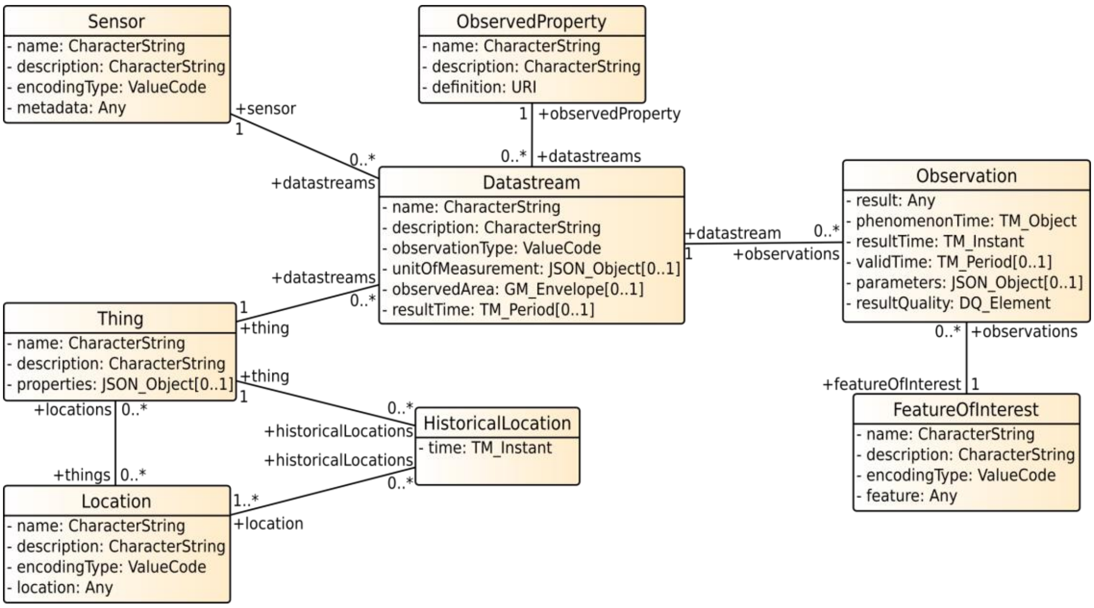

Figure 5: The OGC SensorThings API data model

The relations between these entities are also defined by the data model. Most relations are one-to-many: An Observation must have one FeatureOfInterest and one Datastream, while a Datastream and FeatureOfInterest can have zero or more Observations. A Datastream must have one ObservedProperty, one Sensor and one Thing, while a Thing, ObservedProperty and Sensor can have zero or more Datastreams. A HistoricalLocation must have one Thing, while a Thing can have zero or more HistoricalLocations.

The relations of Location are a bit more involved: A thing can have zero or more Locations, but these Locations must all be different representations of the same physical location. For instance, one geospatial location represented by GPS coordinates, and one symbolic location. A Location can have zero or more Things.

Each time a Thing is linked to a new Location (or set of Locations) a new HistoricalLocation is generated that tracks the time when the Thing was at this Location. A HistoricalLocation also has the restriction that if it has more than one Location, these Locations have to be different representations of the same real-world location.

In the beAWARE platform, an open-source implementation of the SensorThings API used, called FROST-Server [https://github.com/FraunhoferIOSB/FROST-Server] that is developed by Fraunhofer IOSB.

The Crisis Classification component extracts directly from the API the forecasted and observed data in order to exploit them in pre-emergency and emergency phase and assess the overall level of crisis risk in the district of interest, as furtherly explained in the methodological framework below.

4.2.2 Multimedia analysis component

Concept extraction from visual content (image/video), which is available from various resources such as social media, mobile application, drones (UAV cameras), Surveillance Cameras (CCTV), in the beAWARE project is supported by two separate components, namely Image Analytics component (IMGAN) and Video Analytics component (VIDAN). Currently, these have innovative modalities that include a fire and flood detection system integrated, as well as functions for detecting and estimating the severity related to the people and vehicles that are in danger.

For those tasks the image and video analysis components include several interoperable modularities that deploy an array of cutting-edge computer vision techniques, as described in more details in Deliverable D3.3[5]:

a) **Image classification** so as to determine **which images/video frames contain an emergent event or not** (i.e. a fire of flood event)
b) **Emergency localization** in order to detect the regions where fire and flood pixels exist in flood and fire pictures
c) **Object Detection** so as to **find people and vehicles that exist in the images/videos**.

Each one of them is assigned to process an image or a video frame separately from the others in order to decide about the existence of fire and flood concepts and objects that are

[5] *Deliverable D3.3*: Basic techniques for content distillation from multilingual textual and audiovisual material

of particular interest like people and vehicles and later locate their position inside the image. Then, a severity level estimation module is assigned with the task of deciding about the danger that the people and vehicles undergo based on their proximity to the emergent event.

The analysis result is saved in the KB, which updates the incident severity. The *Real-time Monitoring & Risk Assessment* module of Crisis Classification component utilises this information in order to generate an overall estimation of the risk in the region of interest, as described in more details in the methodological framework section.

4.2.3 Crisis events from UAV cameras

With advances in technology, drones can carry high resolution cameras and sensors and are able to capture aerial data in a safe and accurate way. Adding to the equation optimal route planning and autonomous flight capabilities adds the ability to capture valuable information about a specified area, from a different angle, including in locations which are difficult to access on the ground. Passing the information in the form of images and videos captured by the drone, to be analysed by the respective analysis component brings added value to the beAWARE system. To close the loop planned routes can be changed based on the results of the media analysis.

Building safe drone-based solutions involves numerous technical and scientific challenges, such as managing, provisioning, storing and analysing high volumes of data and possibly dynamically changing the route based on insights extracted from this data. Using programmatic autonomous drone piloting and route planning enables reliability, stability and accurate aerial coverage. In addition to the media images the platform is able to perform translation between object positions in imagery data to its GPS location.

The platform consists of a cloud and an edge component. The service which defines the configuration of the autonomous route planning is deployed on the cloud and interacts with an edge device which translates and executes the generic drone-agnostic commands into a specific drone that was chosen for the mission. The platform itself provides predefined services for common missions. In a standard area scanning mission, the service calculates the route, the positioning of the camera and the locations where imagery data should be captured. All the information if steamed to the edge and cloud in real time.

The ultimate goal of the use of the drones platform within beAWARE is to improve civilian lives by using an easy, accurate and safe way to capture aerial data and by extracting actionable insights from it.

Drones in beAWARE participate and abide by the overall architecture and communication guidelines. Media from the drone is stored in the platform object storage service, and a link to the stored media is published on the message bus to be received by all interested analysis components. Analysis components grab the files from the object storage and perform their analysis, similar with the analysis of image/video that mentioned in the previous subsection 4.2.2. If findings of interest ere determined by the media analysis components, results of the analysis are fed to the PSAP and in the future may be sent as feedback to the drones platform to adjust its route accordingly.

4.3 External Resources

In this section the external resources which connect and interact with the Crisis Classification system will be mentioned briefly.

4.3.1 Weather Forecast Models

HIRLAM (High Resolution Limited Area Model) is an operational synoptic and mesoscale weather prediction model. It is developed since 1985 by a consortium of meteorological institutes from Finland, Sweden, Norway, Denmark, Iceland, the Netherlands, Ireland, Spain, Estonia and Lithuania. Finnish Meteorological Institute (FMI) has a special status in HIRLAM, acting as the so called Lead Centre for the RCR (Regular Cycle with the Reference), which includes the special duty of running the official reference version of the HIRLAM model as its operational weather forecast model.

