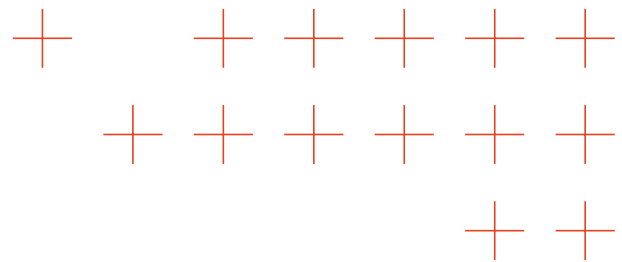




TRUSTED
EXTREMELY PRECISE
MAPPING AND PREDICTION
FOR EMERGENCY
MANAGEMENT

Deliverable D4.1: Report on phenomenon prediction and information fusion

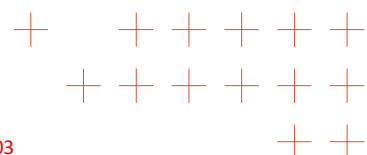


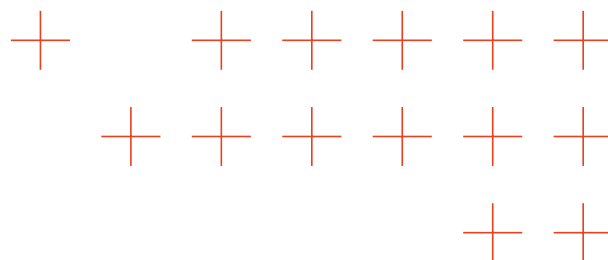


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Executive Summary:	This deliverable outlines TEMA's advanced technologies and strategic plans for forest fire and flood modeling, stressing predictive modeling's vital role in disaster mitigation. It discusses prediction methods, Information Fusion technologies, and ongoing research trajectories within TEMA. An Appendix provides additional technical details, supporting a holistic disaster management approach.		
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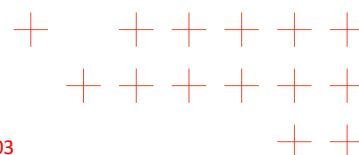


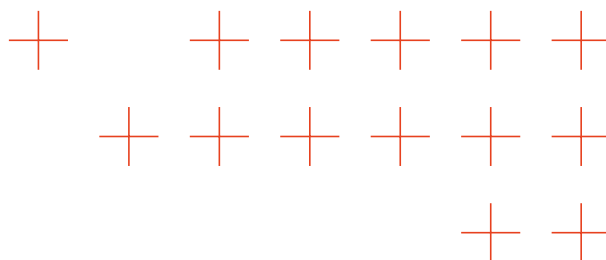
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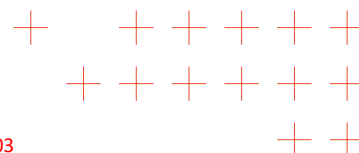
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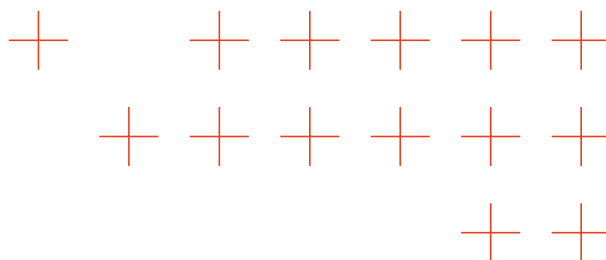
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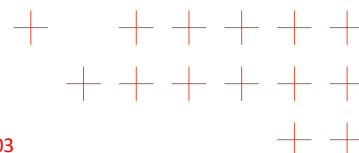


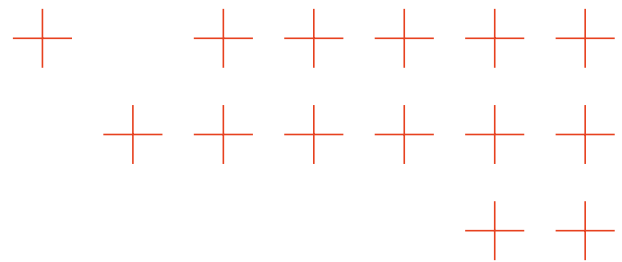
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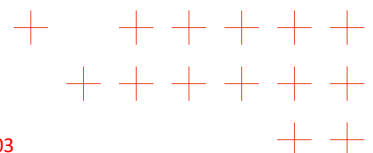




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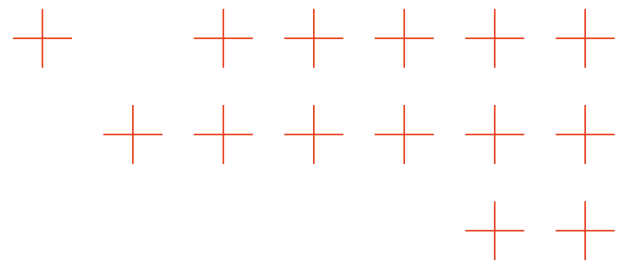
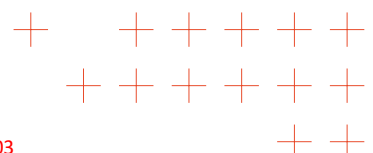
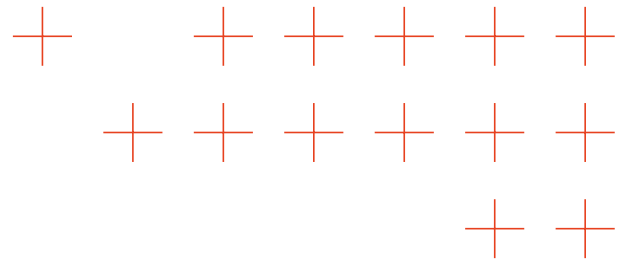


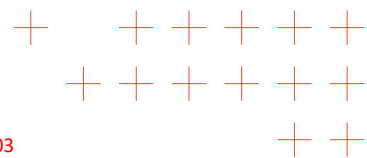
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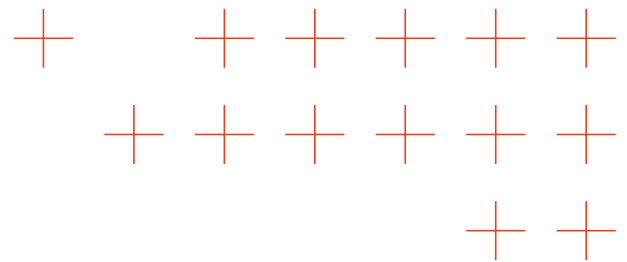
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Executive Summary

This executive summary offers a comprehensive overview of state-of-the-art technologies and the strategic development plan within TEMA, focusing on forest fire and flood modelling. The document underscores the paramount importance of predictive modelling in mitigating the impacts of natural disasters, particularly floods and forest fires, acknowledging the inherent complexity arising from heterogeneous data sources and the subsequent necessity for sophisticated data fusion techniques.

We begin with methods for phenomenon prediction, specifically, forest fire and flood modelling. The discussion elucidates the formal methods employed to represent and predict these phenomena, providing a detailed examination of the hardware and software tools required for detection and continuous monitoring of these events. The document builds upon (and extends where needed) the proposed interactions between the involved technologies, thus augmenting the discourse on technology interactions previously discussed in Deliverable 2.2.

Subsequently, the document delves into Information Fusion technologies, emphasizing their pivotal role in enhancing situational awareness during disasters. Particular focus is placed on Visual Analytics and Satellite Information Fusion, alongside the innovative integration of Drone-Based Information Fusion and the strategic utilization of Social Media platforms. These methodologies are scrutinized as effective means to harmonize diverse data sources, furnishing a comprehensive understanding of disaster scenarios.

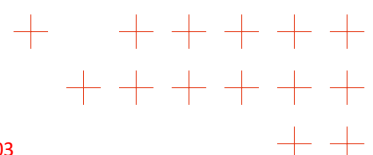
The concluding section underscores the ongoing progress and future trajectories in the research and development of the aforementioned technologies within the dynamic landscape of TEMA. Anticipating evolving challenges and emerging needs, this document will serve as a foundation for continued innovation, collaboration, and refinement of further activities within TEMA.

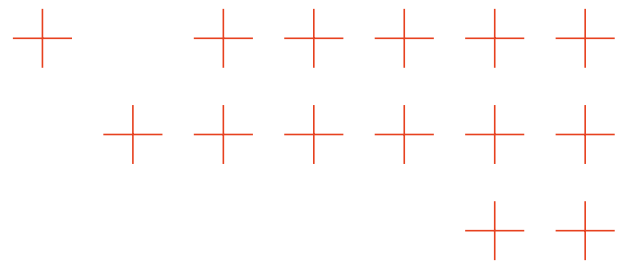
To facilitate deeper comprehension of some tools and methods, the Appendix complements the main document with additional resources and technical details, enriching the discourse on specific facets of the discussed technologies and approaches. Together, this executive summary and its appendices lay the groundwork for a holistic and forward-thinking approach to disaster management within the purview of TEMA.

Progress on selected KPIs

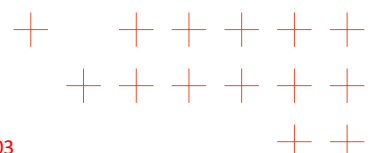
The present state of the WP development will further prioritize achieving the Key Performance Indicators (KPIs) as set out in the project plan. While the deliverable summarizes the initial stage of the individual tasks, there is however some progress on individual KPIs. In particular, **prediction accuracy** and efficiency of modelling techniques have been studied to make modelling more suitable for real-time applications. Also, hybrid models, combining AI and physics-based approaches have been considered, which should further improve the **responsiveness of the models**.

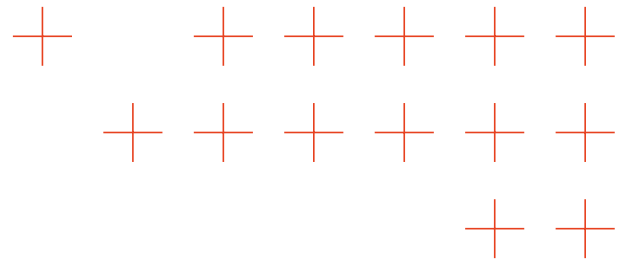
Requested modifications of the deliverable





In response to a request for modifications of the deliverable, new sections has been included in the current version. Specifically, the document now contains separate sections focusing on the State of the Art of individual technologies, their advancement beyond State of the Art as foreseen within TEMA, and the major progress achieved from the start of the work package at M13 till review period at M18.





1 Introduction

In an era marked by escalating climate change and increasingly unpredictable weather patterns, the ability to anticipate and mitigate natural disasters has become paramount. From the devastating spread of forest fires to the perilous consequences of flooding, communities worldwide are grappling with the urgent need for more effective prediction models and innovative approaches to information management. This document delves into two pivotal aspects of disaster preparedness: phenomenon prediction and information fusion.

Historically, forest fire prediction relied heavily on empirical models and statistical analyses based on historical fire data. While these approaches provide valuable insights, they often lack the precision and scalability required to anticipate wildfires in real-time and under changing environmental conditions. Therefore, approaches based on in-situ or remote sensing were developed to augment the empirical or statistical methods.

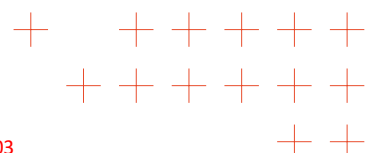
Vision-based systems, such as Ground Optical sensors systems, rely on digital images periodically obtained from cameras and other optical sensors, and a layer of software that process the image and via classification algorithms. These ultimately decide whether to send a fire alert to the operator or not. The sensors in this setting include

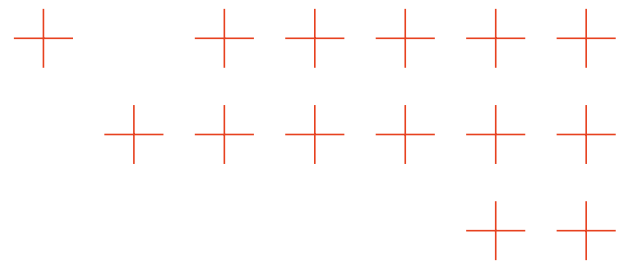
- Video-camera, sensitive to visible spectrum of smoke recognizable during the day and a fire recognizable at night,
- Infrared (IR), thermal imaging cameras based on the detection of heat flow of the fire,
- IR spectrometers to identify the spectral characteristics of smoke,
- Light detection and ranging systems (LIDAR) that measure laser rays reflected from the smoke particles. (Fernandes et al., 2004) (Utkin et al., 2002)

While optical in-situ sensors provide an accurate assessment of the situation close to the location of the possible fire, remote sensing coupled with geographic information systems (GIS) have revolutionized forest fire prediction and monitoring capabilities. Satellite imagery, aerial drones, and ground-based sensors offer invaluable data on vegetation health, fuel moisture levels, and fire hotspots, enabling early detection and assessment of fire risks.

Satellites can provide very high resolution fire images (e.g., using Landsat-8/OLI data (Schroeder et al., 2016), Sentinel-2 (Bertini et al., 2012)). Yet naturally, their performance in early stage detection is poor, thus restricting their use to large/very large fires events. Nonetheless, they provide a valuable input for preparation, response and planning stage. To augment the low-resolution data from Satellite images, UAV-based data acquisition systems can be used.

Typically, a UAV carries an RGB- or thermal imaging sensor, providing in-situ data acquisition. While at present experts/firefighters can “manually” assess the situation based on the live data stream from an UAV, this is very time- and resource consuming. The current research trends foresee a high degree of autonomy both for data





acquisition and perception. Methods range from relatively simple, classical, image processing tools, e.g., (Yuan et al., 2015), to more advanced AI based techniques (Jiao et al. 2019). Also, multiple drones can be deployed (Merino et al., 2005).

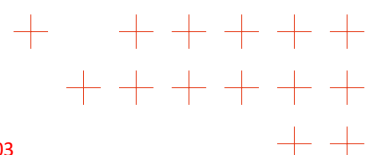
Beyond UAV, stationary low-cost wireless sensor networks (WSN) can also be deployed for detection of forest fires. Wireless Sensor Networks (WSNs) serve as a critical component in detecting and monitoring environmental conditions that may indicate the presence of fires. These networks employ a variety of sensors to measure physical parameters such as temperature, pressure, and humidity, as well as chemical parameters like carbon monoxide, carbon dioxide, and nitrogen dioxide (Son et al., 2006). This comprehensive approach provides a holistic view of environmental changes that may signal the onset of a fire. Such sensor networks often operate within a self-healing and self-organizing wireless network environment, allowing for resilient and adaptive communication among sensors. This capability ensures the continuity of monitoring even if some nodes within the network fail or are disrupted. Examples include FireWxNe (Hartung, et al., 2006) and others (Hefeeda et al., 2007, Yu et al., 2005)

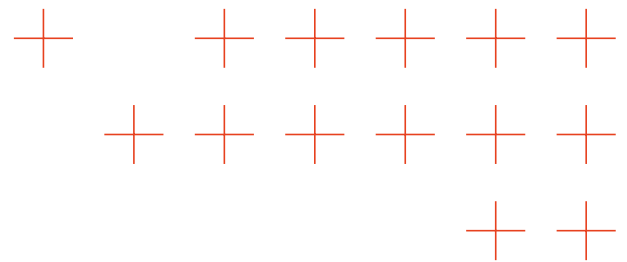
To enhance the accuracy and reliability of fire detection, environmental sensors are often integrated with cameras and other complementary systems, e.g., (Lloret et al., 2009). These multi-sensor systems allow for precise validation and pinpointing of fires, providing crucial data for emergency response teams. By combining sensor data with visual information, authorities can quickly assess the situation and coordinate appropriate responses.

The fusion of different sources of information, exploiting remote sensing applications with GIS platforms, machine learning algorithms, and spatial analysis techniques, will thus permits developing sophisticated predictive models with enhanced spatial and temporal resolution of fire detection and tracking. Such integrated approaches will build the foundation of TEMA developed techniques for forest fire monitoring.

In addition to forest fires, another type of disasters addressed by TEMA are floods. While floods are quite different from forest fires, yet similar methods are often used for their modelling (Brunner et al., 2021). The corresponding models for are quite complex and depend heavily on factors such as topography (Casas, et al. 2006) or human actions. The very nature of floods, which implies a large, often populated, area and rapid development, has generated a focus on floods forecasting to assess possible actions and evacuation plans; detection remains a less researched topic.

Floods forecasting usually exploits statistical models (Ziliani et al., 2019) as well as machine learning tools (Mosavi et al., 2018). Yet probably most popular models remain numerical models based on fluid dynamics/hydrodynamics simulations (Chatterjee et al., 2008), (Ming, et al. 2020). Essentially, they are based on partial differential equation models, which, however, makes them quite computationally intensive. Similar to fire monitoring, stationary sensors can also be used to monitor the water level and issue alert signals, either using vision-based sensors (Sabbatini et al., 2021), or weather sensors (Rani et al., 2020). Unfortunately, one of the main problems of flood modelling remains the low amount of available data. At present, most data come





from satellites imagery (Yan, et al. 2015), yet of the use of other sensor types, including synthetic aperture radar (SAR) (Scotti et al., 2020) and UAV-based sensing (Perks et al., 2016) are gaining momentum.

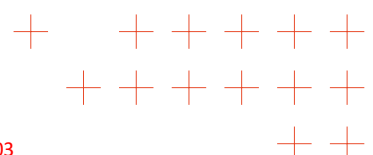
Thus, in TEMA, we focus on bringing heterogeneous data sources together to enhance flood modelling approaches.

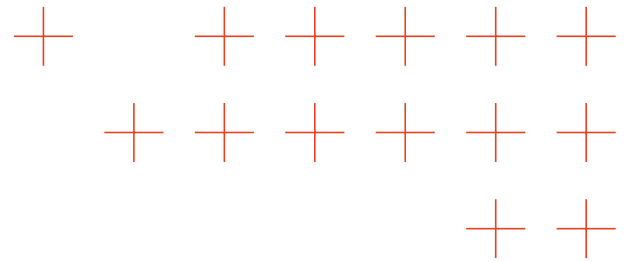
Of course, an accurate understanding of the flood and forest fire phenomena requires a fusion of diverse data sources of information. In an era characterized by an exponential increase in data volume and variety, harnessing the power of information fusion has become indispensable for decision-makers tasked with orchestrating timely and informed interventions.

Here, we examine the convergence of data streams from disparate sources, including satellite imagery, IoT sensors, social media feeds, and traditional observation networks. Through the integration of these heterogeneous datasets, we elucidate how decision support systems can provide actionable insights, enabling pre-emptive measures and real-time response coordination.

Moreover, we explore the role of artificial intelligence (AI) and data analytics in extracting actionable intelligence from vast troves of unstructured data. By employing techniques such as natural language processing (NLP), sentiment analysis, and anomaly detection, we showcase how information fusion facilitates early warning systems, situational awareness, and resource allocation optimization.

By elucidating the synergistic benefits of integrating diverse sources of information, this chapter seeks to empower stakeholders with the tools needed to navigate the complexities of disaster management proactively. Through a synthesis of theoretical frameworks, case studies, and practical applications, this document aims to catalyse advancements in both predictive modelling and information fusion, thereby enhancing the resilience of communities in the face of natural disasters.





2 Phenomenon Prediction

2.1 Wildfire smoke dynamics modelling

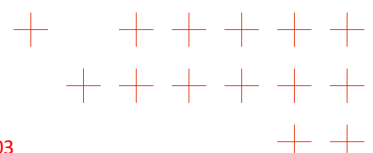
In TEMA the key focus of smoke and wind modelling is to understand the dispersion of airborne substances, particularly forest fire smoke, at initial as well as later stages of the fire. Naturally, an accurate representation of airflow is of key importance here: airflow is often the dominant factor that is responsible for spatial material transport. This is important since accurate airflow information is crucial for evacuations and response planning; during forest fires, real-time wind maps can support fire-fighting activities on the ground (Battiston et al. 2019). In this section we first discuss State of the Art algorithms for smoke plume dynamic modelling, then describe what specifically this TEMA component will add to current research. We then provide details of the modelling algorithms and platform hardware, and finally list the component’s place inside of the TEMA platform at large.

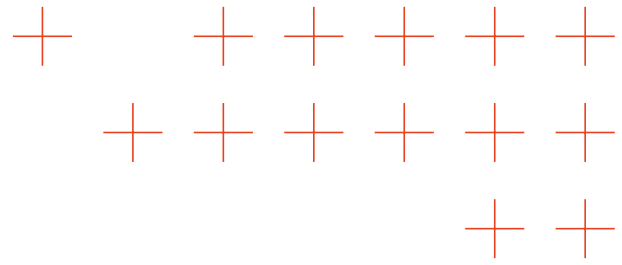
2.1.1 State of the Art for smoke modelling

Real-time wildfire tracking and modelling is a topic that has been receiving more attention as climate change increases its effects on the European continent. Several efforts for wildfire monitoring have focused on satellite-based remote sensing capabilities, which can be very effective at estimating affected areas after a wildfire has spread, and, depending on the part of the electromagnetic spectrum that is used, checking on the status of large active fires. These methods in a broad sense lack real-time responses and fine resolutions necessary for active management of starting fires, due to limitations of satellite technology. However, we direct the interested reader to (Chen, et al. 2024) for more information on remote sensing-based tracking.

In other real-time fire monitoring schemes, data close to the site of the fire is collected, either by autonomous agents like drones and a network of sensors on the ground that collect key data on trace gas concentrations and wind conditions (Alkhatib 2014). These efforts may help in isolation but can often overwhelm first response data. Furthermore, the data by themselves are not immediately helpful to first responders and civil service as they should make decisions about which roads to close due to low visibility or towns to evacuate based on unsafe conditions or dense smoke.

This motivates the need for predictive models of smoke plumes. We direct the curious reader to (Liu, et al. 2022) [Chapter 4] for an in-depth explanation of the state-of-the art algorithms for smoke plume dynamics. State-of-the-art smoke plume modelling schemes, such as CAWFE (Coen 2013) WRF-SFIRE-CHEM (Kochanski, et al. 2015) take into account very complex atmospheric physics and trace gas chemistry to predict smoke and trace gas concentrations over time. However, these models feature package dependencies not optimized for speed and as such are not practical for use in real-time predictions. Additionally, their inputs are often fixed and they are not as flexible in taking in high-resolution data gathered on the field.





2.1.2 Planned Improvements within TEMA

By contrast, TEMA proposes to fuse model assumptions with collected real-world data both of smoke, using chemical sensors, as well as wind information using in-situ wind sensors.

The corresponding solution aims to use both spatio-temporal smoke and airflow models and collected sensor data to estimate otherwise unobservable parameters of interest, like smoke concentrations as well as wind speed and direction. Such problems are often referred to inverse problems. As a result, based on the estimated model parameters and the model itself, we can calculate a spatial map of the smoke and airflow in the considered environment, which should be achieved in real time and yet show a low deviation with reality.