The HIRLAM model is a hydrostatic grid-point model, of which the dynamical core is based on a semi-implicit semi-Lagrangian discretisation of the multi-level primitive equations, using a hybrid coordinate in the vertical (Unden, et al., 2002)

Presently, HIRLAM model version 7.4 is in use, with horizontal resolution of 0.068 degrees, or 7.5 km. On the vertical, a 65 level structure is applied with the lowest model level at ca. 12 m. FMI produces four 54-hour regional forecasts per day for extended European area (Fig. 1). The model is initiated by the ECMWF boundary condition files.

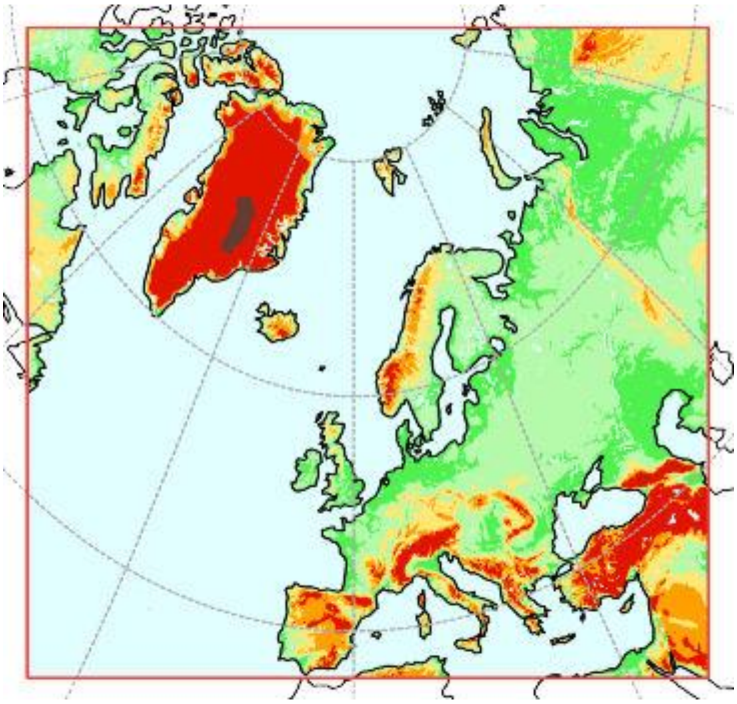

Figure 6: Integration area of RCR HIRLAM v7.4.

FMI's data sets are freely available for public use, including HIRLAM operational forecast data, which is updated four times a day with analysis hours 00, 06, 12 and 18. Corresponding model runs are available roughly five hours after analysis time (after a model run has started) and can be downloaded in gridded GRIB2 format either from FMI Open Data Download Service via API request[6] or from Amazon Web Services Simple Storage Service (AWS S3) buckets[7,8]. The data is licensed under the Creative Commons Attribution 4.0 International license (CC BY 4.0). Native HIRLAM grid projection is rotated lat-lon, with latitude of origin 30°S and central meridian 10°E. Several other projections are supported - EPSG:4326, EPSG:3995, and polar stereographic (latitude of origin 60°N, central meridian 0°E). These can be included in query when obtaining data from FMI Download Service. If projection is not specified, the native projection of data is used. Following parameters are available in the surface data: pressure, geopotential height, air temperature, humidity, dew point, horizontal wind components, precipitation (instant, 1h accumulation), cloud cover (total, low, medium, high), maximum wind speed, wind gust, radiation fluxes (accumulated global, long-, shortwave). Following parameters are available for pressure levels (1000, 925, 850, 700, 500, 400, 300, 250, 200, 100, 50 hPa): geopotential height, air temperature,

[6] currently only surface data is provided: **http://en.ilmatieteenlaitos.fi/open-data-manual-forecast-models**
[7] surface data bucket: **http://fmi-opendata-rcrhirlam-surface-grib.s3-website-eu-west-1.amazonaws.com/**
[8] pressure levels data bucket: **http://fmi-opendata-rcrhirlam-pressure-grib.s3-website-eu-west-1.amazonaws.com/**

humidity, dew point, horizontal wind components, velocity potential, pseudo adiabatic potential temperature.

4.3.2 AMICO Early Warning System for flood crisis

The Alto Adriatico Water Authority (AAWA) developed for the Veneto Regional Civil Protection the flood forecasting system, called AMICO, which is used to predict flood in the Bacchiglione River Basin ((Ferri, et al., 2012); (Mazzoleni, et al., 2017)).

AMICO is an operational semi-distributed hydrological and hydraulic model integrated in a modelling platform which is able to provide:

- Continuous Water balance simulation from the past to the now.
- Autocalibration and Data Assimilation.
- Flood forecast based on several weather forecast (LAMI, ECMWF, HIRLAM).
- Manual configuration of hydraulic structures.
- Data visualization on GIS.

The Veneto Regional Civil Protection uses AMICO results in order to publish reports before and during a flood emergency.

The system is based on a central database (ORACLE) on which all the data input for the different models are stored (parameters, geometry, etc.) and all the results of the different runs are saved to be viewed. The system is composed of several modules. A specific "Data Importer" continuously imports real time measured data and weather provisional data. The runner launches the different models in cascade and the results can be visualized by means of a viewer results module.

As part of the beAWARE platform, AMICO imports meteorological forecasts provided by FMI (HIRLAM), to be used as input for the Flood Forecasting Model. Then the model runs a hydrological-hydraulic simulation to obtain as results the time series of forecasted water level in each river section.

Each Flood forecast includes time series of forecasted water level for a set of river station. The forecasted water levels for each river sections are given by a time step of an hour and the time series covers up to 54 hours (HIRLAM's maximum horizon of forecast) from the data of emission.

This data entity is created by AMICO as link to three .htm, which contain the result of latest run in terms of time-series of forecasted water levels for each river section, and the main attributes of the modelled river sections (e.g coordinates, fixed threshold etc.); these data are provided as a response to an HTTP request to by SensorThings API Server and made available for the CRCL and the other beAWARE modules.

The result provided by the flood forecasting model are one of the main inputs of the crisis classification in the pre-emergency phase, as CRCL checks from AMICO's results which are imported in SENSAN. If the predicted water level exceeds some fixed thresholds in one or more river sections, then Crisis Classification module is able to estimate the severity level of the forecasted crisis. If this exceeding occurs, CRCL generates and proceeds early warning messages to PSAP in order to alert it for extreme weather conditions and dangerous situations before or during a flood crisis.

4.3.3 EFFIS

The European Forest Fire Information System (EFFIS) supports to the services in charge of the protection of forests against fire in the EU countries with reliable information on wildland fires in Europe. In 2015 EFFIS became one of the Emergency Management Services (EMS) in the EU Copernicus program (Copernicus EMS)[9]. The Copernicus EMS provides to all of its services involved in the management of natural disasters, man-made emergency situations, and humanitarian crises with timely and accurate geo-spatial information derived from satellite remote sensing and completed by available open data sources.

EFFIS under the Copernicus program aims to provide EU level assessments during pre-fire and post-fire phases, thus supporting fire prevention, preparedness, firefighting and post-fire activities. Furthermore, it provides harmonised data, methods and standards to complement national fire information systems. Specifically, EFFIS monitors forest fire activity in near-real time and archives historical information on forests fires in Europe, Middle East and North Africa. The EFFIS application[10] enables the user to view and query map layers, giving an indication of the fire situation across Europe for the current date and surrounding short term time frame. The application can also be used to view the situation in past years from 2014 since now. In 2007 the EFFIS network has adopted the Canadian Forest Fire Weather Index (FWI) system as the method to assess the fire danger level in a harmonized way throughout Europe. EFFIS operates using meteorological forecast data received daily from two systems, the European Center for Medium-Range Weather Forecast (ECMWF) and MeteoFrance.