To collect spatially distributed airflow measurements, we will rely on both ground sensor networks, as well as a multi-robot system. The process of collecting these measurements is referred to as exploration.

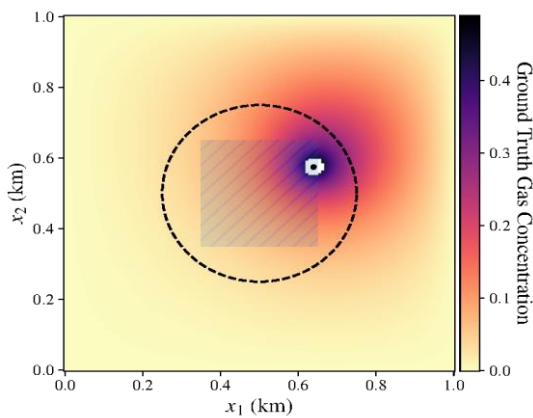


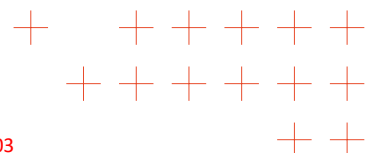
Figure 2.1. A solution to the equilibrium advection diffusion equation in a 2D environment, used to determine trace gas concentrations emitted by a trace gas source such as a forest fire.

While typically robotic exploration focuses on the perception of the geometry of the environment (often in combination with localization), like SLAM, here we are interested in the airflow or concentration field. The use of multiple robots shows distinct advantages. First, in case of fires and hazardous fumes, threats to human operators can be reduced. Second, intelligent autonomous robots can explore the environment on their own without human intervention; this makes the system more (cost) efficient. Third, a multi-robot system can explore the environment faster compared to a single robot, and its natural redundancy can compensate for the failures of individual robots.

The key to this approach is domain knowledge. Specifically, we describe the smoke distribution as well as airflow in terms of Partial Differential Equation models that represent the spatial dynamics of process. These are described in more details in the following sections.

2.1.3 Activities performed in the period M13-M18

Between months 13 and 18 of the TEMA project, DLR-KN have worked to advance progress towards a real-time smoke modelling pipeline. First, we implemented a trace gas dispersion finite-element-method-based solver as in section 2.1.3, which sets out to model the equilibrium distribution of smoke in a region. This solver implements the system physics laid out in this section, solving the advection diffusion equation in the process.



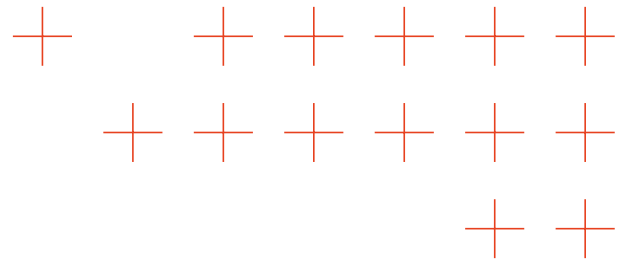


Figure 2.2. Hardware sensor gases measuring trace gases emitted from stationary fumaroles on the island of Vulcano, Italy.

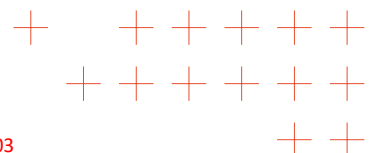
DLR used this solver to investigate a research question involved in solving the inverse problem – in the context of a wildfire, determining which region of trees is on fire based on the gas concentrations we observed. We excluded specifics from the following sections for brevity of the document. This research is associated with TEMA-sponsored congress publications “Gas Source Localization Using Physics-Guided Neural Networks” and “Physics-Guided Neural Networks for Distributed Sparse Gas Source Localization Using Poisson’s Equation and Green’s Function Method”, submitted to ISOEN 2024 and EUSIPCO 2024 respectively.

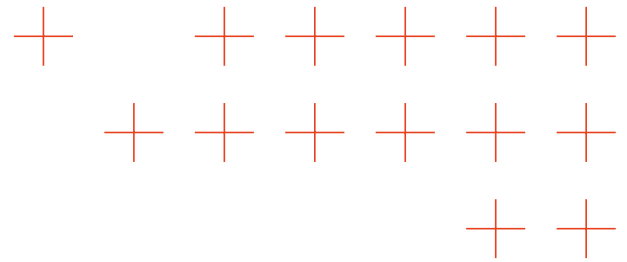
In addition, DLR-KN worked on making and testing hardware used to detect trace gases and collect other environmental conditions, discussed in section 2.1.4. In June of this year, DLR-KN performed the first data collection using this dedicated hardware, consisting of ground-based sensor boxes and drone-based hardware to measure the gases emitted from the fumaroles, with the goal of mapping the gas concentration and determining where the emitting sources are. These fumarole data, while not strictly speaking wildfire data, will help serve to validate both wind flow and trace gas dispersion models to come, and provide a stress test for the hardware to help ensure that the platform is viable for use in TEMA trials. Additionally, the complex terrain of the region is a good analog to the rougher terrain anticipated for the TEMA trials planned for 2025, where the first gas concentration data from a wildfire could potentially be collected.

In the coming months, DLR-KN will work on expanding the modelling capability of its solvers. In particular, the wind flow solver will give the dispersion model more accurate wind flow that adapts to the terrain based on real-time measurements, corresponding to section 2.1.2. In addition, DLR-KN currently develops more refined trace gas models that again take into account the geometry of the environment which could still potentially be used to solve the inverse problem of finding fire locations based on measurements. Finally, we look forward to expanding the range of hardware to be used in the experiments.

In TEMA the key focus of the smoke and wind modelling is to understand the dispersion of airborne substances, particularly forest fire smoke, at initial as well as later stages of the fire. Naturally, an accurate representation of airflow is of key importance here: airflow is often the dominant factor that is responsible for spatial material transport. This is important since accurate airflow information is crucial for evacuations and response planning; during forest fires, real-time wind maps can support fire-fighting activities on the ground (Battiston et al., 2019).

While nowadays, most of the models for wind modelling rely on weather forecasts, which provide rather low resolution information, realistic models of the airflow at the location of the actual fire will provide a higher confidence models, taking into account precise knowledge about propagation environment such as boundary





conditions and terrain. We direct the curious reader to (Liu, et al. 2022) [Chapter 4] for an in-depth explanation of the state-of-the art algorithms for smoke plume dynamics.

Thus, the approach we validate in TEMA is to fuse model assumptions with collected real-world data both of smoke, using chemical sensors, as well as wind information using in-situ wind sensors.

The corresponding solution uses both spatio-temporal smoke and airflow models and collected sensor data to estimate otherwise unobservable parameters of interest, like smoke concentrations as well as wind speed and direction. Such problems are often referred to inverse problems. As a result, based on the estimated model parameters and the model itself, we can calculate a spatial map of the smoke and airflow in the considered environment.

To collect spatially distributed airflow measurements, we will rely on both ground sensor networks, as well as a multi-robot system. The process of collecting these measurements is referred to as exploration.

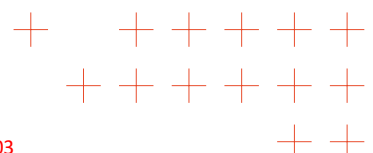
While typically robotic exploration focuses on the perception of the geometry of the environment (often in combination with localization), like SLAM, here we are interested in the airflow or concentration field. The use of multiple robots shows distinct advantages. First, in case of fires and hazardous fumes, threats to human operators can be reduced. Second, intelligent autonomous robots can explore the environment on their own without human intervention; this makes the system more (cost) efficient. Third, a multi-robot system can explore the environment faster compared to a single robot, and its natural redundancy can compensate for the failures of individual robots.

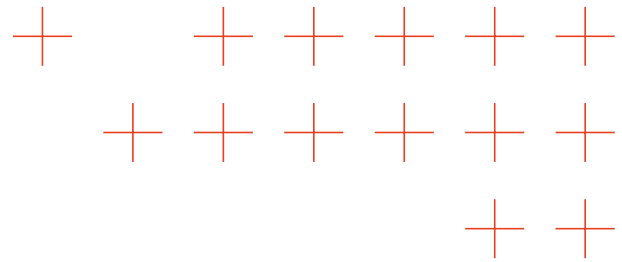
The key to this approach is domain knowledge. Specifically, we describe the smoke distribution as well as airflow in terms of Partial Differential Equation models that represent the spatial dynamics of process. These are described in more details in the following.

2.1.4 Used approach toward wind modelling

Our goal is to generate a map of the airflow field fast and accurately. In our case, we know the dynamic behaviour of the airflow from fluid dynamics. It can be mathematically modelled by the Navier-Stokes PDE. The Navier-Stokes PDEs describe the behaviour of fluids. For the approach considered in TEMA we make a few simplifying assumptions, which are subject to change as the model's performance is tested through pilot trials.

1. We consider the air as incompressible, i.e., having a constant density throughout the exploration area. This assumption is usually justified for small Mach numbers, as in our case, where we expect airflow velocities below 10m/s (approximately Mach 0.03).
2. We consider a linear temperature dependence of the air based on height above the surface.
3. After a certain domain height, air velocity is purely horizontal.
4. We consider a time-invariant (steady) airflow.





This last assumption might seem unphysical. Of course, turbulence causes an unsteady flow on a short time scale. However, in the medium term, we assume the statistical properties of the flow (e.g. statistical distribution of the velocity and its mean) to be constant, and only change over larger time scales (through model update). This assumption can be relaxed later if needed.

These assumptions naturally lead to the steady-state incompressible Navier-Stokes equations:

$$\begin{aligned}
 -\nu \cdot \Delta \mathbf{w}(\mathbf{x}) + (\mathbf{w}(\mathbf{x}) \cdot \nabla) \mathbf{w}(\mathbf{x}) + \nabla p(\mathbf{x}) &= 0 \\
 \nabla \cdot \mathbf{w}(\mathbf{x}) &= 0,
 \end{aligned}$$

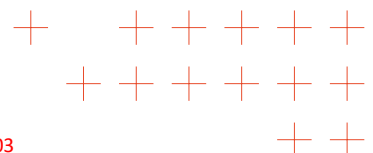
where $w(x)$ is an airflow velocity field and $p(x) \in R^{**}$ represents the pressure at a location x in the exploration domain $\Omega \subseteq R^3$. The first equation – the Momentum Equation – describes the dynamics of the airflow. The first term, $-\nu \cdot \Delta w(x)$, represents a diffusion-like propagation of the velocity field. The parameter ν is the (temperature dependent) kinematic viscosity (see (Houghton, et al. 2017)). E.g., for air at 20°C and set $\nu = 1.5 \times \frac{10^{-5}m^2}{s}$ (see e.g., (Foken 2008)). The second term, $(w(x) \cdot \nabla)w(x)$, indicates advective or convective acceleration (Song 2018). This occurs when a fluid particle is transported by advection to a region with higher or lower velocity. Additionally, the term $\nabla p(x)$ represents the pressure gradient. The temperature of the air will be estimated from measured values of solar intensity and measured temperature from ground and drone-based sensors, and weather forecast.

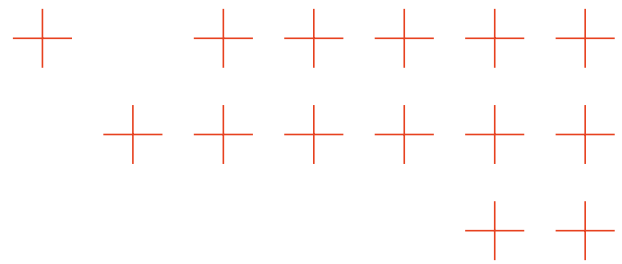
The second equation – the Continuity Equation – states that there is no divergence in the velocity field. In other words, there are no sources of the wind in the area.

For a well-posed and unambiguous description of the airflow field, the Navier-Stokes equations need to be equipped with appropriate boundary conditions. Generally, there are two basic types of boundary conditions: Dirichlet and Neumann. With Dirichlet boundaries, we specify the actual value of a function (like air velocity or pressure), while with Neumann boundaries, we specify the gradient of the function.

In our setup, we have three types of boundaries in the domain Ω (see Figure 2.3):

- 1- Obstacles (Dirichlet boundary): These are areas such as building or structure that are impermeable for the wind. The location of these obstacles is typically known a priori and can be obtained from satellite images. We assume that air cannot flow across their boundaries, which is known as the "no-slip" boundary condition. Additionally, we assume that the pressure gradient $\nabla p(x)$ on the boundary is zero.
- 2- Forced Inflow (Dirichlet boundary): We assume multiple or continuous inflow regions at the boundary. At these boundaries the air is blown into the domain in the normal direction $n(x)$ of the boundaries with intensity ψ_f . Again, the pressure gradient $\nabla p(x)$ is assumed to be zero at this boundary.





- 3- Outer Boundary (Neumann boundary): The outer boundary is open, allowing air to flow off the domain. We assume that the airflow conditions at the boundary are consistent with observed values of airspeed from the sensor network. The precise method of doing so is still under investigation.

For the moment our model does not consider sources of wind in forced airflow.

A closer inspection of the Navier-Stokes equation reveals that they are non-linear: the convection term $(w(x) \cdot \nabla)w(x)$ is bi-linear. A common approach to deal with the non-linearity of Navier-Stokes equations. And the one we will use in TEMA for wind modeling, is the Picard method (Rehman et al., 2008). It is a fixed-point iteration method with shown stability and global convergence.

Final step of the numerical modelling is the use of numerical approximation techniques to solve the equations. To this end we use the Finite Element Method (FEM). FEM is a general numerical method for solving partial differential equations (see e.g., (Zienkiewicz et al., 2013)). This approximation method is likely suitable for finer scale smoke models of ca. 10 ha.

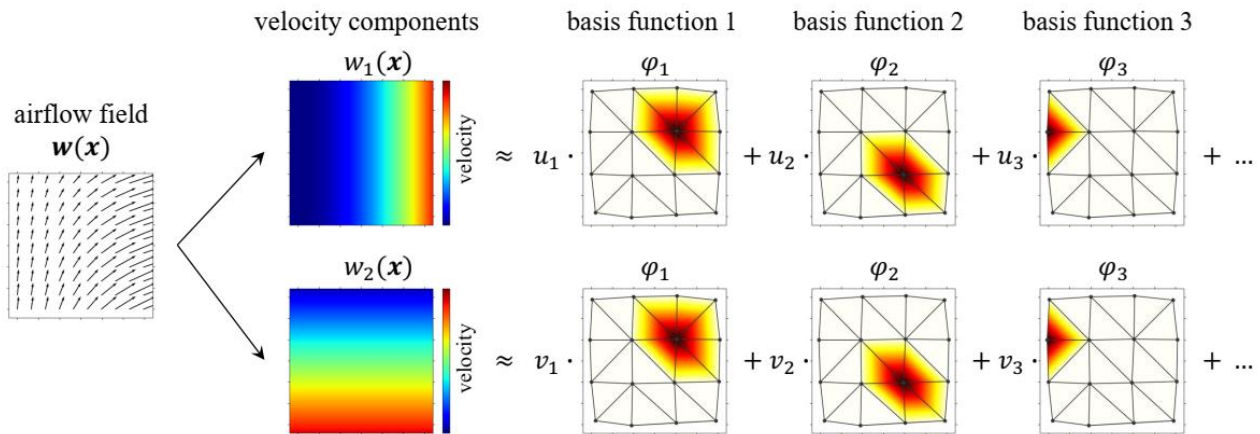


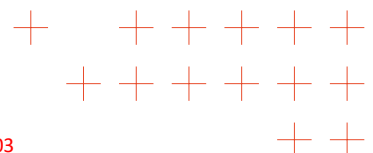
Figure 2.3. The spatial airflow field can be described by its velocity components $w_1(x)$ and $w_2(x)$, etc. in the corresponding directions x_1, x_2 , etc. For the FEM approach, these continuous functions are approximated by a weighted sum of basis functions, where vector u_i and v_i are the weights.

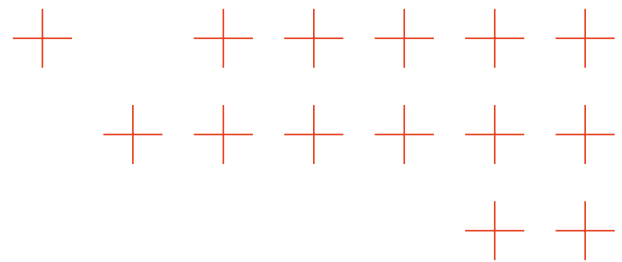
2.1.5 Trace Gas/Particulate Dispersion

To represent smoke/particulate dispersion due to the fire, we also use PDE-based domain knowledge. To this end an advection-diffusion equation over the exploration domain Ω is defined:

$$\frac{df(\mathbf{x}, t)}{dt} = \kappa \Delta f(\mathbf{x}, t) - \mathbf{v}^T(t) \nabla f(\mathbf{x}, t) + q(\mathbf{x}),$$

s.t. $f(\mathbf{x}, t) = 0, \quad \mathbf{x} \in \Gamma, t \in \mathbb{R}_+.$





The first equation consists of three terms: diffusion, parameterized by diffusion constant κ , advection due to the wind vector $v(t)$, and a smoke source term $q(x)$. The latter is the key to smoke source – forest fire – localization. We stress again that the source term is not observed directly; we can only measure smoke or particulate concentration in the air. The goal of the exploration is to estimate this term from the measurement.

The second equation represent the boundary conditions for the equation. This we can model the Neumann boundary condition. This assumption is valid when the edges of the domain are sufficiently far away from the sources that only negligible gradients in concentration levels are expected there. However, these assumptions can be relayed or modified, following more extensive experiments and tests.

Let us also point out that in this setting the model implies incompressible, isothermal flow conditions, which is a valid simplification for early stages of the fire. Yet might be violated at later stages, with high fire intensity.

Note that while the model is quite simple, it can nonetheless capture a major trend of the concentration variation under certain conditions (see Figure 2.4).

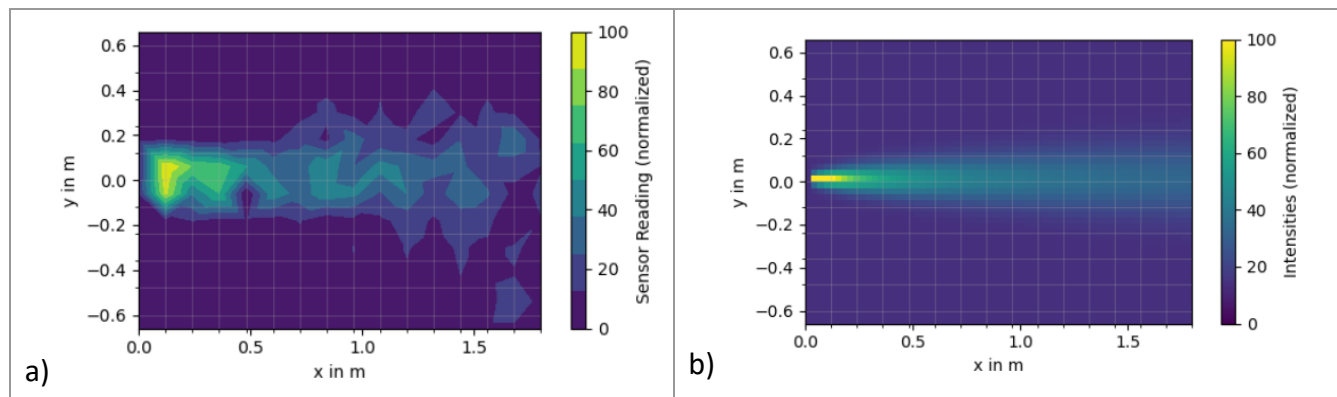
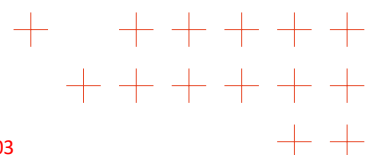
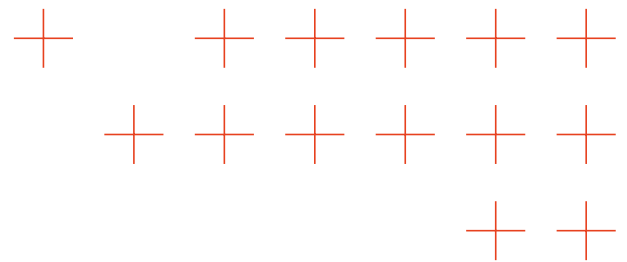


Figure 2.4 a) Measured gas concentration for a single source. b) Predicted concentration based on the advection-diffusion model for a single source (Hinsen et al., 2024).

The performed experiments in controlled conditions show that an advection-diffusion model can capture quite well the key plume width and concentration, while “abstracting” from micro-scale turbulence structure of the plume.





2.1.6 Hardware tools for in-situ and remote measurement

2.1.6.1 Hardware Overview

To effectively model the smoke plume of the forest fire, we aim to collect as much data of the plume as possible. This includes visual and nonvisual data. This section breaks down the data we intend to collect, as well as giving a justification for the sensors used to collect them.

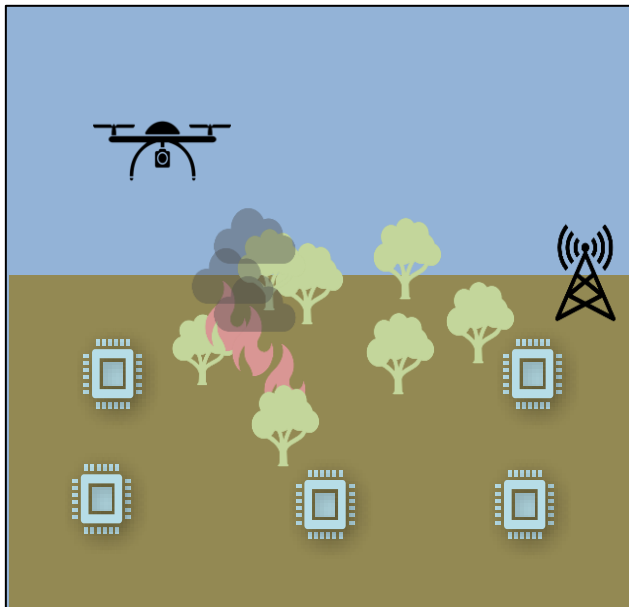


Figure 2.5. Measurement Setup. We show the hardware used to monitor a forest fire. Around the fire, ground based sensor units capture information on the ground. Drones equipped with imaging and gas sensors survey the area from above. A ground station collects the data from the fixed and mobile sensors and relays it to the TEMA platform.

In Figure 2.5 we show an example of the forest fire measurement platform. We can see that there are both stationary ground-based and mobile Unmanned Aerial Vehicle (UAV) - based sensors planned.

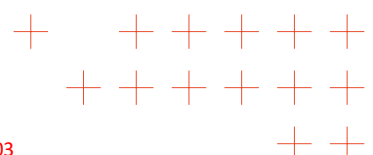
2.1.6.2 Trace Gases Considered

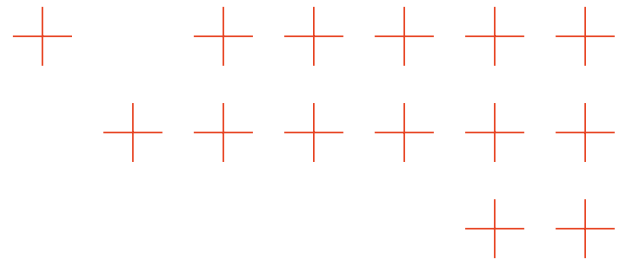
We found papers which measured trace gases emitted in boreal (Guo et al., 2020)[Table 4] and Mediterranean (Garcia-Hurtado, et al. 2013)[Table 1] forest material upon burning in a controlled laboratory environment. In both cases, we determined that key trace gases CO, CO₂, and hydrocarbons varied determined by the species. However, these were found to be within one order of magnitude. In both Mediterranean and boreal forests, the carbon monoxide count was roughly 10% of the CO₂ count.

To determine the trace gases used to identify a forest fire, we also turned to historical data from real wildfire events. To this end we consider trace gas measurements taken from a wildfire in Doñana Natural Park, Spain (Adame et al., 2018). It was determined that Particulate Matter (PM₁₀), as well as NO₂, SO₂, and CO, spike up well

above background levels during the fire event. This is in contrast to ozone, which also spikes but existed at higher levels before the fire.

We chose to exclude ozone and carbon dioxide from the trace gas sensors. This is because these gases have been observed to have a relatively high background levels in the presented study. For completeness, we include the logic for excluding CO₂. It was determined (Adame et al., 2018) that a CO level of 7000 mcg/m³ was observed during a peak. This corresponds to a concentration of ca. 5 ppm. If we assume CO₂ is emitted at a rate of 10x CO, we should expect an increase of the current background level of 400ppm.





2.1.6.3 Hardware for Measurement

As we showed in Figure 2.5, we intend to have ground- and air-based sensors to collect data from fire events. The ground sensors will have trace gas as well as fluid dynamics sensors, collecting data in time series from their fixed (known) locations. In addition to these two categories of sensor, the air-based sensors will collect image data.

Each sensor technology will be connected to a mobile computer such as a Raspberry Pi, and each of these will use a technology such as LoRaWAN to communicate through ROS2 with a central ground station unit. The ground station unit will have Starlink connectivity to the Internet and will thus be the link to the TEMA platform.

2.1.6.4 Gas Sensing Technology

The trace gases will be monitored using electrochemical cells. These types of sensors, as opposed to metal oxide technology, are better suited to mobile remote sensing applications due to their reduced response times of under 15s. By contrast, a sensor with a high response time could take more than a minute to reset its value after observing a peak concentration. At the moment, electrochemical sensors are still relatively new technology and are experimental in mobile remote sensing. We will test sensor technology from two companies, Alphasense, and Semeatech and determine their suitability for trace gas measurement with UAVs.

2.1.6.5 Fluid Dynamic Sensors

Fluid dynamics sensors are included as a separate category because these sensors measure factors that move the wind. The wind will be measured with an ultrasonic wind sensor called the Trisonica Mini Wind. To position the ultrasonic wind sensor on the drone, we will follow the procedure in (Wilson et al., 2022).

2.1.6.6 Image Data

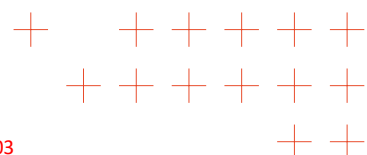
In addition to the drones provided by USE, we will fly drones with visual and thermal cameras to collect information about the fire. If initial tests (see below) show promise, we may supplement this with laser-based rangefinding or LIDAR sensing.

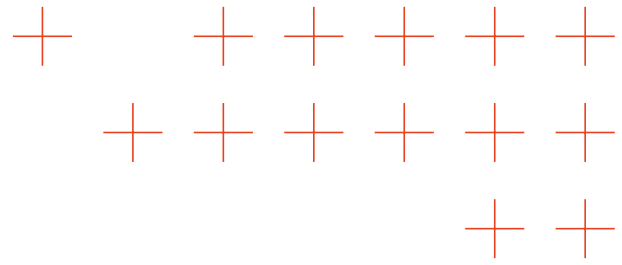
2.1.6.7 Hardware Experiments

In order to test out our hardware, we have planned some measurement campaigns in different locations. By mid-May, we will test initial connectivity of all sensor technologies with the microcomputer and have a unit using ROS.

In June, we will extend this to a measurement campaign on the island of Vulcano, Sicily. The goal of this campaign will be to survey volcanic emissions using a network of ground- and UAV-based sensors. The data collected will provide a validation for the CFD model, as well as give insight into trace gas dispersion, even if the composition of volcanic emissions differs from forest fires.

In the following months, we will plan more campaigns, partnering if possible with other TEMA members, to collect more data from combustion of wood fires – ideally under such scenarios as a prescribed burn.





2.1.7 Realistic 3D smoke modelling and fire detection

This section details the input and output data for smoke modelling and fire detection technology, which builds the core of the **PDM-Tech-03** technology. Interaction diagram for the developed technology is shown in Figure 2.6.

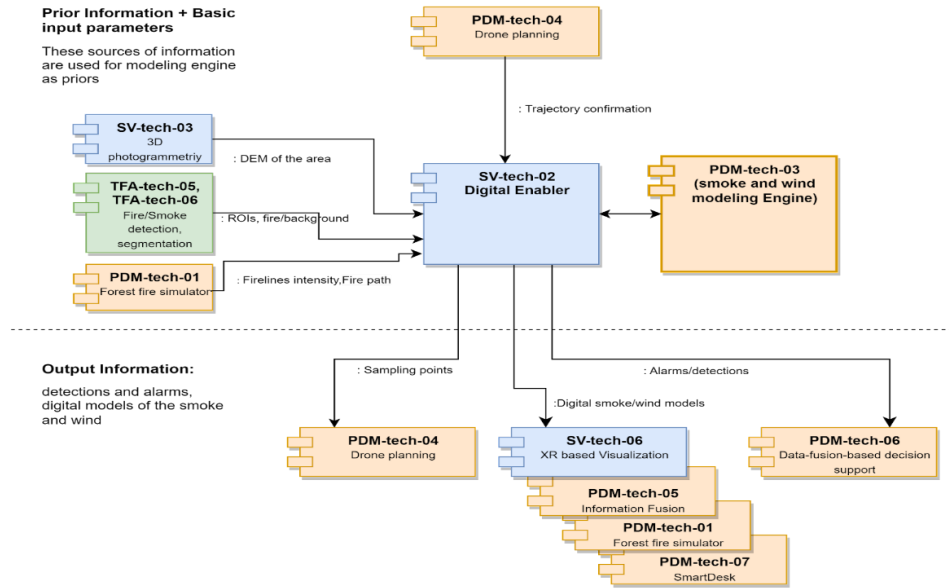
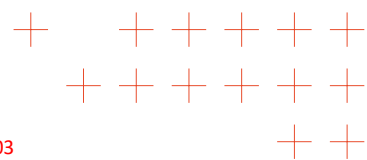


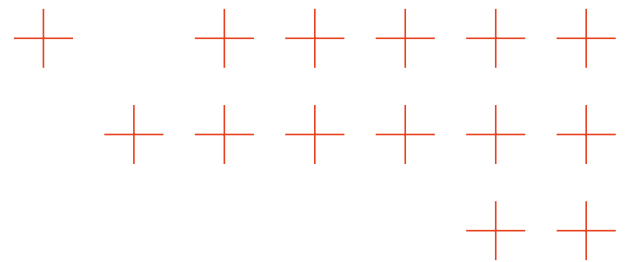
Figure 2.6. Interaction Diagram of PDM-Tech-03.

2.1.7.1 Inputs

As we can see from the Interaction diagram in Figure 2.6 (**PDM-tech-03**) will interact directly with the Digital Enabler (**SV-tech-02**), since this component will receive the main input data needed to update the simulations: Through the Digital Enabler, the technology will receive fire front predictions to produce from **PDM-tech-01**, **TFA-tech-05** and **TFA-tech-06**. Additionally, the Digital Elevation Model provided in **SV-tech-03** to provide important information for the small-scale weather models.

As discussed in the Section 2.1.4, DLR KN will additionally collect data on site to inform the smoke concentration and high-resolution airflow model. To summarize, these geolocalized, time-stamped data, shall be collected on a combination of drone- and ground-based sensors include trace gases (SO₂, NO₂, PM), wind measurements, temp/humidity and solar intensity data (W/m²). These sensor data are then shared via an edge-based station to the rest of the TEMA platform as needed. PDM-tech-01, for instance, will use solar intensity, and wind conditions.





Finally, the desired simulation domain and times for prediction are inputs for the smoke model. These define the grid over which the smoke and wind are computed.

2.1.7.2 Outputs

PDM-tech-03 gives as its primary output a model of smoke and trace gases. Because the estimation of air flow is necessary for smoke dispersion, this intermediate result is also available from the platform. Both data forms are provided in a volumetric format. The format will be raw volumetric data, with the only possible exception that compression may be used if the model size exceeds communication bandwidth.

Additionally, the on-board measurements that PDM-tech-03 uses to give the model are output to the digital enabler. The measurements include information about the specific time and location of collection

2.2 Wildfire behaviour modelling

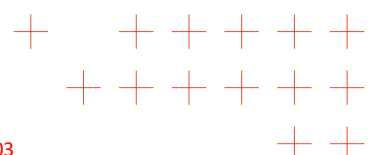
Wildfire Analyst® (WFA) (Ramírez et al., 2011) is a software tool designed to assist fire managers, firefighters, and other stakeholders in making informed decisions regarding wildfire management and response. WFA FireSim module provides real-time analysis of wildfire behaviour and simulates the spread of wildfires in seconds to support real time decision making.

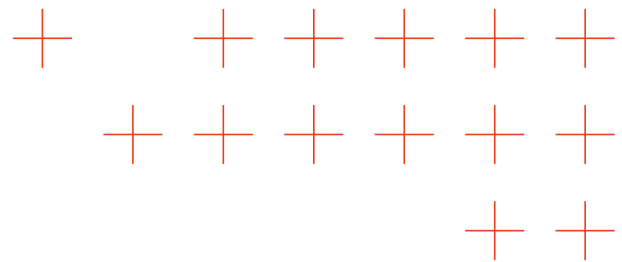
2.2.1 State of the Art and planned advancements

2.2.1.1 State of the Art

Currently, there are other fire simulators that provide basic fire behaviour outputs, such as FamMap, from BehavePlus fire modelling system from Missoula Fire Sciences Laboratory, SPARK from CSIRO (Australia) or WFDDS from U.S. Department of Agriculture (USDA), among others. However, the computing power, speed and number of different fire behaviour outputs provided by WFA is higher than that of other competitors. A detailed description of the fire behaviour outputs can be found in section 2.2.2.4. In addition, these simulators are not operational due to the time required for preparation and integration of input data. Tecnosylva's wildfire simulator won the best Technological Innovation award at the Spanish Symposium on Fires 2010 and is nowadays considered one of the most recognized and advanced wildfire simulators worldwide.

One of the problems with wildfire simulation is the use of a weather forecast model as weather input, which may not be accurate or match reality. In addition, the simulator needs to know the fuel models present in the area, and this information can also be more or less accurate depending on the quality with which this information layer has been elaborated. Because of this, the ability to assimilate data in real time would make a difference when simulating real fires.





2.2.1.2 Planned improvements within TEMA

TSYL technology shall advance in the SotA of operational forest fire simulation modelling through the novel enhancement of the simulator operational data assimilation. This will be achieved by assimilating additional operational sensor data and the consequent simulation results calibration, gradually refining the overall simulation results according to the gathered sensor data and therefore reducing the uncertainty and increasing the reliability of the simulation results.

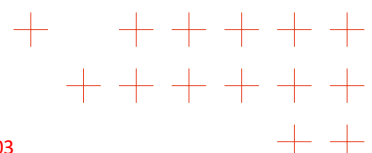
Improvement of weather forecast model: To compute the simulations of forest fire behaviour, the simulation code requires certain weather parameters as input. The system stores this meteorological data, which the forest fire simulation code will use to compute the simulations. These weather variables are: temperature, relative humidity, wind speed and direction and solar radiation, if possible. This weather forecast data will be downloaded and ingested from open-access dataset available for the experimentation sites. In case of KAHY Forest Fire use case, HARMONIE-AROME weather forecast data can be used (<https://data.europa.eu/data/datasets/>). For other areas where this regional data is not available, global data such as Global Forecast System (GFS, <https://www.ncei.noaa.gov/products/weather-climate-models/global-forecast>) will be used despite its more coarse spatial resolution.

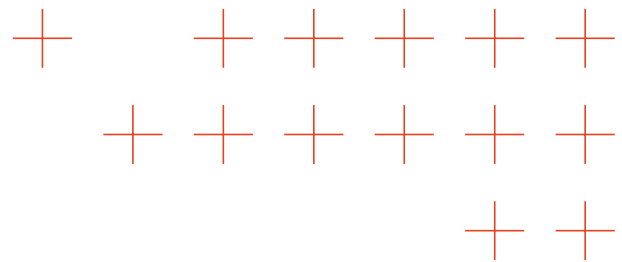
During the use cases, sensors in the field will record real-time weather data from Smoke and wind modelling engine component. This data will be sent to the fire simulator through the Digital Enabler module as JSON file. This new information will be stored and used for upgrade the weather forecast model.

The close to real time fire assimilation will be done by progressively updating the weather forecast as new data from in-situ sensors is available. The weather forecast model will be modified by using an Inverse Distance Weighting (IDW) interpolation method with different exponential factors in the spatial and temporal dimension. This interpolation will be done independently for each weather variable so that different sensors providing different variables could be used in different locations.

Simulation adjustment: The Information Fusion component will process all available information from satellite images, drone images and other information sources to generate fire probability maps. These maps will be filtered over a certain probability threshold to obtain those pixels representing the most likely fire presence. Hence, a GeoJSON file with fire presence positions will be generated and used to feed the new simulations. These points will generate a collection of control points with the actual fire's arrival time known. The technique is based on minimizing the error between the simulated fire growth and the actual fire by identifying the optimal ROS adjustment variables using a least squares approach.

FireSim will extract the locations of the new fire locations, ingesting them as adjustment point and rerunning new and calibrated simulations each time the new information in weather and firefont positions data reached the Digital Enabler.





2.2.1.3 Activities performed in the period M13-M18

During the current reporting period, TSYL has been working on the interaction with the rest of the system components and establishing the main roadmap for improving the accuracy of the simulation results, analysing the best methodology to achieve the proposed improvements. In addition, a historical use case was performed for the Montiferru wildfire (July 2021, Sardinia) assuming meteorological information and fire suppression management data as hypothetical inputs in an actual fire case under TEMA technology. A more detailed description of all activities and methodologies can be found in sections 2.2.3, 2.2.4 and 2.2.5.

2.2.2 Wildfire simulator components

FireSim Main components are briefly described below.

- Simulation Engine

The Simulation Engine Core is the central component of the fire simulator. It is the engine that receives simulation requests and input parameters, host the algorithms that compute the outputs of the fire simulations and act as the container where these outputs are processed and created. Examples of such outputs are the forest fire arrival time, rate of spread, flame length, fireline intensity or fire paths.

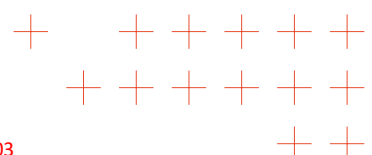
The main surface fire model is based on the Rothermel model (Rothermel, 1972) which includes the modifications proposed by Albin (1976) and the required expansion to include Scott & Burgan fuel types (Scott and Burgan 2005).

- Data repository

The data repository is the storage component which includes a database and a file system. This container stores the outputs of the performed simulations and the impact relevance assessments, as well as the geospatial base input data for the forest fire simulation engine core.

2.2.2.1 Interaction with other technologies

FireSim (**PDM-tech-01**) will interact mainly with the Digital Enabler (**SV-tech-02**), since this component will receive the main input data needed to update the simulations: in-situ weather data from the Smoke and Wind Modelling Engine component (**PDM-tech-03**) and fire front positions from the Information Fusion (**PDM-tech-05**) module (see also Figure 2.7).



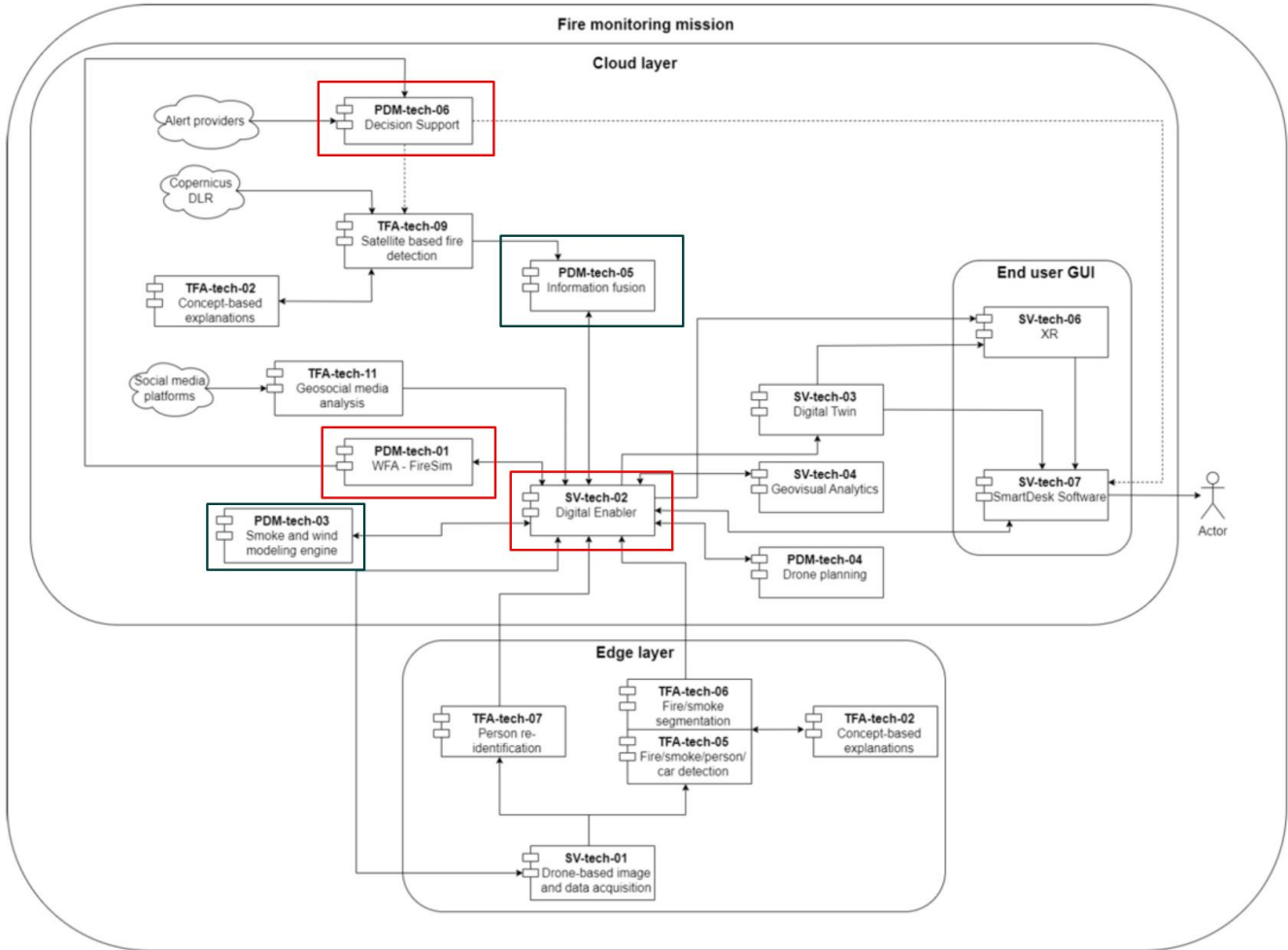
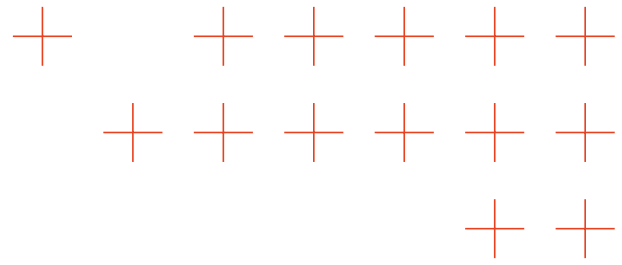


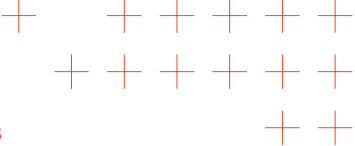
Figure 2.7. Interaction diagram for Fire Monitoring Mission.

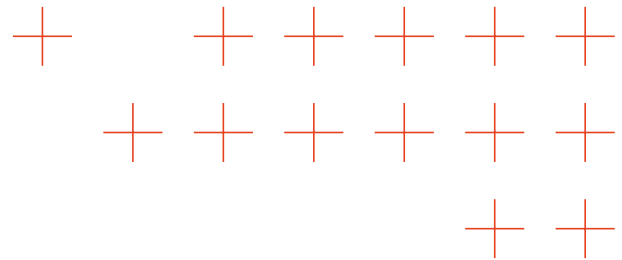
After the simulations are calculated, the fire behaviour results are sent back to the Digital Enabler in order to be used by other technologies for operational use and/or display purposes.

In parallel, and requested by one of the project partners, FireSim could also interact directly with the component Decision Support (**PDM-tech-06**) in order to speed up the data transfer with this technology.

2.2.2.2 Base data

FireSim needs to make use of certain base data to carry out the simulations. This base data creates the foreground for the fire simulator to consider the necessary conditions to simulate the several fire behaviour outputs in a realistic manner. In order to fulfil this, FireSim needs to make use of geospatial data that provides information about the characteristics of the terrain for the Simulation Engine to perform simulations as well as for implementing the topographic effect on other inputs such as wind direction and speed.





Geospatial data

FireSim operates mainly based on geospatial data. It needs this data to consider the characteristics of the terrain, of the vegetation, and the natural and man-made networks infrastructures that affect the way the fire spreads (e.g. rivers, water bodies and roads) in the processing of the fire simulation results. Some of this geospatial data is mandatory for the Simulation Engine to be able to operate, whereas there is other data that could be added optionally. This optional data can be added to provide the simulator with additional information of the terrain or vegetation and hence, allows improving the realism of the obtained results.