CRCL extracts information through an FTP request from EFFIS using the ECMWF forecasts, downloading them in netCDF format. NetCDF (Network Common Data Form)[11] is a set of software libraries and self-describing, machine-independent data formats that support the creation, access, and sharing of array-oriented scientific data. Those files contain data of all the required measurements (i.e. duff moisture, drought, fine fuel moisture) for the Canadian

[9] http://www.copernicus.eu/main/emergency-management
[10] http://effis.jrc.ec.europa.eu/static/effis_current_situation/public/index.html
[11] https://www.unidata.ucar.edu/software/netcdf/docs/netcdf_introduction.html

FWI index (Van Wagner, 1974), as well as the FWI values and the estimated fire danger level for forecasting period of 10 days. Also each file contains the date of measurement which takes place and the latitude and longitude of the area that those values refer to, covering the entire European region.

4.3.4 PSAP

The Public Safety Answering Point (PSAP, provided by MSIL) is beAWARE's command and control module. PSAP is intended to oversee the entire emergency management effort and support the work of the Emergency Operations Center[12]. The PSAP is intended for deployment in central authorities that oversee the emergency management in each one of the beAWARE operational scenarios:

- The Vicenza Municipality and AAWA Situation Room for the Flood Scenario.
- The Valencia Local Police (PLV) for the Forest Fire Scenario.
- The Hellenic Rescue Team Control Center in Thessalonii for the Heatwave Scenario.

As such, it is meant to provide critical information to decision makers, emergency managers, and operators before and during an emergency, with special attention to the specific needs of the operational stakeholders.

The PSAP receives the following types of information:

- Incident reports, after synthesis by the KBS, based on incident reports originated by the citizens through the beAWARE mobile app, social media (twitter), and analysed by the media analytic services, social media analyser and Multilanguage report generator.
- Team reports, including team position and status from the first responder mobile app.
- Metric reports, obtained from Crisis Classification module, including measurements (observations or forecasts) pertaining to data series.

The PSAP provides information to the human operators in the following interfaces:

- A dashboard, which shows various data streams in various visualization modes, such as gauges, plots, bar-charts, line charts, and traffic lights.
- An event map, showing the locations of incidents, teams, and position-based measurements

In addition, PSAP allows the operator to manually send alerts to the public based on predefined templates, regarding general warnings or specific incidents taking place or about to take place.

[12] *beAWARE Deliverable D6.1*: Research results for advanced visualisation and interaction techniques for enhanced situational awareness

PSAP's API for metric reporting consists of a special metric reports topic supported by IBM's Message Hub. The structure of the topic allows for receiving measurement data, organized in data streams[13].

The Crisis Classification module uses the metric reporting interface to send measurements to the PSAP. Each message contains one measurement. The PSAP collects and stores the data, displays position-based measurements (i.e., measurements that are associated with data streams that have positions) on the map, and adds the measurements to metric displays in the dashboard. The layout of the dashboard is determined inside the PSAP according to user needs and requests regarding the visualization of the available incoming data streams.

4.4 Integration Approach

The Crisis Classification System is designed to merge into the beAWARE platform and operate seamlessly and continuously by exploiting the forecasting data in order to warn the authorities and other stakeholders for an upcoming extreme event. Basically, the *Early Warning* module every hour will check for new forecasting values and it will be triggered every time when new data is available to the beAWARE ecosystem. In other words, the Early Warning module will be up and running since the installment and customization of the beAWARE platform to the region of interest.

On the other hand, the *Real-Time Monitoring and Risk Assessment* component will be activated by one of the two options:

a) when the predicted date/time of extreme weather events reaches
b) when the PSAP is launched. Authorities will have received the alarm notification from the *Early Warning* module for an imminent extreme event at particular date/time and will activate the PSAP in that time.

It is worth to note that the first option is recommended and favorable for the rational utilisation of the system resources (i.e. data storages, I/O processes etc.). The *Real-Time Monitoring and Risk Assessment* component will store the observed data in beAWARE databases. Hence, the accumulation of insignificant information should be avoided.

[13] *beAWARE Deliverable D6.2*: Data Source Integration Framework prototype

5 Methodological Framework

In order to achieve the objectives of Crisis Classification system, a methodological framework is proposed, which integrates and combines data and information available from multiple and heterogeneous resources serving the needs of the use cases (flood, fire and heatwave). It is worth mentioning that the proposed methodological framework can be extended to cover all potential extreme natural crisis events.

Depending on the particular goals, purposes and needs for data of each pilot, the Crisis Classification system slightly modifies its behaviour and functionality. For instance, in order to predict the upcoming flood crisis, CRCL module operates as an Early Warning System which is able to collect hydraulic and hydrological forecasting data for river water level from the AMICO system and generate appropriate messages in terms of the level of crisis. In the following sections a detailed description of the beAWARE methodological framework would is exhibited.

5.1 Crisis Classification as Early Warning System

The main goal of the Crisis Classification system in the pre-emergency phase is to employ and aggregate the available forecasts so as to estimate the crisis level of the forthcoming event. Furthermore, it generates the appropriate warnings aiming to timely notify the authorities and first responders.

5.1.1 Flood

In the Flood use case, the Crisis Classification module will be triggered every time in which new forecasting data will be available, usually every 6 hours. As mentioned above, these forecasts, which are generated by AMICO system and are stored to the SensorThings API Server, indicate the predicted Water Level over 304 River Sections in the Vicenza district (Figure 7). The Crisis Classification module grabs this data by requesting them from the SensorThings API Server. Moreover, for each River Section a list of predefined Alarm Thresholds is extracted and inserted into the Crisis Classification module.

Figure 7: Overview of 304 River Sections in Vicenza district

The pre-emergency Crisis Classification algorithm consists of the following steps:

Step 1. For each River Section, a comparison of the predicted Water Level (WL) with its predefined Alarm Thresholds is executed. For the i-th river section a simple rule below is applied:

If $WL_i < AlarmThreshold_1$ **Then Scale$_i$ = 1**

ElseIf $AlarmThreshold_1 \leq WL_i < AlarmThreshold_2$ **Then Scale$_i$ = 2**

ElseIf $AlarmThreshold_2 \leq WL_i < AlarmThreshold_3$ **Then Scale$_i$ = 3**

ElseIf $AlarmThreshold_3 \leq WL_i$ **Scale$_i$ = 4**

Step 2. For all the River Sections the **Overall Crisis Classification Index (OCCI)** is calculated by performing the follows:

i. Define the cardinality of each scale category, $\boldsymbol{Counts} = [\boldsymbol{N_1}, \boldsymbol{N_2}, \boldsymbol{N_3}, \boldsymbol{N_4}]$ where $\boldsymbol{N_1}$ denotes the number of river sections in which their scale is equal to 1, $\boldsymbol{N_2}$ is the number of river sections with scale 2 and so on. The summation of these cardinalities is equal to N.

ii. Using the following formula (2), the **OCCI** indicators is calculated as a generalised (power) mean with power p=4:

$$OCCI = \left\lceil \sqrt[p]{\left(\frac{N_4\,4^p + N_3\,3^p + N_2\,2^p + N_1\,1^p}{N}\right)} \right\rceil \quad (2)$$

where

$N = N_1 + N_2 + N_3 + N_4$ denotes the total number of river sections
$p = 4$ (Default value) indicates the different categories of the scale
$\lceil . \rceil$ denotes the upper bound

Step 3. Calculate the **Predicted Flood Crisis Level (PFLCL)** as follows:

If OCCI = 1 (meaning that the WL for all river sections are below AlarmThreshold$_1$) **Then**

Predicted Flood Crisis Level = 1

ElseIf OCCI = 2 AND $\nexists\ river\ section\ r :\ Scale_r = 4$ **Then**

Predicted Flood Crisis Level = 2

ElseIf OCCI = 2 AND $\exists\ river\ section\ r :\ Scale_r = 4$ **Then**

Predicted Flood Crisis Level = 2+

ElseIf OCCI = 3 AND $\nexists\ river\ section\ r :\ Scale_r = 4$ **Then**

Predicted Flood Crisis Level = 3

ElseIf OCCI = 3 AND $\exists\ river\ section\ r :\ Scale_r = 4$ **Then**

Predicted Flood Crisis Level = 3+

ElseIf OCCI = 4 Then

Predicted Flood Crisis Level = 4

The Predicted Flood Crisis Level can be considered as a general metric-index in which the Water Level forecasts over the river sections would be encapsulated, empowering the capacity of the CRCL system to classify an imminent flood event.