The geospatial base data is stored in the Data repository component of the fire simulator and has been prepared and integrated in the simulator in advance. It is static data that does not require a periodic update (but the fuel model layers after vegetation disturbances). The mandatory geospatial data layers:

- Digital Terrain Model (DTM): The digital terrain model provides the simulator with information about the characteristics of the terrain, namely the slope and the aspect of the terrain.
- Vegetation fuel models: The vegetation fuel models are one of the most important base information layer for the simulator. According to the existing type of vegetation, the fire behaves in a certain manner depending on the fuel load, the type of vegetation and moisture content.

Other optional base data is the canopy characteristics, such as canopy cover, canopy height, canopy base height and canopy bulk density, used when available for modelling crown fires. Regarding firebreaks like rivers, roads and so on, they are already considered within the fuel model layer.

2.2.2.3 Inputs

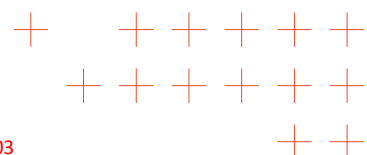
In addition to the base data layers, the simulator needs two essential inputs to be able to run a simulation:

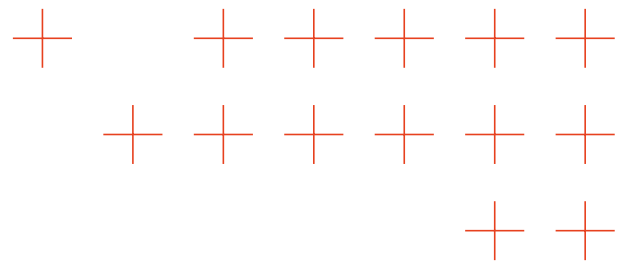
- Ignition points

These ignition points will be extracted from the fused images coming from the Information Fusion component, representing those areas where the fire is located. If this information is not available at the beginning of the emergency, the web application will allow the user to establish the first ignition point based on the available information.

- Weather data

In order to run a simulation and calculate future fire behaviour, it is necessary to use a weather forecast model that provides the necessary information over the selected simulation hours. These weather forecast data will be provided by the end user or, alternatively, an open and updated data service will be used, such as the Global Forecast System model (GFS, www.ncei.noaa.gov/products/weather-climate-models/global-forecast).





In addition, once the emergency is underway, the simulator will receive real-time weather data from sensors in the field, which will be used to correct and calibrate the forecast model to generate a more accurate weather data model.

2.2.2.4 Outputs

FireSim provides outputs within the considered simulation perimeter. This simulation perimeter is defined by isochrones that represent the number of hours of the simulation. Hence, the respective outputs are calculated from the location(s) of the ignition geometry until reaching the maximum of the simulation hours that were defined (i.e. defined by the user through the web application interface) (see Figure 2.8).

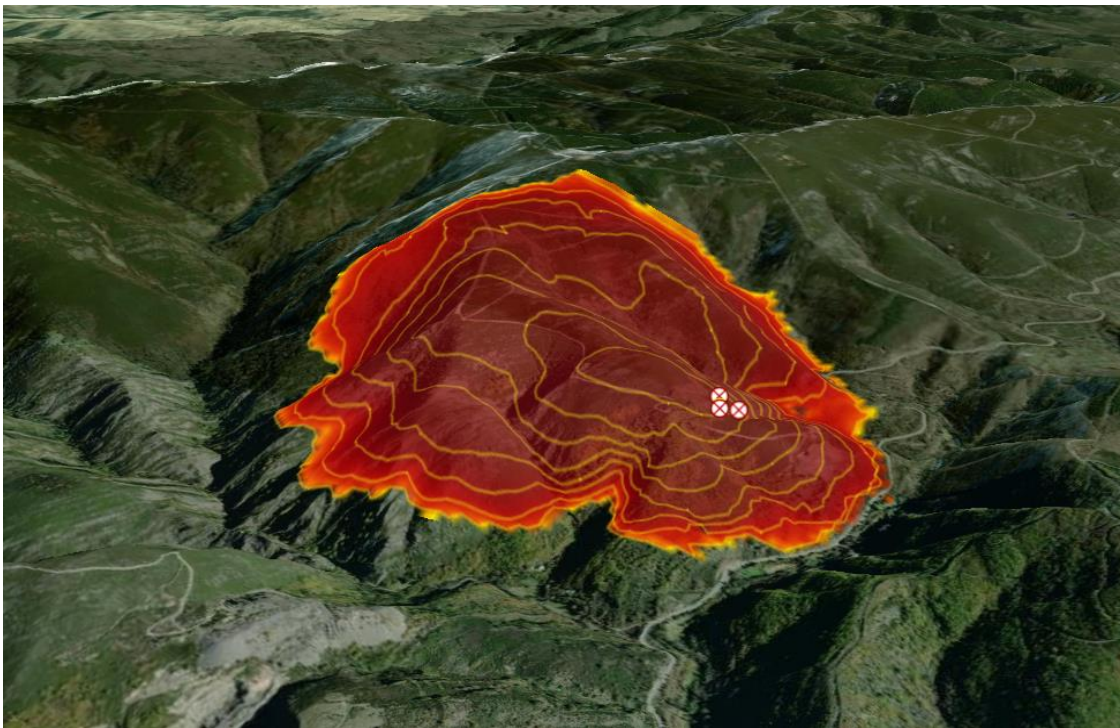
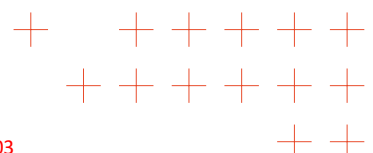


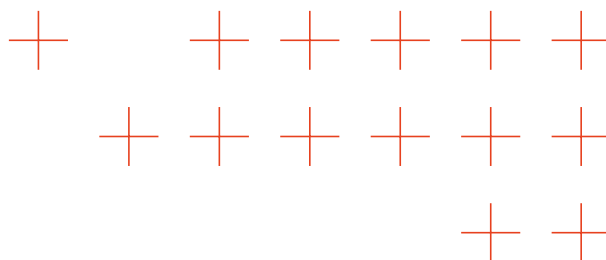
Figure 2.8. Example of arrival time output.

The fire behaviour outputs FireSim can provide are shown in Table 1.

Table 2.1 Fire behaviour outputs generated by FireSim.

Fire behaviour layer	Short description	Format
Animated Simulation	Perimeter affected by the fire animated in hourly increments	kmz
Surface fuels	Fuels affected by the fire	kmz, GeoTIFF





Rate of Spread (km/h)	Speed of the fire for each cell of the simulation	kmz, GeoTIFF
Flame length (m)	Expected height of the flames	kmz, GeoTIFF
Fireline Intensity (kW/m)	Expected intensity of the flames	kmz, GeoTIFF
Arrival Time Vector (h)*	Hourly fire perimeters	kmz, shapefile
Crown Type	Type of crown fire (surface, torching, conditional, crowning)	kmz, GeoTIF
Firepath	Main paths taken by the fire in the simulation. It shows the fire cells that are estimated to be most active in the fire (minor, secondary, main)	kmz, GeoTIF

* Arrival Time can be also provided in raster format (GeoTIFF) representing the time the fire is estimated to arrive for each cell of the simulation.

2.2.3 Near real-time weather forecast model upgrade

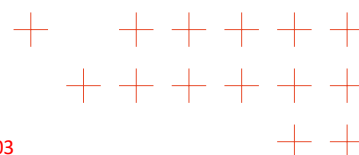
2.2.3.1 Weather forecast model

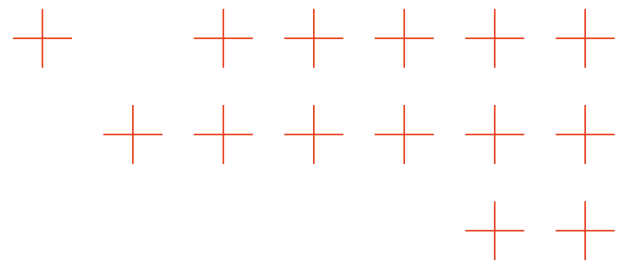
To compute the simulations of forest fire behaviour, the simulation code requires certain weather parameters as input. The system stores this meteorological data, which the forest fire simulation code will use to compute the simulations. The weather variables that the simulator needs to run simulations are listed below:

1. Temperature (°C)
2. Relative humidity (%)
3. Wind speed (km/h, measured 10 meters above the ground)
4. Wind direction (degrees)

If possible, solar radiation (W/m²) variable would be a valuable data in order to calculate the dead fuel moisture content with more accuracy (Nelson Jr, 2000). Both, dead and live fuels moisture content are also basic parameters for fire behaviour and propagation.

This weather forecast data will be downloaded and ingested from open-access dataset available for the experimentation sites. In case of KAHY Forest Fire use case, HARMONIE-AROME weather forecast data can be used (<https://data.europa.eu/data/datasets/>). For other areas where this regional data is not available, global data such as Global Forecast System (GFS, <https://www.ncei.noaa.gov/products/weather-climate-models/global-forecast>) will be used despite its more coarse spatial resolution.





2.2.3.2 Assimilation of real-time weather data from in-situ sensors

During the use cases, sensors in the field will record real-time weather data from Smoke and wind modelling engine component. This data will be sent to the fire simulator through the Digital Enabler module as a JSON file. This new information will be stored and used for upgrading the weather forecast model.

The close to real time fire assimilation will be done by progressively updating the weather forecast as new data from in-situ sensors is available. The weather forecast model will be modified by using an Inverse Distance Weighting (IDW) interpolation method with different exponential factors in the spatial and temporal dimension. This interpolation will be done independently for each weather variable so that different sensors providing different variables could be used in different locations.

2.2.4 Near real-time fire front position adjustment

2.2.4.1 Fire front images reception and pre-processing

The Information Fusion component will process all available information from satellite images, drone images and other information sources to generate fire probability maps. These maps will be filtered over a certain probability threshold to obtain those pixels representing the most likely fire presence. Hence, a GeoJSON file with fire presence positions will be generated and used to feed the new simulations.

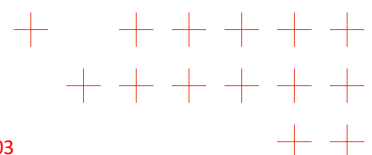
2.2.4.2 Assimilation of pre-processed fire front geometries as adjustment factors

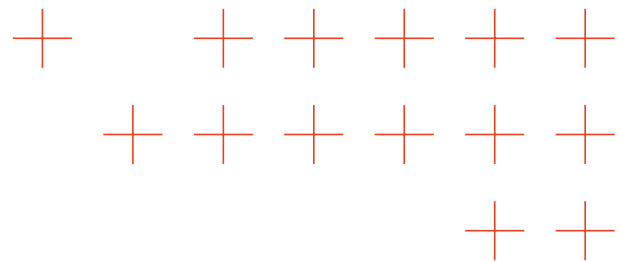
In fire management, operational wildfire modelling is useful in assisting experts in creating more effective suppression tactics. Unfortunately, wildfire predictions frequently become noticeably inaccurate and unreliable due to intrinsic model flaws, a lack of model applicability, or incorrect input data. By using observed fire front data to adjust or calibrate simulations to observed fire patterns, data-driven approaches seek to get around this issue. This is a very interesting method that can be supported by satellite fire data, GPS positions of suppression resources, or observations from unmanned aerial vehicles.

Adjusting the simulated fire growth to match the observed fire progression by adjusting the ROS adjustment parameters is a typical technique to reduce simulation inaccuracies. These adjustment factors are a set of fuel related constants Adj_{fuel} used to modify fire's rate of spread (ROS) in a simulation in the following way:

$$ROS_{final} = Adj_{fuel} \times ROS_{model}$$

Fire practitioners and researchers are familiar with these factors because they offer a straightforward method of matching fire simulations to actual observed fire spread. Nevertheless, manually finding these factors is a difficult and time-consuming task that calls for perseverance and a good number of trial and error attempts to be finished.





A collection of control points or lines with the actual fire's arrival time known serves as the adjustment data. The technique is based on minimizing the error between the simulated fire growth and the actual fire by identifying the optimal ROS adjustment variables (Rothermel, 1983) using a least squares approach.

FireSim will extract the locations of the new fire locations, ingesting them as adjustment point and rerunning new and calibrated simulations each time the new information in weather and fire front positions data reached the Digital Enabler. The Figure 2.9 shows an example of the methodology to be developed.

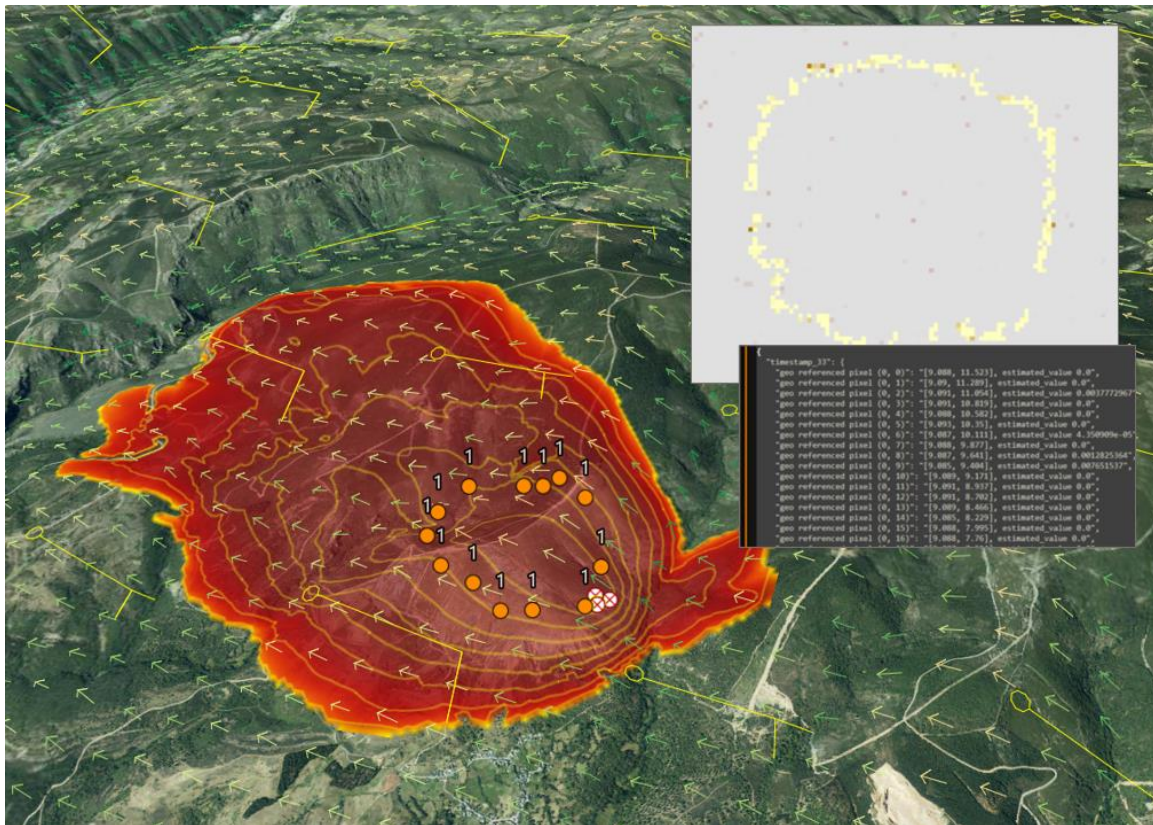
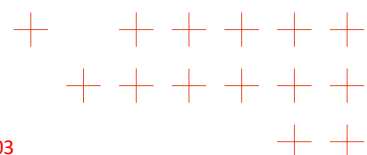
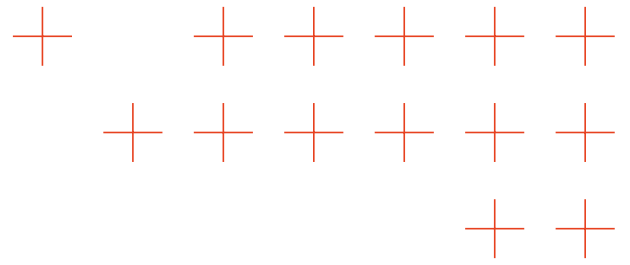


Figure 2.9. Example of adjustment points for the 1 h update.

2.2.5 Montiferru wildfire use case

The Montiferru wildfire (July 2021, Sardinia) is classified as an Extremely Wildfire (EWE) due to both its large burn area (about 13,000 hectares) as well as its erratic and irregular behaviour. Driven by southeast winds, the fire began at 12:00 on July 24 along Provincial Road 15 (Bonarcado-SantuLussurgiu) in the province of Oristano and quickly spread to the southeast slopes of the Montiferru mountain. It quickly got out of control for firefighting crews that were working on the ground.





To demonstrate the improvement of simulation technology in TEMA, two scenarios were recreated as they will be encountered in the actual case studies:

1. Simulation using a weather forecast model. This is the common procedure used once a fire has started and the behaviour of the fire in the hours to come is intended to be simulated. In this case, data from the GFS model were used.
2. Simulation using observed data from stations (SCANO DI MONTIFERRO RU station), together with wind information shown in a fire technical report provided by RAS. In addition, the positions of the fire fronts were used at certain times for adjustment purposes. This information was concluded from maps found in the report showing the different phases of the fire's evolution. This would be the case where real-time weather data would come into the simulator, along with the fire presence maps. Spatio-temporal techniques to adapt weather forecast model were not used since they are still under development.

In addition to this, a fuel model layer (Scott & Burgan fuels family) was generated for the area, trying to make it as accurate as possible.

Derived from the fire report, two fire evolution phases were used to test the technology. These phases are shown below:

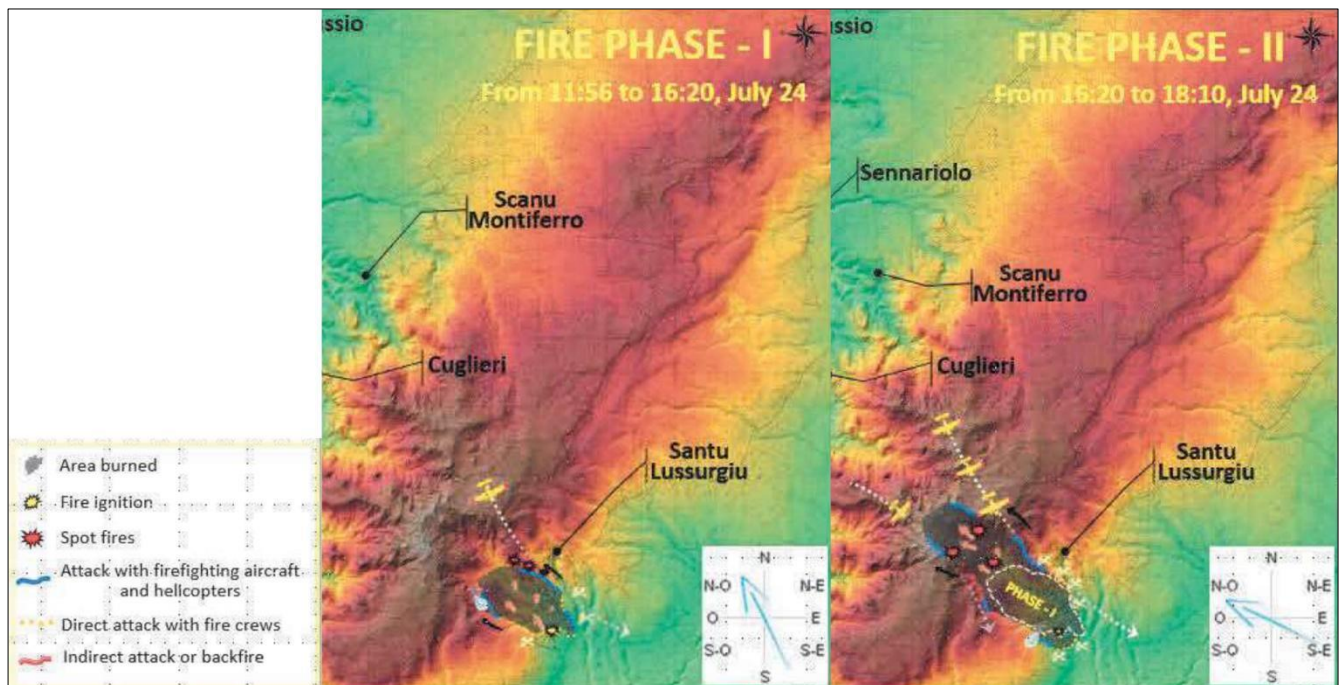
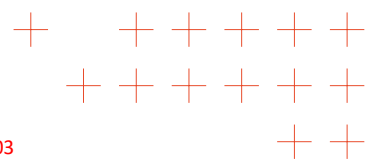
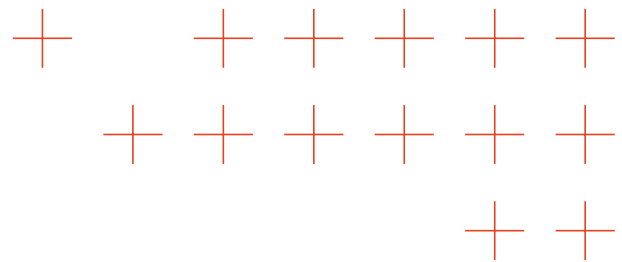


Figure 2.10. First two fire evolution phases in Montiferro wildfire (Source: edited from "European Commission, Joint Research Centre, Almeida, M.,





Ribeiro, L., Alves, D. et al., *Analysis of 2021 critical wildfire events in the Mediterranean region*, Publications Office of the European Union, 2023”, [https://data.europa.eu/doi/10.2760/562495.](https://data.europa.eu/doi/10.2760/562495))

The phases’ perimeters were considered as actual fire perimeters at that time. Phase 1 lasted 6 hours, so simulations of that duration were run using weather forecast data and station and report weather data. Always keep in mind that the simulator does not have as input data the firefighting actions carried out by firefighting crews. Live fuel moisture content (LFMC) were set to summer conditions (30% and 65% for herbaceous and woody LFMC respectively) and dead fuel moisture content (DFMC) was established using the information contained in the report (4%, 5% and 6% for 1h, 10h and 100h DFMC respectively).

The figure above shows the perimeters of the two phases on the left, the simulation done with the GFS forecast model in the center, and the simulation output done with the observed meteorology on the right (arrival times metric). Upon this last simulation, a dashed blue line shows an intervention line where the fire was attacked by firefighting crews.

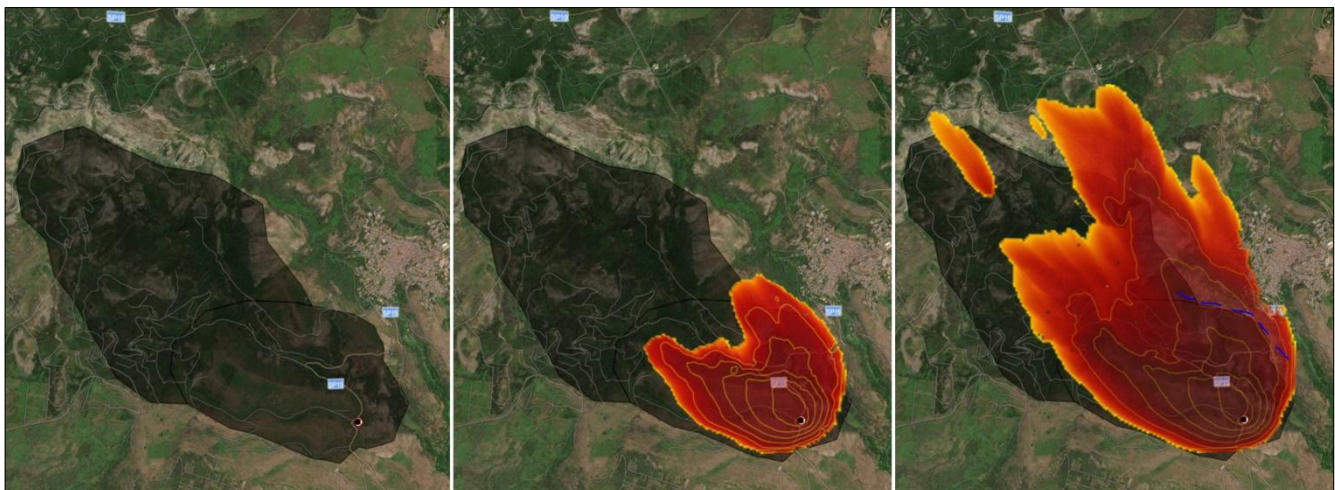
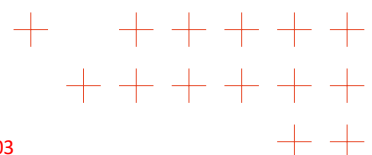
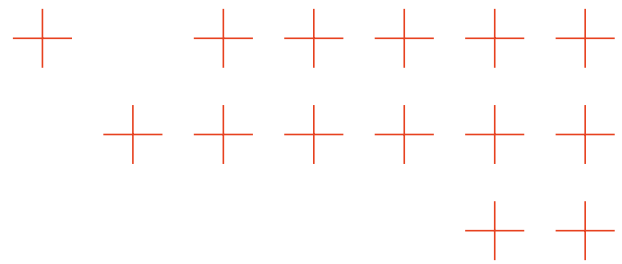


Figure 2.11. Fire simulations (arrival times) using forecast data and observed data.

As shown in the figure, the forecast model greatly underestimates the wind speed with respect to that observed, providing values between 8 and 10 km/h for the simulation hours. On the other hand, station data reached values over 30 km/h from 4:00 p.m. onwards, as also confirmed by the report. This fact could greatly compromise the decision making process by considering an option of fire spread that is lower than the actual one. In addition, and as already mentioned, the effects of the suppression activities have not been taken into account.

To test the performance of the adjustment technology, the positions of both phases’ perimeters were considered as actual positions of the fire fronts. To make this as realistic as possible, control points were taken only in those areas where no suppression actions had been carried out. From the report, it is known that phase 1 concludes at 6 hours and phase 2 at 8 hours. Therefore, 8-hour simulations were run using the forecast model on the one





hand (figure on the left), and using the observed meteorology and adjusting the position of the fire fronts on the other (figure on the right). The blue dashed line shows again the areas where fire suppression and/or containment activities were carried out.

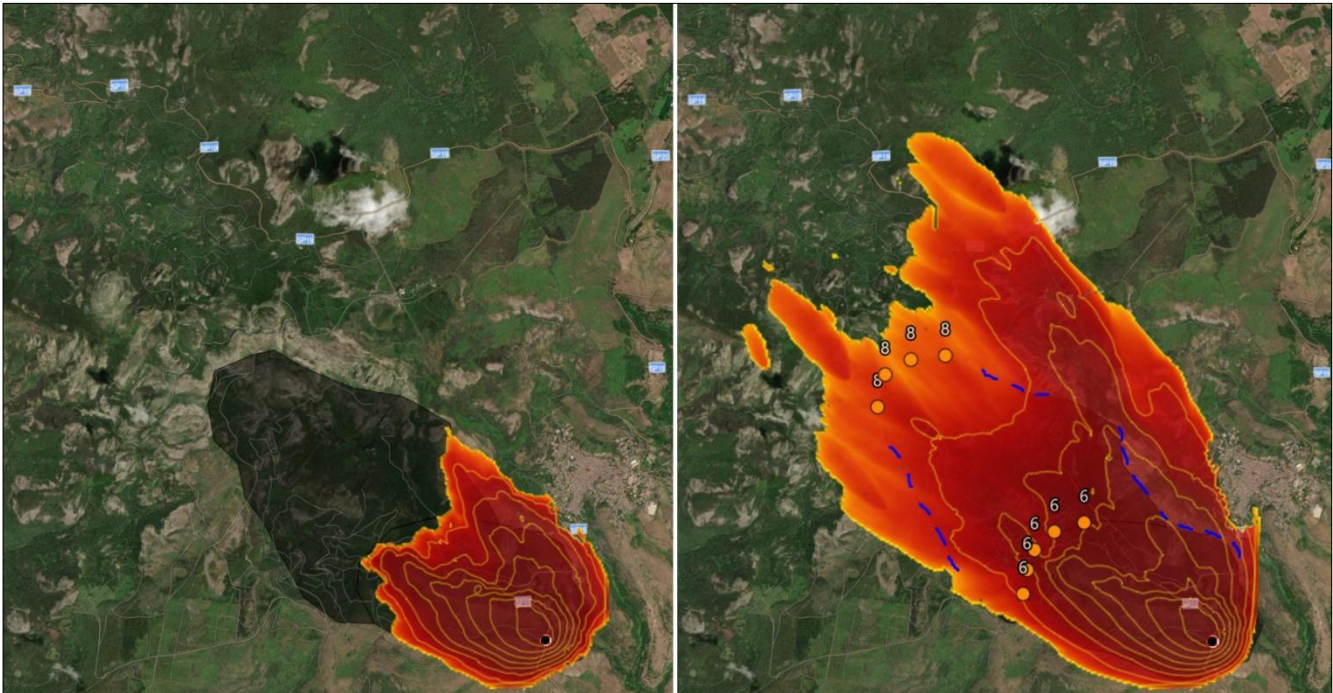
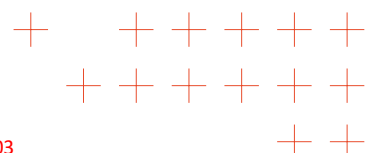


Figure 2.12. Comparison of the basic simulation result and the one intended to be developed for the TEMA platform.

As the image shows, at the end of the second phase the simulation considering weather forecast data barely reaches half of the real propagation. On the other hand, considering observed meteorology and generating adjustment parameters for fuels models and their rate of spread, the simulation generated with the technology to be developed in TEMA perfectly reaches the limit of the affected area at the end of the phase.



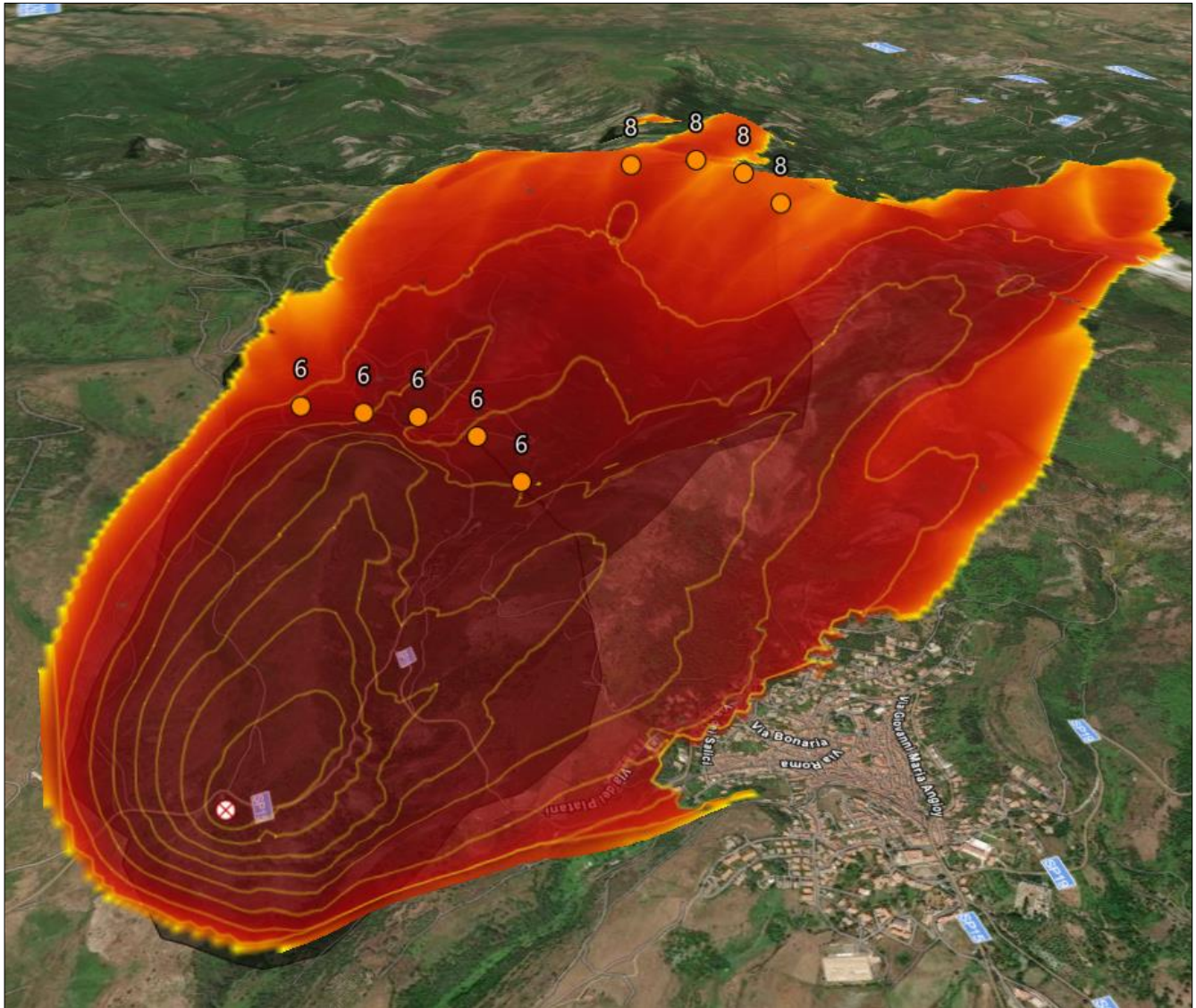
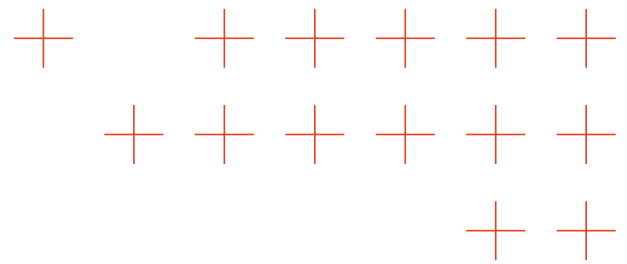
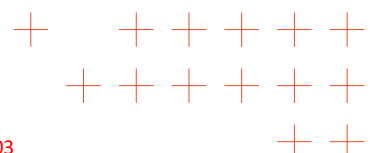
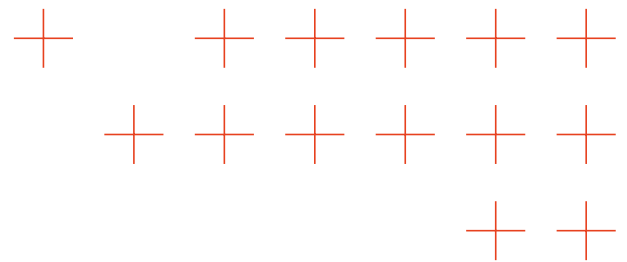


Figure 2.13. General overview of the final simulation.

In TEMA, knowing that observed meteorology data cannot be obtained for the hours to come, the weather forecast model will be corrected through spatio-temporal interpolation as real time data arrives. In addition, adjustment parameters will be calculated using the coordinates extracted from the fire probability maps, generating simulations with the most updated data possible. As new data is received, recurring simulations will be run, increasingly refitting the weather forecast model and calculating better adjustment parameters for the fuels present.





These simulation results (arrival time metrics) were exported in KMZ format aggregating all the arrival times and its symbology, so that it could be easily represented and animated in the digital twin generated by ND.

2.3 Near real-time flood modelling (NS)

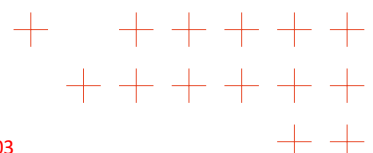
2.3.1 Introduction to 3Di hydrodynamic modelling software

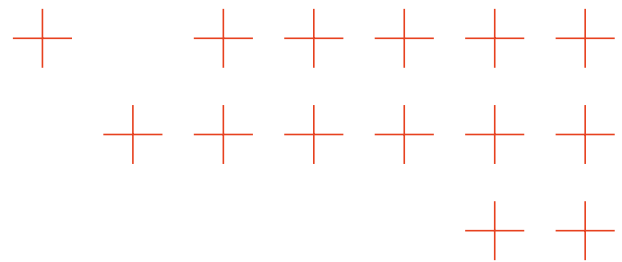
Natural disasters, such as floods, occur more often in recent times and their impact becomes far more extreme in severity because of high urbanization rates. Today's cities face huge challenges in both preparing for and recovering from this growing impact. Predictions of floods are crucial to be able to act and to protect individuals and local communities. Floods can be caused by a wide range of natural hazards, like heavy precipitation events, overtopping and breaching of levees. For lots of areas it is not feasible to prepare inundation maps in advance as the source(s) and the combination of circumstances, and as a result the flooding itself can vary largely. Therefore, these predictions need to be made during the events based on real-time information. Under these circumstances, time is of the essence, and the predictions need to be made fast and accurate. Consequentially, a strong interest in fast and accurate hydrodynamic models exists.

The physical processes of flooding and modelling are complex. Floods are characterized by specific flow conditions which are indirectly related to the forcing of the flood, e.g., rainfall events upstream in combination with a certain topography of the area. Water depths of floods are relatively shallow compared to their horizontal extent. So, even when the water depth reaches several meters, horizontal scales are generally about kilometres. Naturally at the start of a flood event extensive wetting occurs in the area, but in the aftermath of the flood, drying processes are crucial. In addition to these flow characteristics, the areas of interest also share some similarities. Besides local variations of elevation and land use that affect the flow, the soil's storage capacity might be of interest too. All these characteristics should be considered, to end up with a reliable prediction of the flood propagation and a physics-based model is still the one which is applied the most. Even nowadays with new machine learning models, they are often trained on the output of physics-based models.

To simulate the propagation and impact of floods accurately, 3Di Water Management software is used as technology in PDM-tech-02. In paragraph 2.3.2, the state-of-the-art hydrodynamic simulation software 3Di Water Management is introduced. Paragraph 2.3.3 describes the objectives and planned improvements for PDM-tech-02 to achieve near real-time flood modelling in TEMA. Additionally, a brief overview is given in paragraph 2.3.4 of the activities performed during the period M13 - M18 in the TEMA project.

Furthermore, this deliverable provides a more detailed technical description of techniques used in 3Di Water Management in paragraph 2.3.5. This is followed by paragraph 2.3.6 in which the technical interaction and the interoperability of PDM-tech-02 with other technologies in the TEMA platform is described. All the underlying





technical developments that will be researched, tested, and potentially incorporated to achieve near real-time flood simulations will be outlined in 2.3.7. Concluding with the last paragraph 2.3.8 where developments are tested in one of the use-cases of TEMA in Germany (Ahrtal region).

2.3.2 State of the Art (SotA) 3Di Water Management software

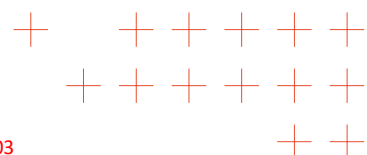
In this paragraph, we introduce and describe the state-of-the-art hydrodynamic simulation software 3Di Water Management. Most of the techniques used within the 3Di computational core are published in scientific papers (e.g., Casulli et al., 2009; Casulli et al., 2011; Casulli et al., 2013; Volp et al., 2013; https://docs.3di.live/l_literature.html).

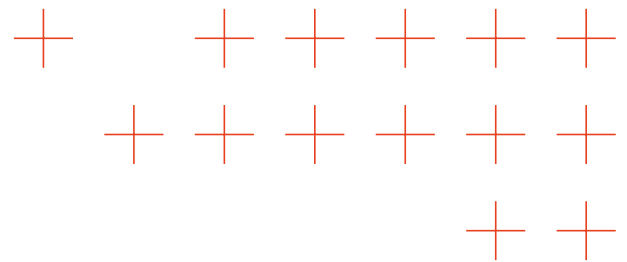
As mentioned in the introduction (paragraph 2.3.1), flood forecasting in TEMA needs to be fast, so that the results can be incorporated in briefings to emergency response teams or first responders on short notice. Simultaneously, there is always a trade-off between accuracy and computational time. 3Di Water Management is especially suited for our application, as it uses a subgrid-based method. The subgrid-based method (Casulli, et al., 2009) (Volp et al., 2013) allows for a strong increase in accuracy, without a significant increase in computational cost. Moreover, it can capture the process of wetting and drying areas naturally.

3Di Water Management is the first commercial hydraulic modelling suite which applied the subgrid method. Some years later it was followed by others like HEC-RAS modelling software developed by the US Army Corps of Engineers. Now, 3Di is SotA modelling software by incorporating not only overland flow but also hydrological processes like groundwater flow and interflow via subgrid modelling in combination with embedded 1D elements.

3Di Water Management distinguishes itself from other hydrodynamic software products because of its option to edit a model interactively during a simulation. This is SotA functionality for end-users to adjust a simulation via an interactive website or machine-to-machine via the API. This kind of interaction during a simulation is not offered by other hydraulic modelling software, e.g., HEC-RAS from the US Army Corps of Engineers ([HEC Software \(army.mil\)](https://www.hec.com/software)) or Delft3D modelling suite of Deltares ([Delft3D Flexible Mesh Suite | Deltares](https://www.deltares.com)). A model can be forced by boundary conditions, rainfall, lateral inflow, surface sources and sinks, leakage, or wind. Editable events include breaches, controls over hydraulic structures, bed level edits or obstacle edits. These forcings and events can be added before and changed during the simulation.

3Di Water Management runs all computations in the cloud via the REST API, scripts, and software applications from third parties which can easily interact with all 3Di functionalities. Specifically, for the TEMA platform the ability to perform automated runs and using 3Di software as an operational system





during natural disasters or run batch simulations with all different rain events for training exercises can both be of interest for emergency responders.

3Di Water Management is benchmarked in two studies in which it scored top of the list [Benchmark Studies On Modelling Instruments - 3Di \(3diwatermanagement.com\)](#) and these new developments need to be sure it will keep its status as SotA hydraulic modelling software.

2.3.3 Objectives and planned improvements for PDM-tech-02 in TEMA

To achieve near real-time flood modelling in TEMA, the objectives of PDM-tech-02 are to:

- OB1 - Increase the model-based prediction responsiveness/speed for evolving phenomena

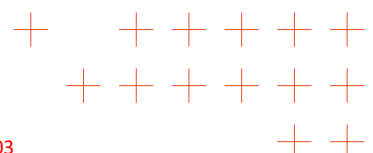
To achieve this objective, NS will research methods to reduce the computational cost of the software of 3Di Water Management, so that alterations due to changing circumstances during the natural disaster are updated in near real-time in the flood model. Additionally, it is of major importance that after the updates, simulations should run fast to compensate for time-loss. Therefore, to reduce the computational cost, **parallelization** is being investigated. With this method, the calculation workload will be spread over multiple CPU cores (hardware).

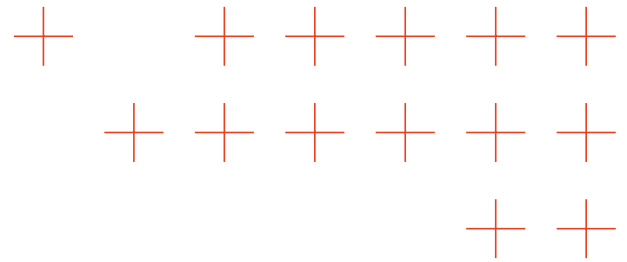
Other improvements are being made to 3Di Water Management by **automating** the building of a flood model, **setting standards** for typical scenarios, and automatically incorporating third-party data such as data from rain gauges, meteorological forecasts or incorporating remote sensing data like for example satellite data. Automating these processes allows for quicker updates to the flood model based on the best available data.

- OB2 - Increase model-based prediction accuracy for evolving phenomena by increasing the accuracy of the flood simulation results.

To improve the accuracy of the flood simulation results, **clone cells** will be investigated in TEMA to diminish the amount of calculation cells and improve its accuracy by limiting the number of unknowns in the software. 3Di Water Management will be the first commercial hydraulic modelling suite which is applying this new innovative methodology. As part of this, additional research will be performed on hybrid modelling processes like AI models.

- OB3 - Improve responsiveness and interactivity of visualization mechanisms for evolving phenomena where the response time of flood models will be near real-time, and the data-to-visualization time will be reduced.





To improve responsiveness and interactivity a new concept of data visualization is being investigated for 3Di Water Management. Currently, data is displayed as 1D (vector) or 2D-raster (GeoTIFF / NetCDF) information. In TEMA, the automated transformation and post-processing of 3Di simulation results from 2D-raster data to so-called '3D-tiles' (according to the Open Geospatial Consortium standard) is being researched. Immediate post-processing of 3Di simulation data and data transformation will reduce the data-to-visualization time in the Digital Twin environment of TEMA. This functionality is not yet offered by other hydraulic modelling suites.

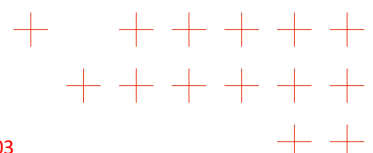
In paragraph 2.3.8 a more elaborate description of techniques to accelerate the flood modelling process is provided.