5.1.1.1 **Predicted Flood Crisis Level per group of River Sections**

A modification of the above algorithm has been also proposed aiming to maximize the accuracy and estimation of the crisis level and providing the flexibility to the authorities to handle in different manner the river sections which are more significant to the population. Motivated by this, the River Sections have been clustered into 6 main groups, defined by domain experts (authorities, etc.). The distribution of river sections per group is shown in the following figure (Figure 8).

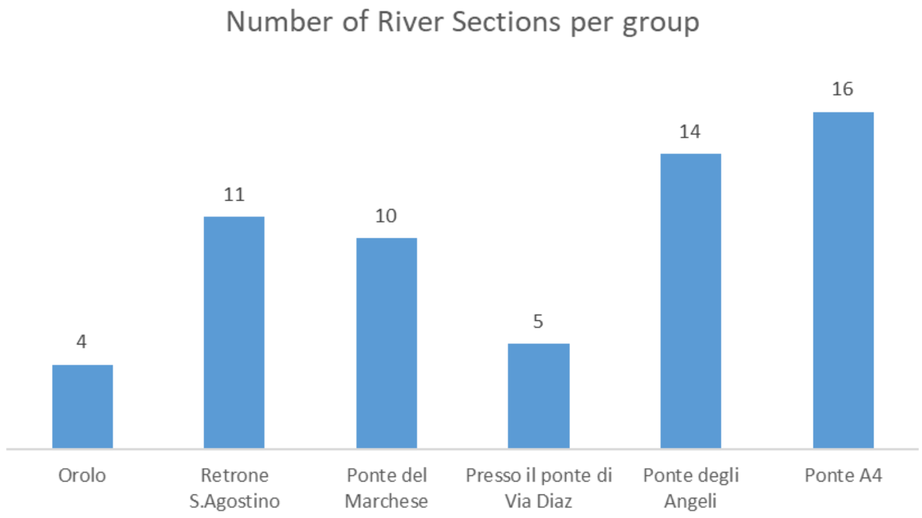

Figure 8: Distribution of River Sections per Group

The modified algorithm differs from the above algorithm to the 2nd and 3rd step, as in the 1st step the algorithm should estimate the scale of water level in each river section. Particularly, it calculates the Overall Crisis Classification Index and Predicted Flood Crisis Level per group of river sections.

Step 2b. For each group of River Sections (k=1,…,6) the **Overall Crisis Classification Index (OCCI)** is calculated as follows:

i. Define the number of river sections which belong to each one of the scale categories (1, 2, 3 and 4). Let's suppose that $\mathrm{Counts_k} = [\mathrm{n_{1k}, n_{2k}, n_{3k}, n_{4k}}]$ presents a list of categories' cardinality in the k-th group of river sections. $\mathrm{n_{ik}}$ denotes the number of river sections which classified to scale *i*, where *i*=1, … ,4.
ii. Calculate the $OCCI_k$ using the generalized (power) mean with power p=4 by the following formula:

$$\boldsymbol{OCCI_k} = \left\lceil \sqrt[p]{\left(\frac{n_{4k}\,4^p + n_{3k}\,3^p + n_{2k}\,2^p + n_{1k}\,1^p}{n_{*k}}\right)} \right\rceil \qquad (3)$$

where

$n_{*k} = n_{1k} + n_{2k} + n_{3k} + n_{4k}$ denotes the cardinality of the k-th group, number of river sections that belong to the k-th group
$p = 4$ (default value)
$\lceil . \rceil$ is the upper bound

Step 3b. For each group of River Sections (k=1,…,6) the CRCL module calculates the **Predicted Flood Crisis Level per group** ($PFLCL_k, k = 1, \dots, 6$) based on the above Step 3.

Step 4b. In order to estimate the overall **Predicted Flood Crisis Level** for the whole region of interest, CRCL module aggregates the corresponding flood crisis level of each group taking under consideration the significance of each group.

Let assume that $0 \leq W_k \leq 1,\ k = 1, \cdots, 6$ denotes the significant level of the k-th group of river sections, where the maximum value of a weight ($W_k = 1$) presents the highest significance. The lower significance could be 0 which indicates that the particular group does not play any importance role when it is flooded. Thus, the overall **Predicted Flood Crisis Level** for the region of interest can be estimated by the weighted average over the groups Predicted Flood Crisis Levels:

$$\boldsymbol{PFCL} = \frac{\sum_{k=1}^{6} W_k \times PFCL_k}{\sum_{k=1}^{6} W_k} \qquad (4)$$

5.1.2 Fire

In the Fire use case, the Crisis Classification module will be triggered every time in which new forecasting data from EFFIS will be available. These data, which are provided in the netCDF format, map daily of 1 to 10 days the forecasted fire danger level using numerical weather predictions. In the framework of beAWARE project the Canadian Forest Fire Weather Index (FWI) is employed in order to anticipate the fire danger in seven (7) pre-defined points of interest (Figure 9). The first five (5) points are arbitrary chosen around the Parc Natural de l'Albufera in Valencia district. The other two points are located into a popular and crowded area which contains restaurants, camping and other infrastructures (Table 5).

Table 5: Points of Interest around the Parc Natural de l'Albufera in Valencia district

Name	Latitude	Longitude
Sueca	39.30394	-0.31038
Sollana	39.25350	-0.37901
Silla1	39.34060	-0.39512
Silla2	39.36415	-0.37133
Catarroja	39.37183	-0.35057
El Saler	39.35517	-0.32047
Les Gavine	39.38690	-0 .33149