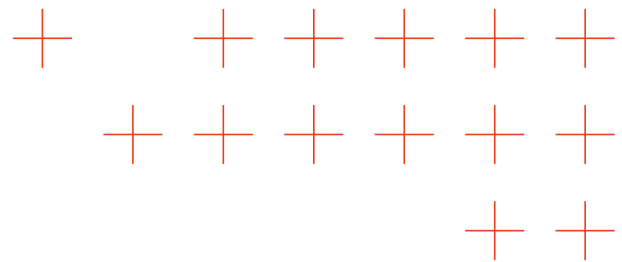
2.3.4 Performed activities for PDM-Tech-02 during M13-M18

The aim of PDM-tech-02 in TEMA is to achieve near real-time flood simulations. Therefore, research is performed to accelerate 3Di Water Management software by reducing the computational cost without decreasing the accuracy. Additionally, improvements will be made to the model-building and simulation process and new techniques to decrease data-to-visualization time are explored.

During M13 to M18 of the TEMA project, the following activities are performed. Some of the underlying activities will be explained more thoroughly in the coming paragraphs.

- ICON Forecasting module is added to the 3Di Live Site and the Modeller Interface to automatically import the latest available meteorological forecasting data for the entire Europe. Before, this information needed to be imported manually.
- Adjustments to the API are made by increasing the memory usage for bulk file laterals, allowing the processing of more data at once and so decreasing the required modelling time.
- In the Calculation core of 3Di Water Management changes are made to the result output files (single vs. double precision) to potentially increase the processing.
- For the grid-builder, software is updated and made compatible with Python 3.12 so it can be used in combination with new libraries.
- NS started with a sensitivity analysis on the hardware (CPU) to assess its current performance and its influence on the matrix solvers of 3Di Water Management. In other words, profiling all the steps in the calculation core.
- Improvements are made on the automated transformation and post-processing of 3Di simulation results of 2D-raster data to 3D-Tiles (b3dm files).





Besides technical improvements, in cooperation with the BRK (end-user for Ahrstal region) a test-case is set up and end-user requirements are retrieved in an interactive workshop session.

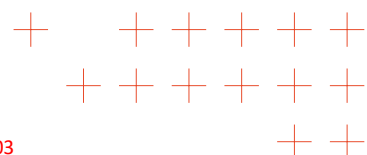
2.3.5 Technical description of 3Di Water Management techniques

Subgrid

As above mentioned, flood forecasting needs to be fast, so that the results can be incorporated in briefings to emergency response teams on a short notice. Simultaneously, there is always a trade-off between accuracy and computational time. 3Di¹ is especially suited for our application, as it already uses a subgrid-based method. The subgrid-based method (Casulli, et al., 2009) (Volp et al., 2013) allows for a strong increase in accuracy, without a significant increase in computational cost. Moreover, it is able to capture the process of wetting and drying of areas naturally. Although 3Di is fast and accurate compared to more traditional computational methods, in these hazardous circumstances, where new information is crucial for the perspective of action, any reduction of computational cost can be crucial.

The subgrid technique Figure 2.14 is based on the principle that bed level variations are generally stronger than water levels variations. As such, 3Di uses two grids: a coarse computation grid and an underlying subgrid with a higher resolution. The bed level is defined on the subgrid and the water level is assumed to be uniform within a coarse-grid cell. Besides, all input data, such as the roughness and infiltration rates can be defined on the high-resolution grid. The computations of cell volumes (cell-integrated depth) and cross-sections are performed using the high-resolution data (Volp et al., 2013).

¹ 3Di is a depth-averaged, shallow water hydrodynamic model, including several hydrology processes, which can be used as a modelling tool in water management studies. It allows the user to simulate real-world scenarios and adjust them. This way, water experts can predict and mitigate the impact of pluvial, fluvial and coastal floods, and perform climate impact studies. 3Di offers the option to incorporate open channel and sewer networks. This supports the analysis of a full hydraulic analysis of a system and testing the connectivity of system-components under extreme conditions.



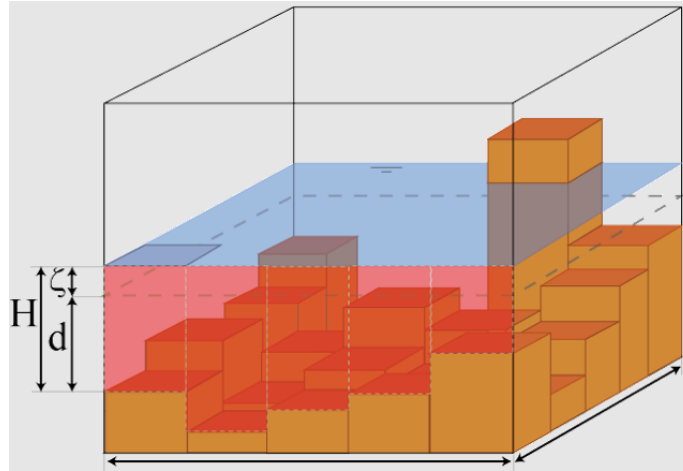
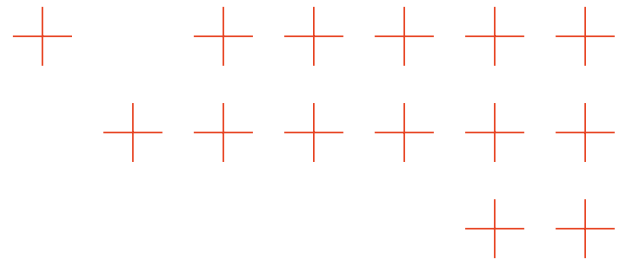


Figure 2.14. An example of a computational cell with a uniform water level and a high-resolution bathymetry Reprint: (Volp et al., 2013)

Conservation laws

In 3Di is the flow computed based on two fundamental laws of physics: conservation of mass and momentum.

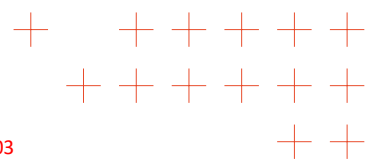
To capture or predict flow under varying conditions, one is often forced to use the computational power of computers. Since the introduction of computers various methods have been introduced and improved. Some aspects are true for all types of methods. Here, we will limit ourselves to the methods used in the computational core of 3Di.

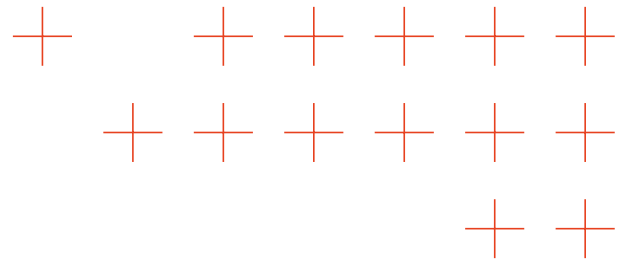
Conservation of mass states that mass cannot disappear or appear in a certain domain without a clear source. For a defined domain, when all fluxes in and out of that domain are known, the change in mass can be computed. This can be described mathematically as:

$$\frac{\Delta V}{\Delta t} = \sum_i^{in} Q_i - \sum_k^{out} Q_k + \sum_i S_j$$

In which V_{Ω} is the volume, Q is the discharge and S is the source or sink term.

The counters i, j, k count over all existing discharges, sink and source terms. 3Di does not account for density variations, so the density ρ is assumed uniform and constant and thus left out of the formula. In the finite volume approach, used in 3Di, a volume domain equals a computational cell, i.e. the water level domain. For such a domain, as shown in the figure below, all discharges (in blue) sources and sink terms (in yellow) entering and leaving the domain are to be defined or computed (Figure 2.15). The discharges are computed based on the momentum equations. Sources and sink terms are terms for water that is added or extracted in a domain. Examples of source and sink terms are infiltration and rain. In 3Di, the conservation of volume combines all flow





phenomena. This is independent of the origin of the flow (1D, 2D surface or subsurface domain). This allows a fully integrated approach of a water system.

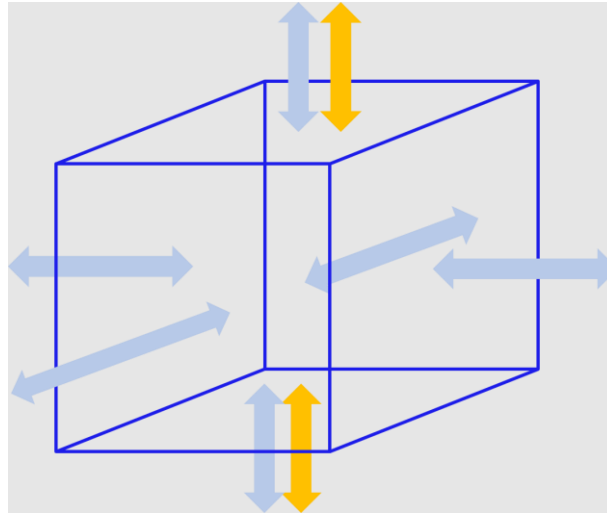


Figure 2.15. A virtual box for conservation of mass.

Flow in 1D networks, represented in, for example a sewer pipe, a channel or a hydraulic structure is computed over its full cross-sectional area. Thereby considering variations in depth and width of the 1D element, But the flow within a segment has only one direction. The flow is computed using the conservation laws and more specifically the 1D depth-averaged shallow water equations. The momentum equation for 1D flow is:²

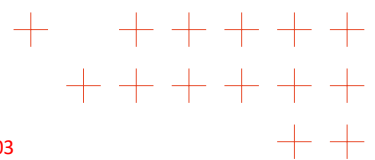
$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial s} = -g \frac{\partial \zeta}{\partial s} - \frac{\tau_f}{R\rho} - \frac{\tau_w}{H\rho}$$

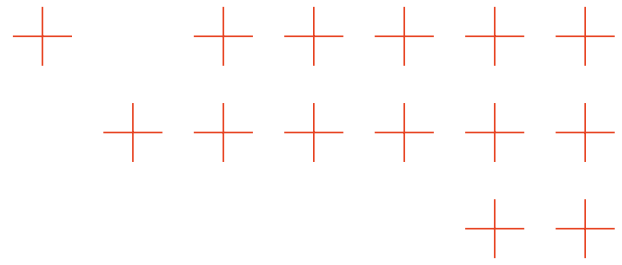
3Di takes inertia, advection, pressure gradients, bottom friction and wind shear stresses into account. These methods are thoroughly described and published in (Volp et al., 2013) (Casulli et al., 2011) (Casulli et al., 2009) (Stelling, 2012).

Schematization and model set-up

In the modelling workflow that will be followed for the TEMA use-cases as well, first a schematization is set up and uploaded to the server. On the server, a 3Di model is generated. With this 3Di model, simulations can be run by adding scenario information such as initial conditions, forcings or (climate) events (Figure 2.16).

² In which u is the cross-sectionally averaged velocity, s the 1D coordinate along the network, g the gravitational acceleration, the density of the water, f the shear stress due to bottom friction, w the shear stress due to wind, H the water depth and R is the hydraulic radius.





A 3Di schematization is a simplification of the real-world and contains the specific information of an area and situation. It is the data you work with locally and the way to generate your 3Di model. It contains all data and parameters that 3Di needs to generate a 3Di model. The data of the schematization is a spatialite (.sqlite file) and one or several rasters. A spatialite is a sqlite file database, extended with functionality for GIS data. The 3Di spatialite contains the schematization's GIS vector data (points, lines, and polygons) and settings tables.

The spatialite file also contains data that is not used to generate the 3Di model but stored in a simulation template. This applies to all data that is not required for the creation of the computational grid and the subgrid tables:

- Physical, numerical, time step and aggregation settings
- Time series of boundary conditions and laterals
- Initial water levels
- The name of the simulation

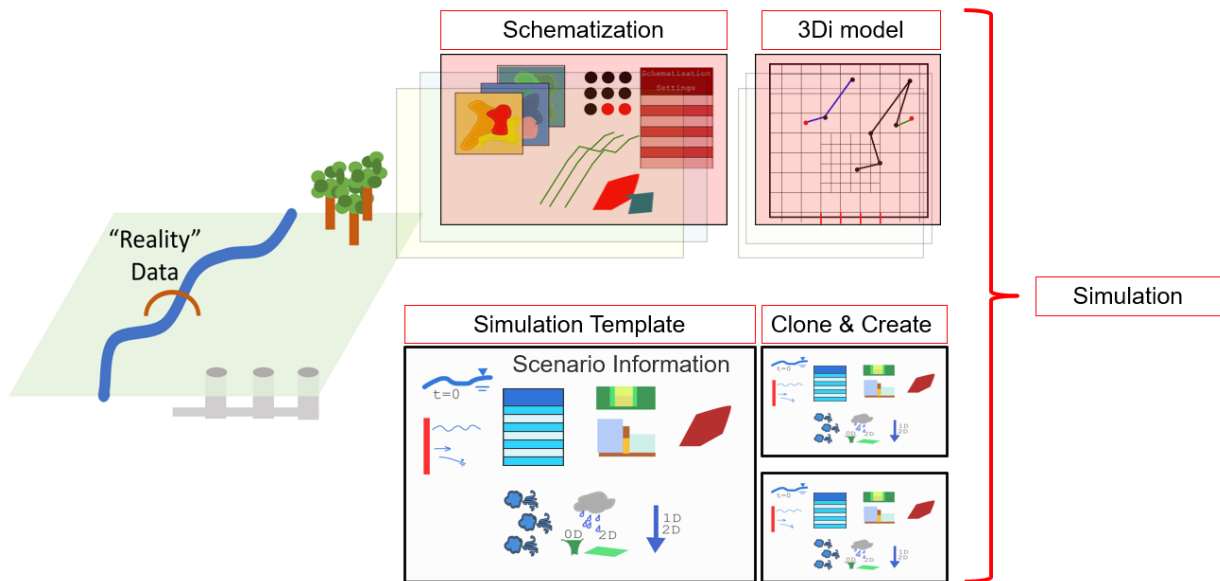
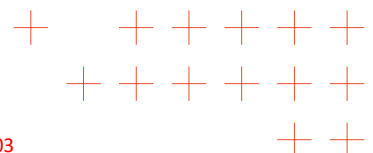
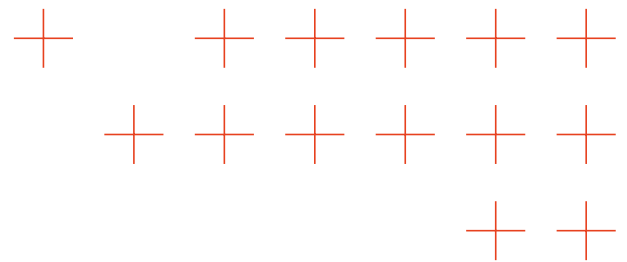


Figure 2.16. A schematic overview of the 3Di workflow modelling concept.

3Di distinguishes itself from other hydrodynamic software products because of its option to edit a model interactively during a simulation. A model can be forced by boundary conditions, rain, laterals, surface sources and sinks, leakage or wind. Editable events include breaches, controls over hydraulic structures, bed level edits or obstacle edits. These forcing and events can be added before and changed during the simulation.

For the historical TEMA use-cases in T6.3 specific simulation settings will be used, based on the available data of the event. When the historical data is incorporated in the schematization and simulation settings, historical





simulations can be run to generate missing information from (remote) locations for chosen time steps during the event. The simulated information can be used to complement the missing data in the Information Fusion (PDM-tech-05). Also, the simulation will provide new insights and data of the behaviour of the water during natural disasters in the regions of interest.

3Di runs all computations in the cloud. Via the REST API, scripts and software applications from third parties can easily interact with all 3Di online resources (Figure 2.17). Specifically, for the TEMA platform the ability to perform automated test runs, use 3Di as an operational system during natural disasters or run batch simulations with all different rain events can be of interest.

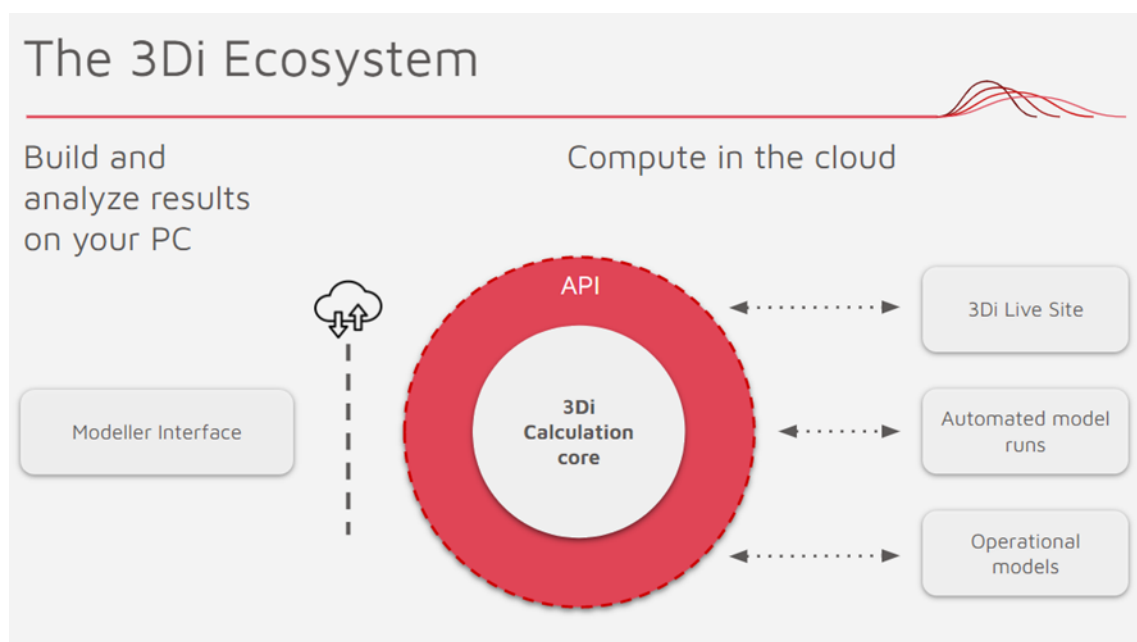


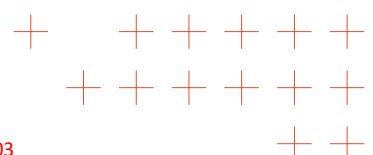
Figure 2.17. The 3Di ecosystem with the interaction between the calculation core and the REST API.

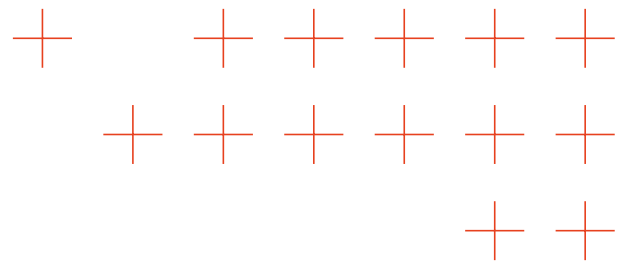
2.3.6 Technical interaction in TEMA platform

During the TEMA pilots from Task 6.3, 3Di schematizations and models will be generated for the regions of interest from the flood business missions.

For historical use-cases, meteorological data will be used. Either from rain gauges or historical radar data, whilst in future scenario's weather forecasting modules (for example ICON forecast) are used to predict the meteorological conditions driving the flood propagation and its impact.

The outputs of WP3 analysis methods are used to enrich and accelerate response to emergencies/disasters, via novel approaches to fast modelling engines for the TEMA use-cases, automated response planning for making



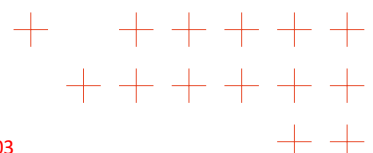


optimal sensor placement recommendations and decision support services for remote sensing. The processed information from WP3 will be fused by the information fusion technology (PDM-tech-05) and can be used in PDM-tech-02 (3Di Hydrodynamic Modelling) to calibrate, validate and enrich the available datasets and simulation results. More importantly, PDM-tech-02 generates new flood simulation results of the evolution of the natural disaster event that will be incorporated into the information fusion in the occupancy grids. This technology will estimate the status of the flood propagation with the 3Di results and subsequently update the estimated status using observed measurements. It is obligatory for the 3Di results to be georeferenced and timestamped in order to be integrated by the information fusion.

Furthermore, the output of PDM-tech-02 will be used in the several visualization techniques, such as:

- SV-tech-03: Digital Twin
- SV-tech-04: Geovisual analytics
- SV-tech-07: SmartDesk software

All but one interaction with 3Di between the TEMA technologies will be set-up via technology SV-tech-02 (Digital Enabler). The exact method of interaction between these technologies is described in the TEMA platform architecture deliverable D2.2. – Report on TEMA platform design, data models and architecture. Figure 2.18 shows the interaction diagram for PDM-tech-02. Besides communication through the Digital Enabler, a direct communication will be generated with PDM-tech-06 (Decision Support System) to speed up the data transfer and prevent a delay in data-availability.



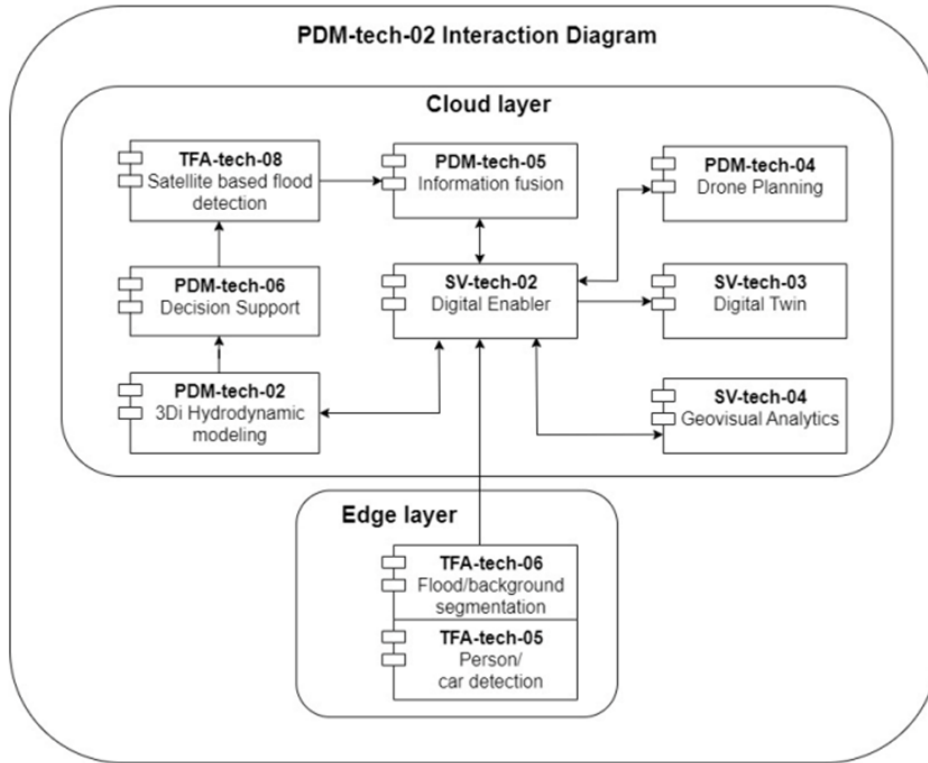
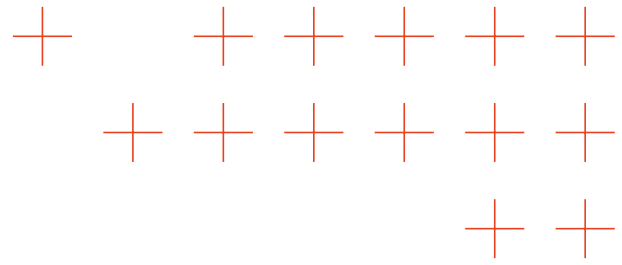


Figure 2.18. The proposed technological interaction between TEMA technologies and PDM-tech-02.