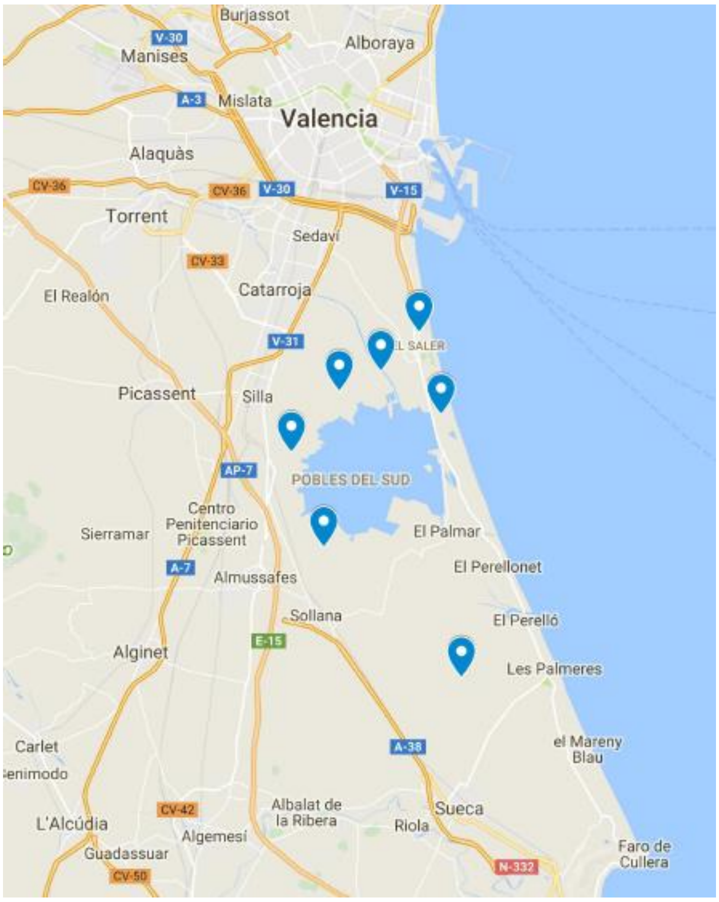

Figure 9: Points of Interest around the Parc Natural de l'Albufera in Valencia district

To anticipate the fire danger on those preset points, the Early Warning module of the Crisis Classification system applies an interpolation algorithm. The aim is to estimate the Fire Weather Index (FWI) of the points of interest by utilising the FWI values over a district set of points. Those values are stored into the netCDF files obtained from EFFIS system. The interpolation algorithm is follows:

Step 1. For each point of interest, find an adjoin point for which an estimation of the Fire Weather Index exists. As an example, in the following figure (Figure 10) the neighbor point of 'Sollana' point of interest (green pin) with label 22.

Step 2. For this adjoin point, define the district set of points for which the FWI value has been estimated. In the example below (Figure 10) the algorithm defines a set of 36 grid points.

Step 3. Extract the Fire Weather Index (FWI) values for all the grid points and apply a piecewise 2D cubic, continuously differentiable interpolation algorithm.

Step 4. Set the interpolant value as a Forest Fire Weather Index for a point of interest. The above steps is performed sequentially for each one of the seven points of interest in order to estimate the Fire Weather Index over the forecasted period of 10 days.

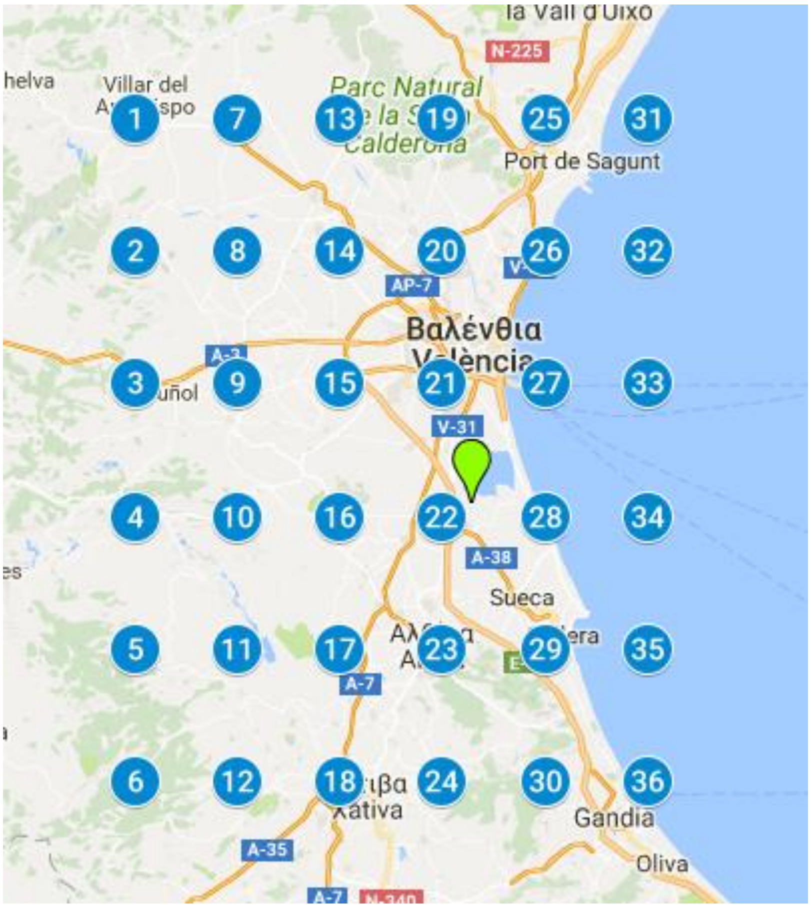

Figure 10: District set of interpolation points for 'Sollana' point of interest (green pin)

Step 5. Then, Crisis Classification module classifies each FWI value into one of the 6 danger levels in which the specific index is divided (Table 6). It is worth to note, that the specific danger classes are proposed by the EFFIS over Europe. However, it is possible to re-calibrate the FWI classes for a specific region by utilised a freely available R software called CALIVER[14], as described in (Vitolo, Di Giuseppe, & D'Andrea, 2018)

Table 6: The fire potential scale of FWI

Fire Weather Index ranges	Fire Risk	*Color*
< 2	Very Low Danger	
[2, 6)	Low Danger	

14 https://github.com/ecmwf/caliver

[6, 13)	Moderate Danger	
[13, 26)	High Danger	
[26, 48)	Very High Danger	
>= 48	Extreme Danger	

Step 6. After that, Crisis Classification module calculates the overall fire crisis level which is estimated for each day taking under consideration all the predicted FWI values over all the points of interest, into the particular day. Thus, the following formula is employed:

$$PFRCL_d = \left[\sqrt[p]{\left(\frac{n_{6d}\, 6^p + n_{5d}\, 5^p + n_{4d}\, 4^p + n_{3d}\, 3^p + n_{2d}\, 2^p + n_{1d}\, 1^p}{n_{*d}} \right)} \right] \quad (5)$$

where:

- PFRCL indicates the Predicted Fire Crisis Level. It takes discrete values between 1 to 6.
- p is set to 6, due to the fact that the FWI index as well as the PFRCL divided to 6 district categories
- n_{id} denotes the cardinality of the i-th category of Fire Risk in d-th day
- $n_{*d} = n_{1d} + \ \dots + \ n_{6d}$ denotes the total number of instances. In our case, $n_{*d} = 7$

The Early Warning Crisis Classification module generates alerts and forwards them to the PSAP every time a fire condition is estimated, meaning that the FWI in any point of interest is classified as "High Danger" or higher. Furthermore, it assesses the overall fire danger per day and notifies the authorities sending appropriate messages if it is needed (greater than ‘High Danger’ category).

5.1.3 **Heatwave**

In the Heatwave use case, the Crisis Classification module will be triggered every time in which new forecasting weather data which are generated by HIRLAM model will be available. Early Warning Crisis Classification module is able to obtain these data by request them from FMI Download Service. In order to facilitate the goals of the analysis, six (6) points have been chosen by covering a wide range at Thessaloniki district and attempting to take under consideration the potential differences to climate conditions of those areas. The names and coordinates (lat/lng) of each point is presented in the following table (Table 7) and corresponding figure (Figure 11).

FMI provides forecasts for a series of weather parameters in the surface data such as Air Temperature, Humidity, Pressure, Geopotential height, Dew point, Wind Speed, Direction and Gust, Precipitation (instant, 1h accumulation), cloud covering are among the others. The forecasts values are updated every six (6) hours and provided for a time slot of 55 hours ahead. It is worth to note that the extracted data are available in the Geography Markup Language (GML) text file format, which is an XML grammar defined by the Open Geospatial Consortium (OGC) to express geographical features. GML serves as a modeling language for geographic systems as well as an open interchange format for geographic transactions on the Internet[15].