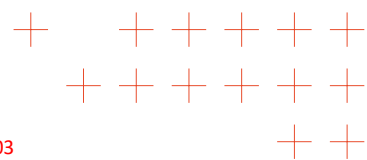
2.3.7 Acceleration techniques to achieve near real-time flood simulations.

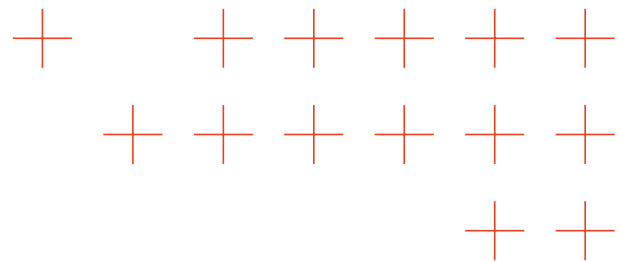
As stated in the introduction of chapter 3, the aim of technology PDM-tech-02 in TEMA is to achieve near real-time flood simulations. Therefore, research is performed to accelerate the computational cost of 3Di Water Management software without decreasing the accuracy. Additionally, improvements will be made to the model-building and simulation process and new techniques to decrease data-to-visualization time are explored. For now, the ICON Forecasting module is added already to automate and speed up the simulation process.

Within the TEMA platform, PDM-tech-02 is one of many important technologies focusing on creating added value to disaster response units. We have considered this coherence and defined several solution directions to achieve near real-time flood simulations.

In PDM-tech-02, the following techniques will be investigated to speed up the computational cost of the physics-based 3Di Water Management software:

- **Clone cells:** improving accuracy to limit the number of unknowns
- **Parallelization:** improving the use of hardware by spreading the workload over multiple cores.





Foreseen novelty in the coming months is profiling of the calculation core code. This incorporates an assessment of all the individual parts of the Calculation core and its time consumption. At the same time, functions or definitions used most often are analysed to determine its speed and will be assessed to improve the code's performance. Focus will be on the matrix solver of 3Di Water Management. Several solutions will be tested, such as a parallelization of its library to accelerate its performance.

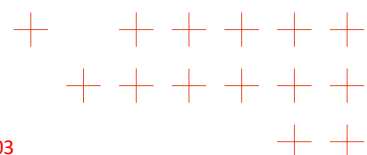
Furthermore, additional research is performed on the potential added value of **hybrid modelling** techniques. In this research track, the interaction between AI-based models and physics-based models is investigated. Additionally, a **sensitivity analysis** on the hardware (CPU) is performed to assess the performance of the current hardware and the influence on the used matrix solvers of 3Di Water Management.

Lastly, in TEMA, PDM-tech-02 focuses on decreasing the **data-to-visualization time** by automatically post-processing hydrodynamic simulation results into Open Geospatial Consortium (OGC) 3D-Tiles. With this additional post-processing step, the standardized 3Di simulation results will be transformed to 3D Tiles (b3dm format), which can be incorporated immediately in a Digital Twin model or environment. Currently, the data transformation can be executed, but the process to automatically integrate these data is still work-in-progress.

2.3.7.1 Speed up the computational cost.

a) Clone cells

Hydrodynamic simulations predict velocities and water levels in time and space. The computational cost of these required solvers depends strongly on the number of unknowns and the allowed time step of the methods. Although there is a wide range of solution techniques available, practical applications still require balancing and optimizing the computational cost and the accuracy.



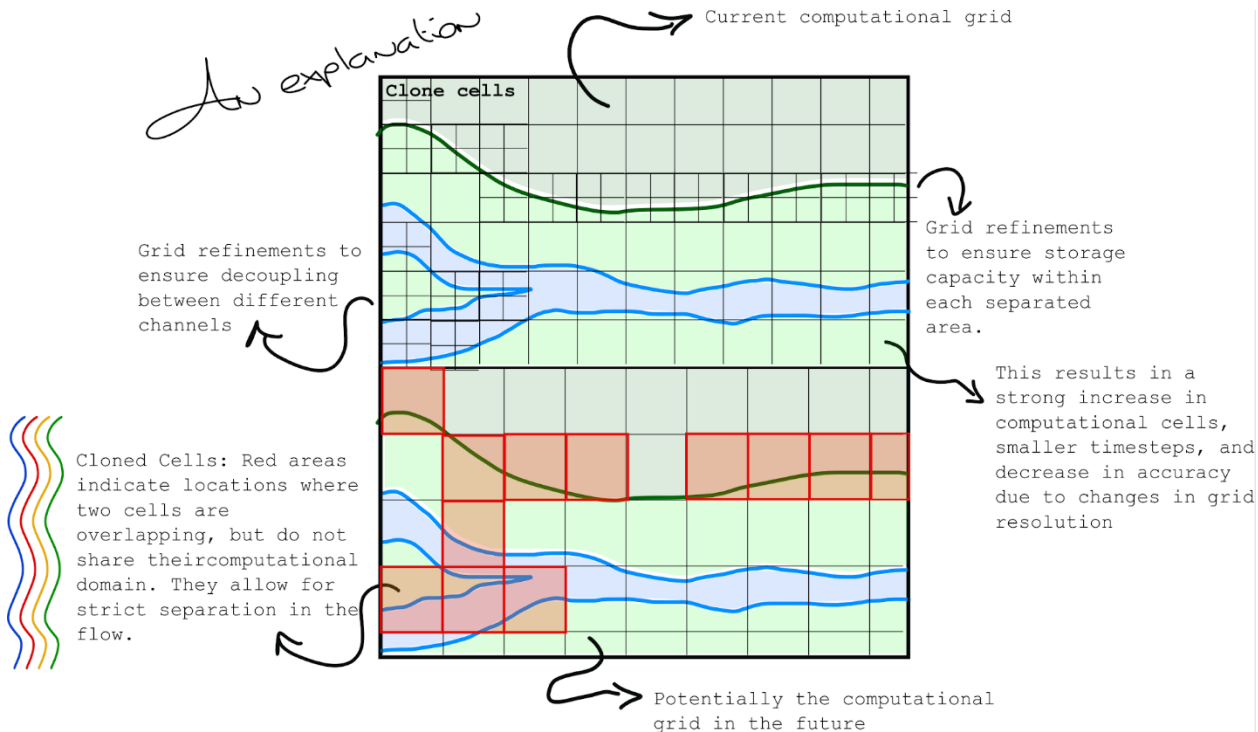
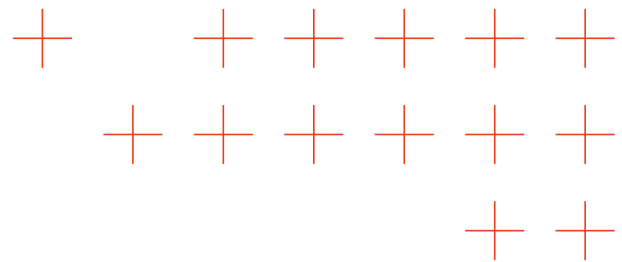
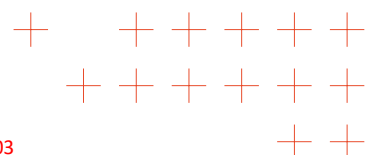


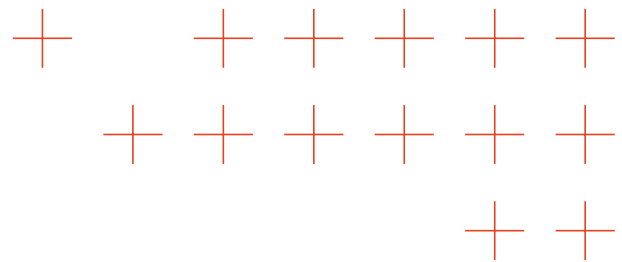
Figure 2.19. An illustrated example of clone cells.

Subgrid already allowed for a strong improvement in this balance, but local obstacles that are key features in determining the flooding extend, could require to increase the number of computational cells or might be missed. This results in either less efficient computations or inaccurate results. Clone cells will be able to avoid the need to reduce the cell size, as they allow for cells to overlap. The combination of the subgrid-based method and clone cell allow to make areas active/ inactive and doubling of the storage is avoided (Figure 2.19). Authors in (Casulli, 2009) show that it is feasible to set this up for deeper water areas. We see great potential for it in areas where there are multiple human-created obstacles, like for example flood walls, quays, and houses. It will be challenging to formulate a correct and stable formulation when the cells become connected for water levels higher than the obstacles.

b) Parallelization

Parallelization techniques aim at spreading the workload over several computer cores. The work can be done simultaneously and thereby reducing not the computational cost, but reducing the waiting time, or the wall clock cost of a simulation. For our applications, the challenges lie in the complexity of the set-up, where we not only need to solve a coupled system of equations. We need to solve a non-linear system of equations. In addition, we require it this work in the cloud. This complex system is of the essence when we want to keep the interactivity, the cloud-based flexibility and the on-demand hardware availability. In this setting, parallelization methods must





be investigated that allow for consistent domain selection, dealing with the non-linearity of the set of equations and be able to choose from a set of (virtual) computer cores (see Figure 2.20).

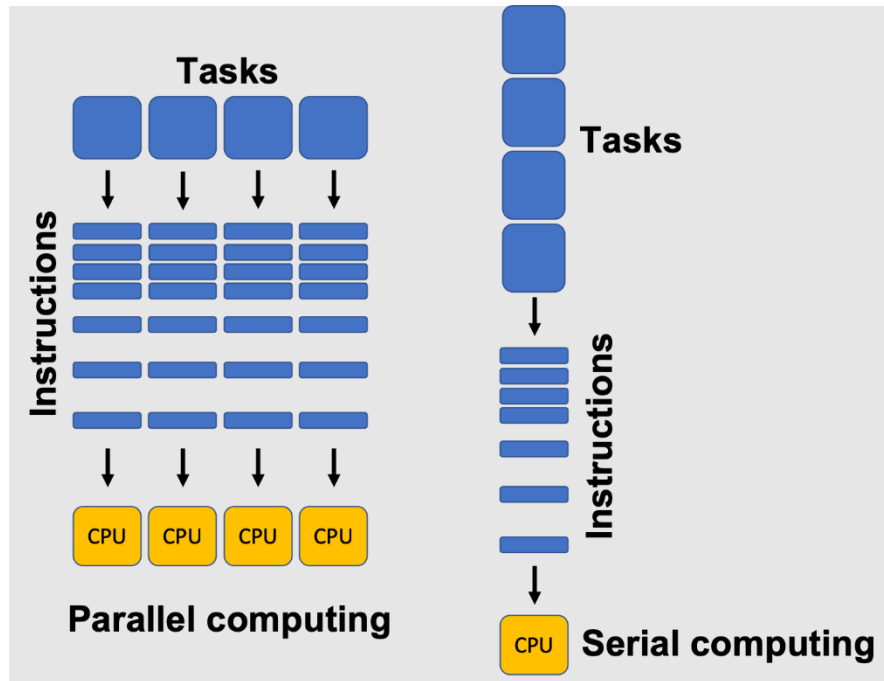


Figure 2.20. An example of parallelization in numerical computational models.

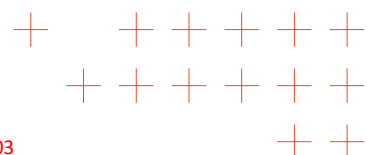
2.3.7.2 Hybrid modelling

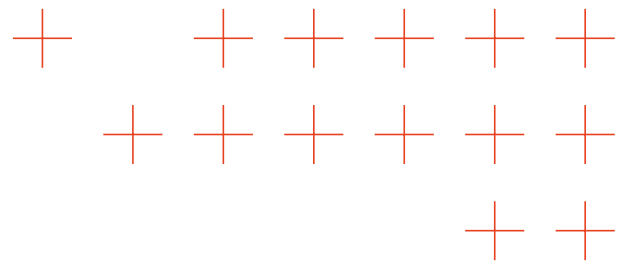
In hybrid modelling, physics-based models are integrated with AI-models and connected in such a way that the generated output of one model is used as the input for the other. For example, a physics-based model such as 3Di can generate simulation data as a novel data set to effectively train an AI (Artificial Intelligence) model. In this way the issues related to data quality and availability will be addressed.

Examining the potential advantages of using AI, reveals several noteworthy points:

- Complexity and non-linearity
- Data-driven approach
- Adaptability to real-world complexity
- Cost-effective training

While AI models offer potential advantages, they encounter pitfalls such as data quality and availability issues, model overfitting, scale and resolution challenges, and susceptibility to changing environmental conditions. By increasing the size and diversity of the training data provided by physics-based models, one can better generalize





and minimize the possibility of model overfitting. The added value of 3Di for generating training data will be investigated.

2.3.7.3 Optimizing interfacing for 3D-viewers

Visualization of the flood simulation results in emergency situations needs to be fast and intuitive for end-users (Figure 2.21). Visually, a 3D-environment such as the Digital Twin (SV-tech-03) helps end-users to better understand the situation and get a grip of the natural disaster and its evolution. Therefore, we aim to generate Open Geospatial Consortium (OGC) 3D-tiles of the 3Di simulation results (NetCDF and Gridadmin files) besides the usual 2D-raster or 1D-vector output in respectively GeoTIFF or geopackage/shapefile-format. 3D Tiles is designed for streaming and rendering massive 3D geospatial content. It defines a hierarchical data structure and a set of tile formats which deliver renderable content. Explicitly, it is mandatory to align the projection (coordinate system) of the output flood data to the coordinate reference system of the Digital Twin environment that is created in SV-tech-03 as a Cesium 3D Geospatial environment.



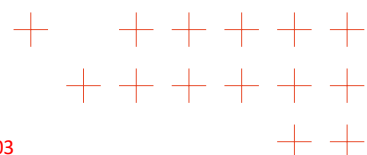
Figure 2.21. An illustrated example of a visualization of 3D tiles in a Digital Twin environment.

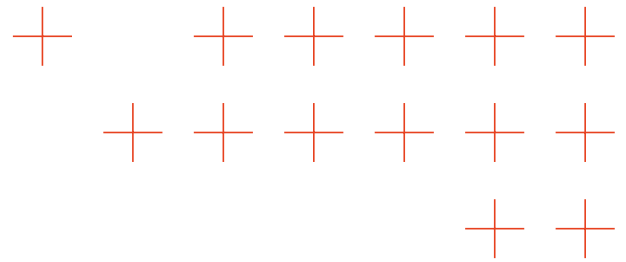
2.3.7.4 Sensitivity analysis on the hardware (CPU)

Matrix solvers, like those of 3Di are sensitive to CPU use. Therefore, one of the approaches is to conduct a sensitivity analysis on CPUs to explore the effect on simulation times. More specifically, run the simulation on the IBM Power10 platform. The IBM Power10 platform represents the latest generation of IBM's Power Systems servers, designed to deliver enhanced performance, scalability, and security for enterprise workloads. With innovations in core design, instruction set architecture, and memory bandwidth, Power10 offers faster processing speeds and improved throughput. The sensitivity analysis will explore the potential improvements of simulation times by selecting specific CPU specifications.

2.3.8 Use-case Ahrtal – historical flood simulation

In July 2021, flash floods in the region of Altenburg, Altenahr and Mayschoß (Germany) occurred. The flood started on 14/07/2021 due to extreme rainfall and lasted a few days with maximum rainfall intensity up to 200





mm/hr at certain locations. It was the most severe flood in this region of Germany in the last 100 years. Roads and bridges were destroyed in the floods. The Ahrtal is a valley situated in a low mountain range, making it vulnerable to floods, which are expected to occur more frequently in the future due to climate change. NS sets up a flood model with 3Di for the area, which will be calibrated based on information of the historic flood event, including a wide range of multimodal data collected and produced by DLR-DFD during the Ahrtal flood.

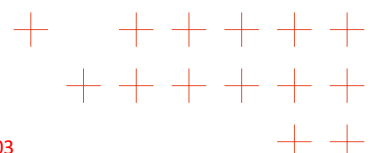
The following information was delivered to set-up a model.:

- Area of interest (Ahrtal region) – bounding box (.JSON)
- Copernicus Digital Elevation Model (30x30m) (.geoTIFF)
- Meteorological data (timeseries in .csv from measurement stations)
- Satellite data (.geoTIFF) with georeferenced heights
- Segmented flood data (.geoTIFF)
- Public alerts with expected amount of rainfall

With above data, a hydrodynamic model is generated. The default Copernicus elevation data is enriched with the georeferenced heights of the satellite data to add more detail to the area of interest and increase the accuracy of the hydrodynamic calculation. Normally, just one elevation dataset with similar resolution is used.

Usually, 3Di models are generated by a modeller, but for TEMA the Ahrtal model was automatically generated via scripting to accelerate its process. Simulation settings, hydrodynamic boundary conditions and (historical) meteorological data are chosen or set by a modeller of NS to assure the quality of the simulation output. Specifically, a new module was integrated to automatically carve out the rivers in the model, thus resembling better the real-world scenario.

Some test simulations of the Ahrtal use case are run to examine the simulation results and validate it with the segmented satellite flood data. During an iterative model building process, the 3Di hydrodynamic model is finetuned to simulate the rainfall event more accurately. To meet the end-user requirements of (new) data availability, 3Di model alterations are applied to accelerate the computational time required for rerunning simulations for the Ahrtal use-case.



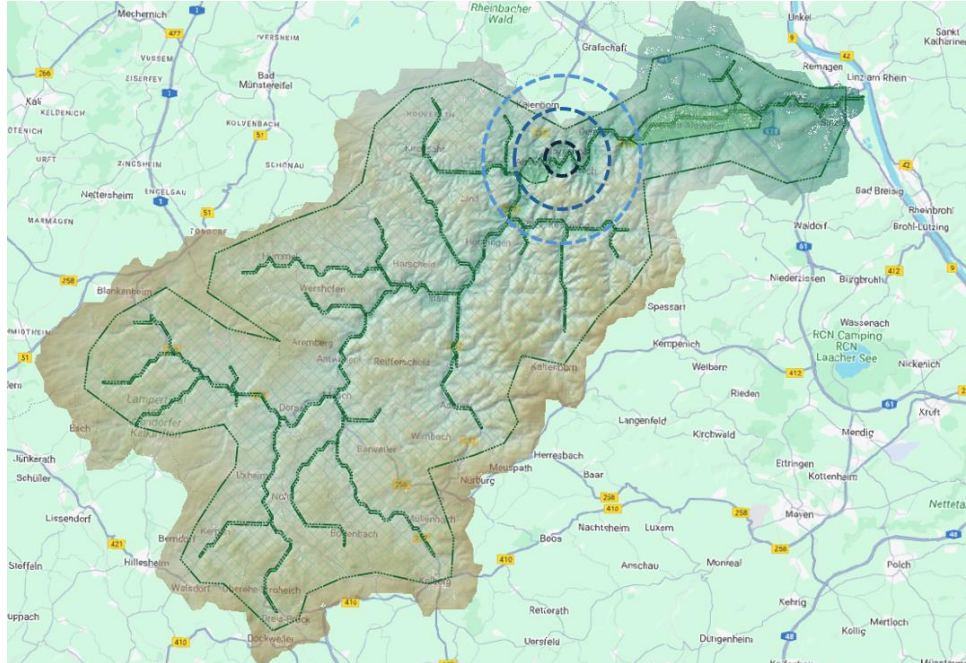
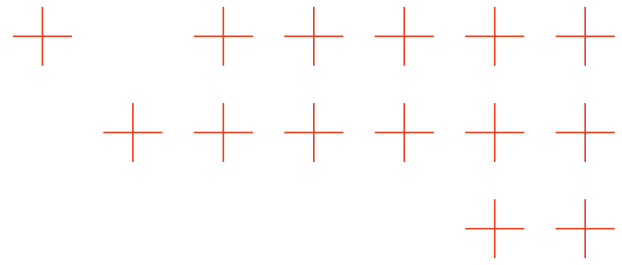


Figure 2.22. A schematization of a 3Di model in a GIS-environment. The delivered Copernicus DEM is enhanced by local high-resolution elevation data, rivers are carved out and grid refinement is added for more accuracy.

To anticipate to floods in the near future, the ICON Forecast is added as a module to the 3Di hydrodynamic software. Therefore, allowing to incorporate an accurate and updated prediction of the expected rainfall event in the simulation.

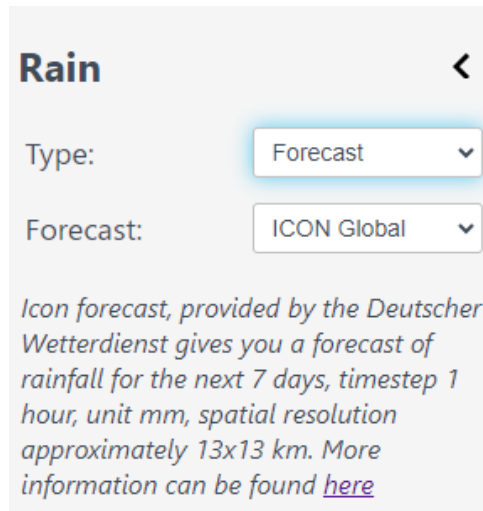
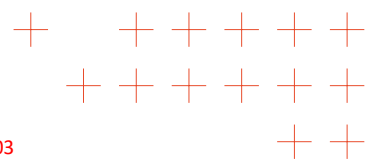


Figure 2.23. ICON Forecasting module added to 3Di.