Table 7: Points of Interest in Thessaloniki district

Name	Latitude	Longitude
Euosmos	40.66428	22.89838
Aristotelous Sq.	40.63290	22.94040
Faliro	40.61978	22.95799
Kostantinoupolitika	40.61134	22.99218
Thermi-Xortiatis	40.58137	23.09799
Airport	40.51435	22.98664

[15] https://en.wikipedia.org/wiki/Geography_Markup_Language

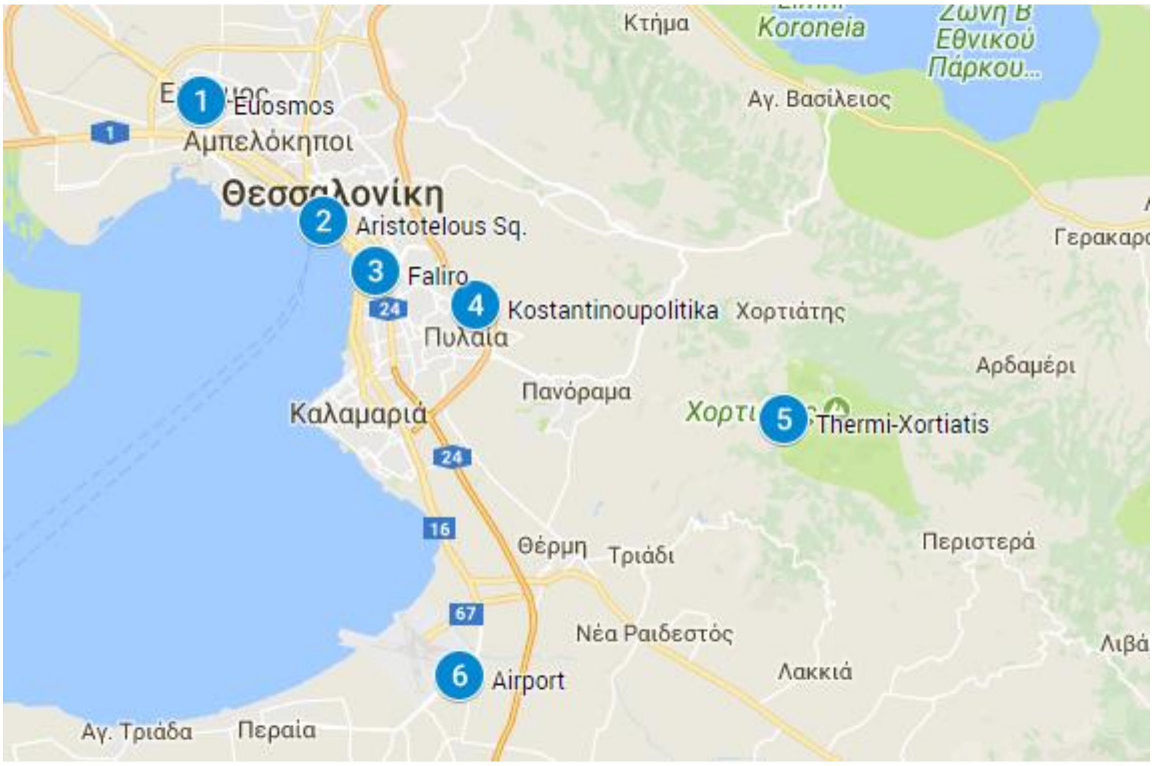

Figure 11: Map of points of interest in Thessaloniki region

The Early Warning module of Crisis Classification system utilises the hourly predictions for Air Temperature and humidity and estimates the Discomfort Index (DI) for each one of the points of interest. Furthermore, it attempts to anticipate the overall heatwave crisis level per day combining the estimations of Discomfort Index as described in the following algorithm:

Step 1. For each point of interest, acquire forecasts hourly data for temperature and humidity

Step 2. Calculate the Discomfort Index per hour over all points of interest using the formula:

$$DI = T_a - 0.55 * (1 - 0.01 * RH) * (T_a - 14.5) \qquad (6)$$

where:

- T_a is the hourly average of air Temperature (°C)
- *RH* is the Relative Humidity (%)

Discomfort index is one of the outdoor thermal comfort indexes that determine the human discomfort level based on the combination of ambient temperature and relative humidity ((Angouridakis & Makrogiannis, 1982); (Md Din, et al., 2014)). The Thom's discomfort index (DI) (Thom, 1959) was used to measure the degree of human discomfort for the selected locations by the evaluation of how current temperature and relative humidity can affect the discomfort sensation and cause health danger in the population. It is divided into a discomfort sensation scale of six (6) levels, as shown in the Table 8

Table 8: Interpretation of Thom's Discomfort Index[16]

DI (°C)	*Condition*	*Color*
Up to 21°C	**No discomfort**	
[21°C, 24°C)	**Less than half population feels discomfort**	
[25°C, 27°C)	**More than half population feels discomfort**	
[28°C, 29°C)	**Most population feels discomfort** and deterioration of psychophysical conditions	
[30°C, 32°C)	The whole population feels an **Heavy Discomfort**	
Over 32 °C	Sanitary emergency due to the **Very Strong Discomfort** which may cause heatstrokes	

Step 3. Aggregating the DI estimations of the above step, the assessment of the heatwave overall crisis level, namely **Predicted HeatWave Crisis Level** (**PHWCL**), can be calculated using the following formula:

$$PHWCL_d = \left[\sqrt[p]{\left(\frac{n_{4d}\,4^p + n_{3d}\,3^p + n_{2d}\,2^p + n_{1d}\,1^p}{n_{*d}} \right)} \right] \quad (7)$$

where

- p = 4 indicates the number of categories (scale = 1,..,4) of the PHWCL index
- n_{id} is the cardinality of the i-th category of index in d-th day
- $n_{*d} = n_{1d} + n_{2d} + n_{3d} + n_{4d}$

It is worth to mention, that due to the fact that the Crisis ClassificationSystem should alert the authorities for the upcoming heatwave crisis, the most interesting classes to be considered are those which affect most of the population feeling discomfort and deterioration of psychophysical conditions. Thus, DI classes below this threshold can be merged and the new categories for the PHWCL index are described in the following table (Table 9):

[16] http://www.eurometeo.com/english/read/doc_heat

Table 9: Interpretation of PHWCL index

DI (°C)	*Condition*	*PHWCL Categories*
Up to 21°C	**No discomfort**	**Warm (1)**
[21°C, 24°C)	**Less than half population feels discomfort**	
[25°C, 27°C)	**More than half population feels discomfort**	
[28°C, 29°C)	**Most population feels discomfort** and deterioration of psychophysical conditions	**Hot (2)**
[30°C, 32°C)	The whole population feels an **Heavy Discomfort**	**Very Hot (3)**
Over 32 °C	Sanitary emergency due to the **Very Strong Discomfort** which may cause heatstrokes	**Extreme (4)**

The Early Warning Crisis Classification module generates notifications and forwards them to PSAP every time where an imminent heatwave event has impact on the most of the population. Additionally, it assesses the overall heatwave crisis level per day and notifies the authorities sending appropriate messages if needed (greater than “Hot” category).

5.2 Crisis Classification as DSS and Risk Assessment System

The objectives of *Real-Time Monitoring and Risk Assessment* component of Crisis Classification system are to identify, track and classify crisis events into levels of severity based on data acquired from heterogeneous data sources. Crisis Classification system should fuse and analyse this information to support authorities and local stakeholders during the risk assessment as well as during the decision making process.

To achieve the above goals, the system has been equipped with functionalities and capabilities to collect multiple types of data and information related with the crisis during the emergency phase. Specifically, sensing data from weather stations as well as aggregated data from other beAWARE's components[17] would be available to CRCL system for assessment the risk and classify the crisis. Thus, a proposed holistic multimodal fusion approach considers the analysis results from multimedia analysis, including image (IMGAN), video (VIDAN) and audio (ASR) components, multilingual text analysis (MTA) component, mobile applications from citizens (SCAPP) and first responders (FRAPP) as well as social media (SMA) component and encompasses with real-time sensory data.

The *Real-Time Monitoring and Risk Assessment* component is divided into two phases: a) Information/Data Fusion phase and b) Decision Fusion phase for Risk Assessment. In the former phase, methodologies of information/data fusion will be employed aiming to combine the sensory real-time data and result in reliable estimates regarding the crisis level. In the latter phase, methods and techniques are conceived and employed for exploiting the synthesis of the decisions, which are obtained based on individual beAWARE modalities. The goal is to make a fused decision which is analyzed further to obtain a final decision about the risk of ongoing crisis event.

In the following section, the methodological approach is specialized to the flood use case, but similar approaches will be utilised for the other two pilots, namely fire and heatwave. Slightly variations could be occurred depending on the modalities that employed in each case. For example, instead of sensors, which are used in flood pilot, the images and videos from drones will be employed in the fire pilot. However, the methods for the assessment the risk will be similar.

5.2.1 Flood

In the content of flood use case the *Real-time monitoring and Risk Assessment* component will be triggered when the new data from physical sensors are available to use or when the PSAP is activated. The Sensor Fusion Module aims to fuse the acquired data from sensors

[17] Hereinafter, the terms 'component' and 'modality' will be used interchangeably having the same meaning.

employing information fusion methods. The result of this process indicates the observed level of flood crisis and assists to monitor the state of the ongoing crisis. Moreover, it proceeds to the next unit and encompasses with the outcome of the analysis of other modalities resulting in a general overview of the flood crisis risk. In the following subsections, the above process is further described.

5.2.1.1 Flood crisis level evaluation from sensors

Sensors are established in weather stations in the Vicenza district (Figure 12), providing hourly measurements regarding weather parameters like air temperature, humidity, precipitation as well as for the river Water Level. In this use case, the CRCL system exploits the measurements of water level by the sensors in specified weather stations and rainfall intensity from rain gages. The measurements are stored periodically to the SensorThings Server API enabling the seamless acquisition process of the new measurements by the CRCL system.

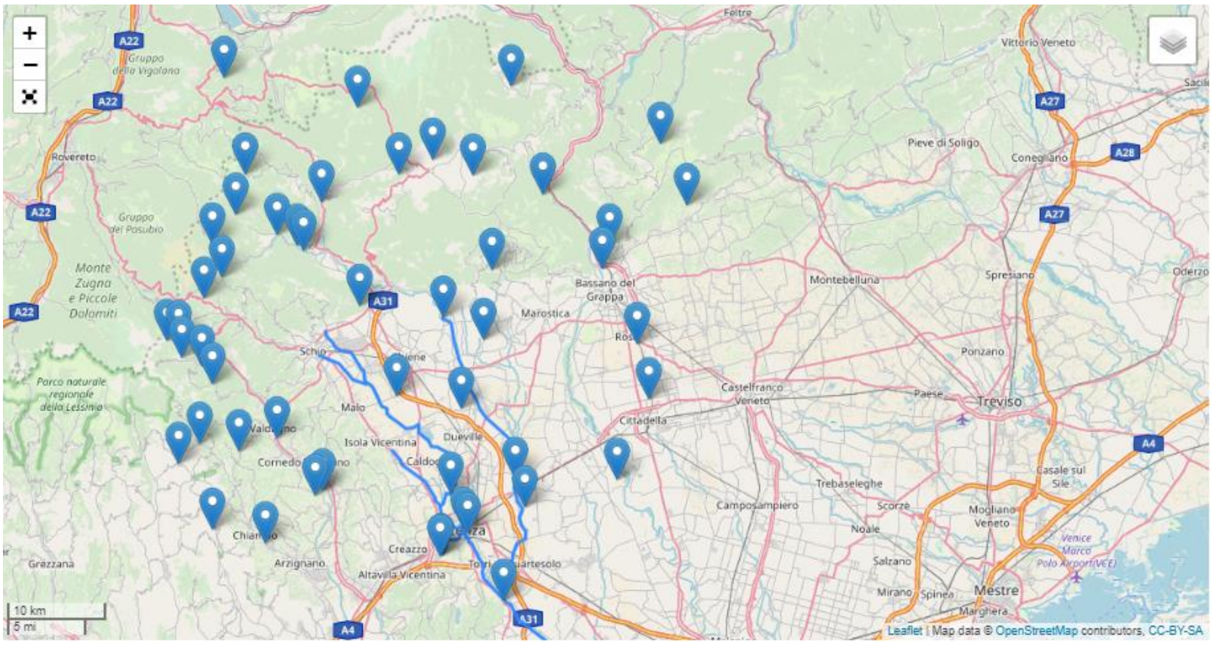

Figure 12: Overview of Weather Stations in Vicenza district

The *Sensor Fusion Module* estimates in real-time the progress of the flood crisis in terms of the **Observed Flood Crisis Level** (**OFCL**) by the aggregation of the observed water level in each one of the examined weather stations. In order to achieve this, the observed water level values, which are obtained by a weather station every hour, are compared with the pre-defined alarm thresholds and the particular weather station classified according to the result of the comparison. After that, using a similar approach as this one for the pre-emergency phase, namely the OFCL index is estimated over all the weather stations, by performing the following steps:

Step 1. For each Weather Station, CRCL acquires real time sensing data (measurements) for river Water Level and Precipitation

Step 2. Compares the river Water Level measurements with pre-defined alarm threshold for each one of the Weather Station. Then for the i-th Weather Station:

If $WL_i < AlarmThreshold_1$ **Then Scale$_i$ = 1**
ElseIf $AlarmThreshold_1 \leq WL_i < AlarmThreshold_2$ **Then Scale$_i$ = 2**
ElseIf $AlarmThreshold_2 \leq WL_i < AlarmThreshold_3$ **Then Scale$_i$ = 3**
ElseIf $AlarmThreshold_3 \leq WL_i$ **Scale$_i$ = 4**

Step 3. Calculate the **Overall Crisis Classification Index** (**OCCI**) over all examined Weather Stations by using the formula:

$$OCCI = \left\lceil \sqrt[p]{\left(\frac{N_4\, 4^p + N_3\, 3^p + N_2\, 2^p + N_1\, 1^p}{N} \right)} \right\rceil \quad (8)$$

where

- $p = 4$ (Default value) indicates the different categories of the scale (1,2,3,4)
- $N = N_1 + N_2 + N_3 + N_4$ denotes the total number of Weather Stations and $N_i, i = 1,..,4$ denotes the number of Weather Stations that belong to each category
- $\lceil . \rceil$ denotes the upper bound

Step 4. Calculate the **Observed Flood Crisis Level (OFLCL)** as follows:

If OCCI = 1 (meaning that the WL for all Weather Stations are below AlarmThreshold_1) **Then**

Observed Flood Crisis Level = 1

ElseIf OCCI = 2 **AND** ∄ Weather Station ws : $Scale_r = 4$ **Then**

Observed Flood Crisis Level = 2

ElseIf OCCI = 2 **AND** ∃ Weather Station ws : $Scale_r = 4$ **Then**

Observed Flood Crisis Level = 2+

ElseIf OCCI = 3 **AND** ∄ Weather Station ws : $Scale_r = 4$ **Then**

Observed Flood Crisis Level = 3

ElseIf OCCI = 3 **AND** ∃ Weather Station ws : $Scale_r = 4$ **Then**

Observed Flood Crisis Level = 3+

ElseIf OCCI = 4 **Then**

Observed Flood Crisis Level = 4

The Observed Flood Crisis Level can be considered as a general metric-index in which the Water Level real-time measurements from sensors at the specified Weather Stations are encapsulated, empowering the capacity of the CRCL system to classify and monitoring the progress of a flood event.

5.2.1.2 Severity estimations from other beAWARE modalities

One of the main goals of the Crisis Classification system for the flood pilot is the real-time risk evaluation (severity of crisis) from various modalities. The incident reports, which are sent by citizens and first responders through the mobile app and the social media, the multimedia results of analysis (severity levels) as well as the outcome of the textual content analysis should be considered as input to the *Real-Time Monitoring and Risk Assessment* module. Specifically, the concept extraction from multimedia content (image/video) results to the identification of people and vehicles which are exposed to flood hazard and the estimation of their severity level is provided and stored to the KBS, as described in more details in the Deliverables D3.3[18] and D4.2[19].

The *Real-Time Monitoring and Risk Assessment* module extracts the useful analysed data from the Knowledge Base Service (KBS) component. Particularly, KBS is responsible for the

[18] *beAWARE Deliverable D3.3*: Basic techniques for content distillation from multilingual textual and audio visual material

[19] *beAWARE Deliverable D4.2*: Semantic Representation and Preliminary Report on Reasoning

incorporation of the semantic reasoning mechanism to infer underlying knowledge and discover links between incidents during a crisis. Moreover, the KBS enables to spatially cluster the incidents generating new enriched knowledge through its reasoning mechanism. Thus, via the KBS component, the Crisis Classification system will be able to receive the severity level of each incident or groups of incidents, as well as the type and number of affected objects.

It is worth mentioning that the information of the incidents or the group of incidents can be considered and exploited from the Crisis Classification system in a similar way as the observed data from the sensors. In this sense, a set of methods from the field of Information Fusion is available and utilised in the purpose of beAWARE project.

5.2.1.3 Multimodal Fusion approaches for Flood Risk Assessment

In the framework of the *Real-Time Monitoring and Risk Assessment* module state-of-the-art fusion strategies will be extensively probed in order to evaluate their performance in terms of their accuracy to estimate the overall risk level of an ongoing crisis at the whole region of interest or/and specific areas in the region. The fusion of multiple modalities can provide complementary information and increase the accuracy of the overall decision making process (Atrey, Hossain, El Saddik, & Kankanhalli, 2010). For example, fusion of sensing data, along with audio-visual features and other textual information from social media have become more effective in detecting people in danger when a flood crisis event occurs, comparing from a video, which would otherwise not be possible by using a single medium.

A rule-based fusion approach would be employed combining multimodal information by including a variety of basic rules. Specifically, statistical rule-based methods, such as linear weighted fusion, majority voting and custom-defined rules will consider and evaluate their performance.

Linear weighted fusion for assess flood risk

Linear weighted fusion approach combines in linear fashion the information obtained from different modalities. To fuse the information for the level of severity during the flood crisis event, normalised weights are assigned to each one of the modalities.

The general methodology of linear weighted fusion for assessing the risk of a flood crisis can be described as follows. Let $R_i, 1 \leq i \leq n$ be a decision obtained from a modality regarding the risk or severity of the flood crisis. Thereupon, let $w_i \epsilon [0,1], 1 \leq i \leq n$ be the normalised weight assigned to i-th modality. Thus, a high-level decision regarding the flood risk is estimated by the formula:

$$Risk = \frac{\sum_{i=1}^{n} w_i \times R_i}{\sum_{i=1}^{n} w_i} \quad (9)$$

The following assumptions should be made in order to the above equation be able to assess the flood risk:

- The **Observed Flood Crisis Level** obtained by the sensors should be re-formulated into a [0, 1] scale so as to be in aligned with the crisis level available from incident reports.
- The categories of **Severity Level** from multimedia analysis, which follow the CAP protocol, should be enumerate in the [0, 1] scale.

Finally, the Risk classified into one of the following classes as shown in the

Table **10**. The risk levels are totally coherent with the European Directive 2007/60/CE (European, 2007), thus they are utilised in the beAWARE framework for the flood use case.

Table 10: Risk Levels for Flood Management Plan corresponding with severity level

Risk	Risk Level for Flood Management Plan from Flood EU Directive 2007/60/CE		CAP Severity Level
	Eng.	It.	
0 ≤ Risk < 0.2	Low	Moderato	Minor
0.2 ≤ Risk < 0.5	Medium	Medio	Moderate
0.5 ≤ Risk < 0.9	High	Elevate	Severe
0.9 ≤ Risk ≤ 1	Very high	Molto Elevate	Extreme

Majority Voting

Another multimodal fusion approach is the majority voting. The final decision is the one where the majority of the modalities reach into the same decision. The only limitation here is that the decisions obtained from the modalities should be expressed into the same scale. For simplicity and uniformity reasons, the CRCL system employs the scale which is compliant with the European Directive 2007/60/CE, namely all the decisions should take one of these values: Low, Medium, High, Very High.

Custom-defined rules

Unlike the above approaches that use standard statistical rules, a Decision Fusion unit can be empowered with custom-defined rules which integrate inputs from different beAWARE modalities. Although, the decision fusion using custom-defined rules has the flexibility of adding rules based on the requirements, however, in general, these rules are domain specific and defining the rules requires proper knowledge of the type of crisis and the characteristics of the region of interest.

6 Conclusions and Future Plans

This deliverable reported on the work carried out within the **Task 3.1: Crisis Classification** in the content of the **WP3: Early warning generation**. Specifically, it includes the following key contributions:

- A high-level architecture of the Crisis Classification and its components. The system consists of two modules: the Early Warning and the Real-Time Monitoring and Risk Assessment component.
- Integration of into external and internal data sources.
- Methodologies and approaches have been presented and analysed. Some of the proposed approaches have been already implemented in the content of the first release of the Crisis Classification system.

The above methodological framework and components will be further refined and improved during the validation and evaluation phase of the system. The execution of pilot trials will have significant role to highlight potential issues and limitations of the system. The following directions for enhancements are foreseen:

- Develop the full functionalities of the Real-Time Monitoring and Risk Assessment component.
- As the Crisis Classification system collects data from heterogeneous resources, more powerful and intelligent *Classification-based fusion* methods would be applied, enhancing the CRCL system to assess the risk of crisis (Atrey, Hossain, El Saddik, & Kankanhalli, 2010). This category of methods includes a wide range of classification techniques that have been used to classify the multimodal observation into one of the pre-defined classes. Support Vector Machines, Neural Networks, Bayesian inference, dynamic Bayesian networks are among them.
- In the Decision Fusion unit of the Real-Time Monitoring and Risk Assessment component, more intelligent fusion techniques should be considered.
- Methods from the domain of Multi-Criteria Analysis will consider their applicability to the domain in order to estimate the overall risk of the crisis.
- Extensively experiments and tests should be done in order to evaluate the performance of the system in terms of its precision and accuracy.
- The accuracy of Fire and Heatwave Indices should be evaluated and compare with other indices from the literature.

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