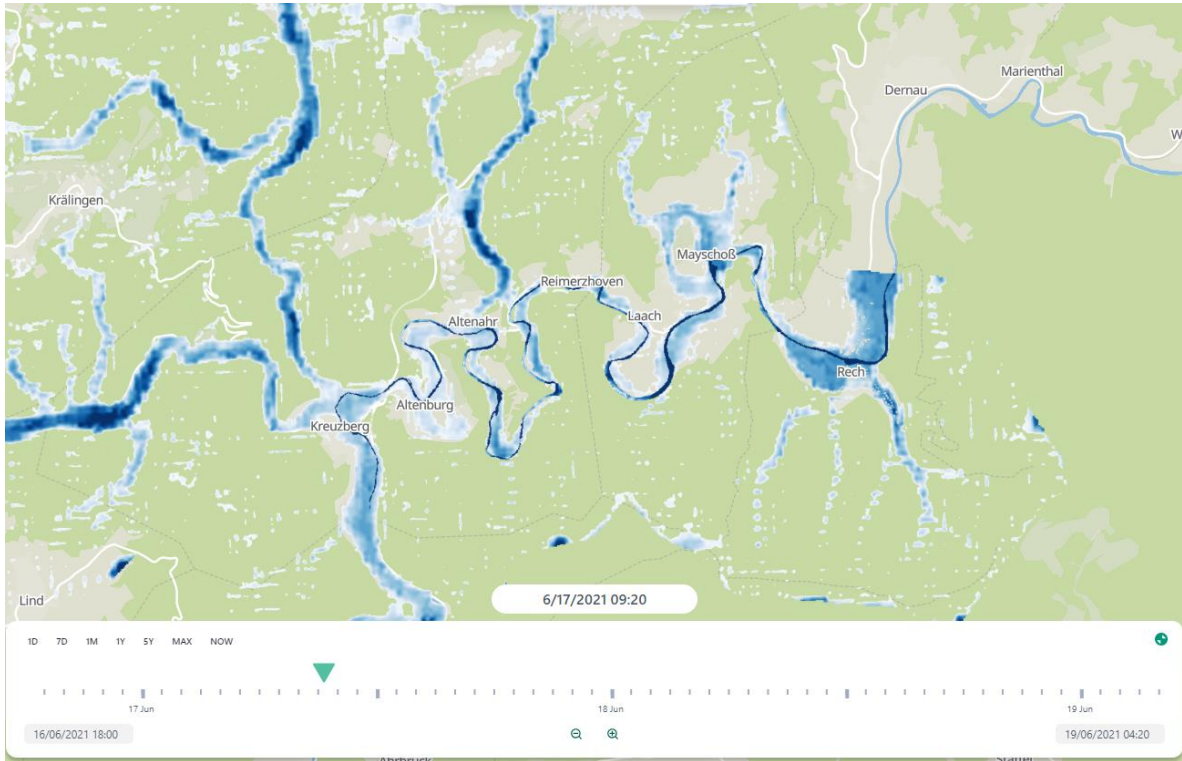
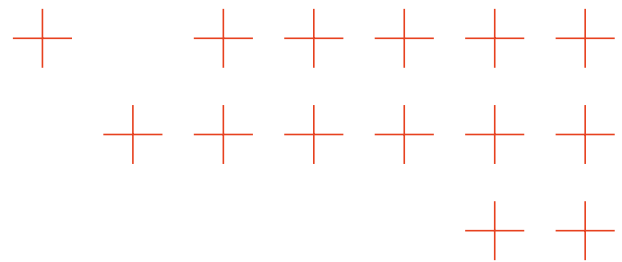
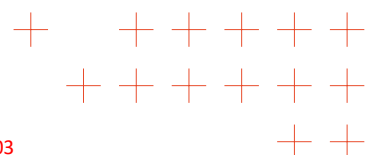


Figure 2.24. Flood extents with maximum water depth levels as simulation output.

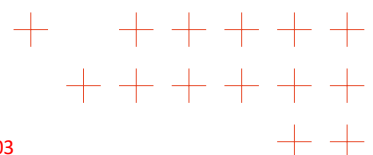
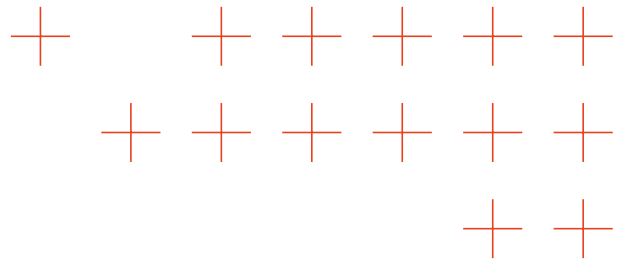
Once a simulation is finished, results are automatically being post-processed to generate simulation outputs, such as the flood propagation per timestep, the maximum water depth, flow velocities or the flood extend. Also, various ways to automatically derive information about impact-based assets (such as houses or bridges) are investigated.

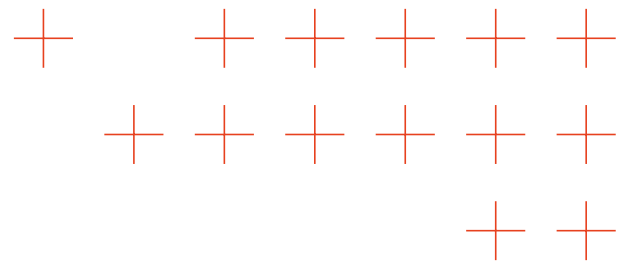
To accelerate the data-to-visualization process, NS aims to process the output of the water level per timestep from a two-dimensional raster format (geoTIFF) to a three-dimensional 3D-tile (b3dm format). Because the post-processing is already performed with our technology, the transformation and implementation to a 3D Digital Twin environment will speed up, allowing a clear visualization for the end-user in the Digital Twin and XR-services of Northdocks. This process is still being improved and is work-in-progress by NS.





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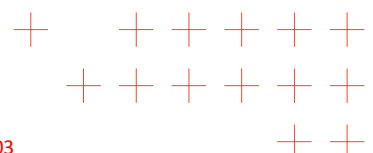


3 Information Fusion

3.1 Introduction to Information Fusion

This section summarizes the design of the Information Fusion (IF) module of the TEMA platform architecture. Information Fusion is a central module of the TEMA platform architecture, which objective is to optimally merge the results of WP3 analytics into a consistent, unified, and georeferenced outcome that reflects the updated state of the monitored natural disaster (ND).

Information Fusion will fuse in real-time the results of the analysis of the drone images (output from the method developed in task T3.2), the results from the analysis of the satellite imagery (task T.3.2), and the geosocial analytics results (task T3.3). Information Fusion will provide the updated state of the ND combining the heterogeneous inputs and ND prediction models. The output of Information Fusion is of critical importance to understand the evolution of the ND and is required by a significant number of other TEMA modules. Information Fusion is implemented in the TEMA platform architecture as technology PDM-tech-05. Fig. 3.1 shows an overview of the TEMA concept, illustrating the inputs and outputs of Information Fusion.



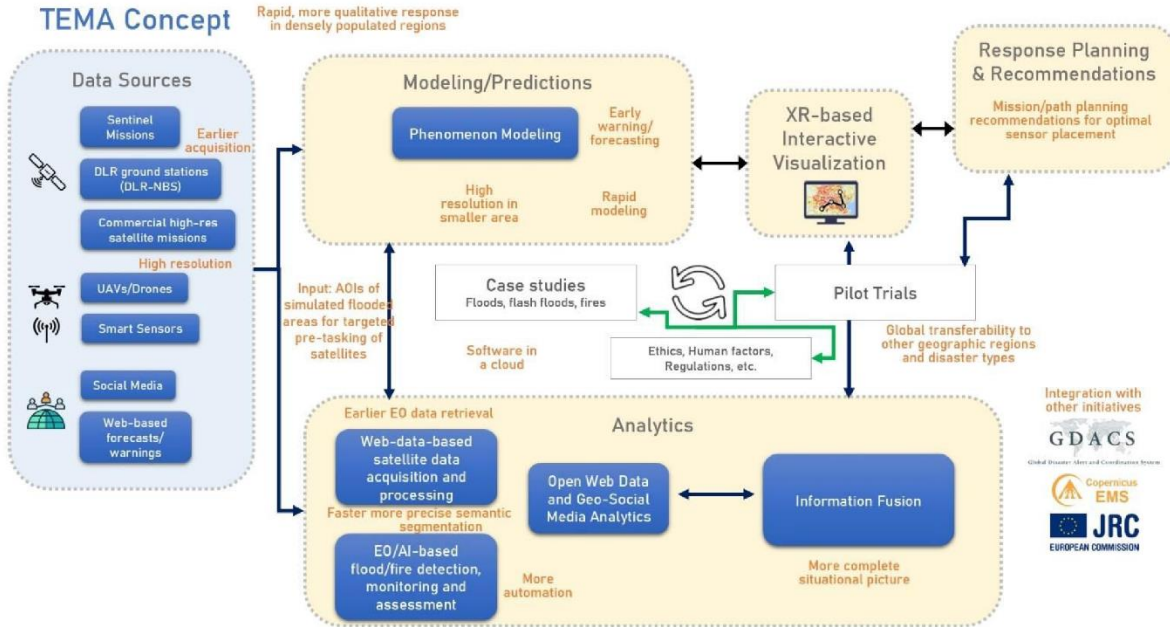
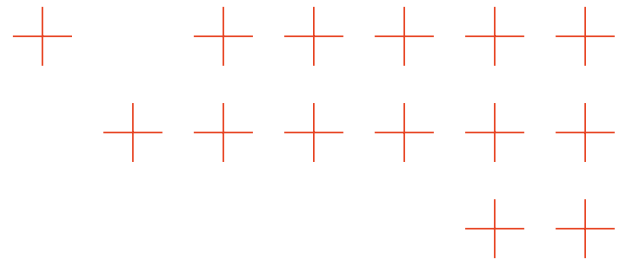


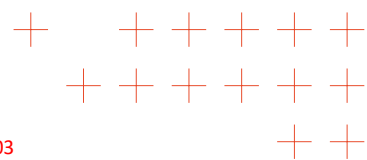
Figure 3.1. General TEMA concept

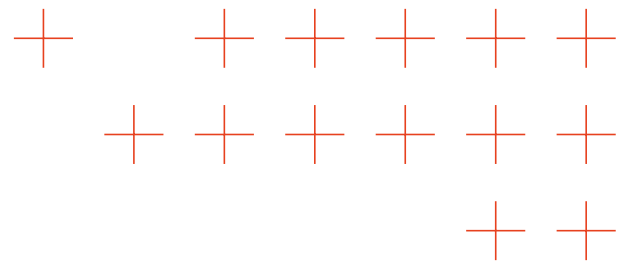
The structure of this section is as follows: Section 3.2 summarizes the State of the Art before TEMA in information fusion for ND management, the planned advancements in TEMA, and summarizes the main activities performed in the first reporting period from M13-M18. The next sections present in a summarized way the main activities performed in this period. In Section 3.3, the requirements of end-users with respect to the information fusion for TEMA are outlined. Section 3.4 introduces the overall design of information fusion technology. Section 3.5 presents the first prototype of information fusion module for TEMA. Finally, in Section 3.6 the conclusions are presented.

3.2 State of the Art and Planned Achievements

3.2.1 State of the Art before TEMA

Effective ND management requires timely and accurate information to mitigate risks, allocate resources efficiently, and facilitate rapid response and recovery efforts. With the advancement of data acquisition technologies, notably remote sensing and the Internet of Things, the collection of disaster-related data has become rapid and efficient. Nonetheless, these data exhibit variances in acquisition methodologies, resulting in discrepancies in geographic coverage and temporal and spatial resolutions. ND environments are prone to noise, inaccuracies, and uncertainty. Information fusion techniques are required to merge the gathered ND measurements and obtain ND state estimates with the required level of accuracy, quality, and reliability. This section summarizes the related works utilizing information fusion and their applications in natural disaster management (NDM), along with the associated challenges.

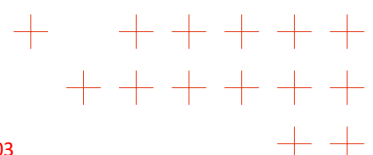


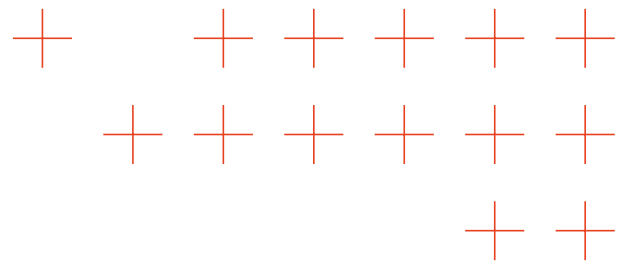


In the event of ND, information fusion will fuse data from multiple sources, which involves combining information from diverse sources, such as satellite imagery, social media feeds, IoT sensors, and crowdsourced data.

Bayesian filtering is a well-known and solidly mathematically founded probabilistic approach for fusing data from multiple heterogeneous sources (S. Thrun et al., 2005). Applications include flood mapping, land cover classification, wildfire estimation and prediction, and damage assessment (Ahmad, D. & Afzal, M., 2019, Munawar et al., 2022, Charizanos et al., 2023, Naderpour et al., 2020). Several research studies have been conducted for flood monitoring and modelling. For instance, (Bauer-Marschallinger et al., 2022) utilized satellite images from Sentinel-1 Synthetic Aperture Radar (SAR) Datacube (Wagner et al., 2021) for flood mapping in Thessaly, Greece, based on Bayesian inference. Furthermore, (D'Addabbo et al., 2016) introduced a Bayesian network aimed at integrating remotely sensed data, including multitemporal SAR intensity images and interferometric-SAR coherence data, with ground-based geomorphic information and other relevant data. They applied this methodology to a specific case study concerning a flood event in the Basilicata region of Italy. Moreover, multiple research studies have investigated NDs in the form of wildfires. For instance, (Crowley et al. 2019) proposed a method for synthesizing burned-area information from a range of remote-sensing platforms, including Landsat-8, Sentinel-2, and MODIS satellites. This approach, which utilized Bayesian Updating of Land Cover (BULC), supported the mapping of the active phase of the Elephant Hill fire in British Columbia. In (Cleland et al. 2020) proposed a technique for data fusion based on Bayesian Maximum Entropy (BME) to estimate the wildfire smoke concentrations of fine airborne particulate matter (PM) of size 2.5 microns during the October 2017 California Fires. Hence, the authors used observed and modelled data in addition to satellite-derived concentrations. When employing Bayesian approaches for multisource data integration, challenges such as spatial and temporal heterogeneity, uncertainty, inconsistency, and delays in data delivery arise. Additionally, in the realm of remote sensing and GIS, factors like data resolution, cloud cover, and processing time pose significant hurdles (Zhang et al., 2023, Angeles et al., 2022, Abdelmajeed et al., 2024, MohanRajan et al., 2020). However, the information fusion module developed for TEMA addresses these drawbacks, as it will incorporate online various heterogeneous inputs that will be more reliable, robust, and accurate in estimating the ND status, as outlined in Section 3.5.3. It has been specifically designed to handle the complexities associated with heterogeneous data sources and the various challenges encountered in remote sensing and GIS applications.

In recent years, there has been an increasing involvement of machine learning techniques in information fusion for natural disasters, particularly deep learning approaches, due to advancements in computational power technologies such as CPUs, GPUs, TPUs, and big data availability. These technologies empower the analysis and processing of large volumes of data, enabling the identification of patterns and the prediction of disaster events. Deep learning models, such as convolutional neural networks (CNNs), are commonly used for image analysis (Valdez et al. 2021). Furthermore, a CNN can be trained to detect buildings damaged by earthquakes or identify landslide-prone areas from satellite imagery (M. Ji et al. 2018). Authors in (Shanshan et al., 2022) developed a deep-learning-based model to retrieve sea surface hurricane winds from synthetic aperture radar (SAR) imagery. Challenges in such approaches include data labelling, model interpretability, and overfitting (Tufail et al., 2023). Additionally, big data analytics tools enable real-time processing and analysis of heterogeneous data (Yu et al. 2018, Abdullah et al. 2017). Applications include anomaly detection, pattern recognition, and predictive





modelling (AL-Sai Zaher Ali et al., 2022, Vassakis et al., 2018). For instance, anomaly detection algorithms can identify abnormal behaviour in sensor data, such as sudden changes in temperature or air quality, indicating a potential disaster and forest fire risk prediction (Erhan et al., 2021, Hill & Minsker, 2010). Challenges in big data analytics include scalability, data quality, and algorithm complexity (Hill & Minsker, 2010).

Crowdsourcing and participatory sensing platforms incorporate human-generated data into disaster management (Poblet et al., 2013). Applications include disaster reporting, damage assessment, and resource allocation (Poblet et al., 2019). For example, social media reports can provide real-time information about road closures, shelter availability, and emergency services during a disaster. The authors in (Oliveira et al. 2019) proposed a crowdsourcing information system (FDWithoutFire) to generate alerts for monitoring forest fires in the Cerrado Biome in the Brazil Federal District (FD). It supports local brigades and firefighters in making informed decisions through data fusion and enhances their understanding of fire events. Challenges in integrating human intelligence include data quality, accuracy, integrity, credibility, and privacy concerns (Wang et al., 2019).

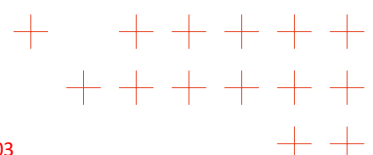
Information fusion enables integrating multi-source data, leveraging advanced technologies, and incorporating human intelligence, exploiting the synergies between the different heterogeneous data sources to improve the accuracy (reduce uncertainty) of the fused ND state estimates. However, several challenges, such as data heterogeneity, reliability, and privacy concerns, need to be addressed in order to realize the full potential of information fusion in disaster management.

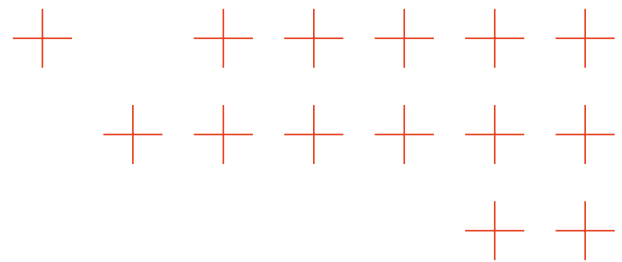
Current methodologies exhibit limitations in their ability to simultaneously integrate numerous heterogeneous inputs for an accurate ND state estimation. Moreover, the dependency on historical data for predicting event status may not accurately reflect the real-time ND status observed through actual data observations. This discrepancy highlights the need for a more sophisticated approach that can effectively integrate many online data sources to provide more precise state estimations of ND.

To the best of our knowledge, no existing study has achieved the level of comprehensive information fusion required for TEMA. While prior work focused on merging heterogeneous data, the information fusion module developed for TEMA stands out for its unique capability to simultaneously incorporate inputs from various heterogeneous sources. Specifically, the information fusion for TEMA will integrate satellite imagery, drone-based imagery, geosocial media analysis, and simulated data related to wildfire and flooding events, resulting in a more accurate state estimation of the status of the ND. The information fusion module for TEMA represents a significant advancement in the field, enabling a more holistic understanding of complex and dynamic ND events.

3.2.2 Planned improvements within TEMA

The objective of TEMA regarding Information Fusion is to design, develop, and validate a tool that optimally merges the results obtained from data analytics tools developed on WP3 to provide a consistent, unified, and georeferenced outcome that reflects the updated state of the monitored natural disaster (ND). Information Fusion is intended to be a practical tool capable of dealing with the uncertainties and noise level in ND environments and of providing ND estimates useful for planning the activities to attack the ND or minimize its





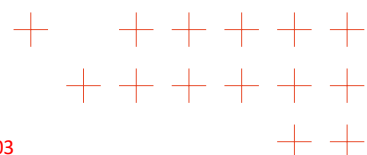
effects. It will use novel architecture using geo-referenced Bayesian estimation tools capable of integrating capable multiple sources of information with heterogeneous spatial and temporal resolutions including synchronous and asynchronous data. The Information Fusion module within TEMA focuses on enhancing the ability of the system to assimilate diverse data sources, handle heterogeneities in spatial and temporal resolutions, and improve computational efficiency. The following improvements will be implemented in the Information fusion module:

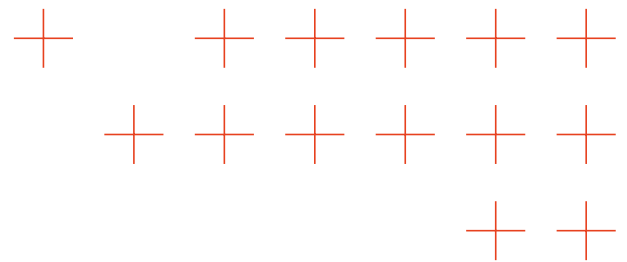
- **Handling Spatial Resolution Heterogeneity:** The Information Fusion module will improve the unification of spatial resolutions across input data sources (e.g., low-resolution satellite images vs. high-resolution drone images). This will involve upscaling or downscaling spatial resolutions to meet the requirements of the Occupancy Grid Mapping (OGM), ensuring that all input data can be effectively integrated despite their differences.
- **Handling Temporal Resolution Heterogeneity:** The asynchronous update mechanism of the Information Fusion module will be optimized to deal with varying temporal resolutions of inputs (e.g., satellite images arriving once or twice per day, compared to drone images that have higher frame rates). This enhancement will allow for more accurate and timely predictions, even when data sources provide information at irregular intervals.
- **Efficient Management of Computational Costs:** To improve computational efficiency, the system will optimize the balance between the resolution of the occupancy grid maps and available computational resources. Higher resolution grids provide more detailed estimations but come with greater computational demands, so this tradeoff will be further refined.
- **Extended Integration of Simulated Models:** The Information Fusion module will better incorporate advanced wildfire and flood propagation models, such as the forest fire simulation (PDM-tech-01) and the 3Di hydrodynamic flood model (PDM-tech-02). These models will be used to improve the Prediction stage, allowing more accurate future state estimations of natural disasters.
- **Incorporation of Additional Sensor Data:** Beyond satellite and drone the Information Fusion module will integrate also geosocial data, which provides very interesting and distributed data from social networks. In addition, due to its open architectural approach, Information Fusion is capable also of integrating additional sensor data sources, such as ground-based environmental sensors. This expansion will allow the system to provide even more detailed and diverse insights into the monitored disaster events.

3.2.3 Activities performed in the period M13-M18

During the period M13-M18, the following activities were carried out:

- **Analysis of the related work regarding Information Fusion for ND management:** The analysis is summarized in Section 3.2.1.
- **Analysis of the Information Fusion assumptions and requirements:** The functional and operational assumptions and requirements analysis is performed considering the end-users perspectives. The analysis is summarized in Section 3.3.





- **General design:** The Information Fusion module was designed considering the requirements and assumptions and the planned inputs and outputs. The design including the main decisions and planned approach to deal with the challenges are summarized in Sections 3.4 and Sections 3.5.
- **Asynchronous RBF Methodology:** The Information fusion module utilized an asynchronous RBF methodology for occupancy grid mapping. This highlighted its adaptability to adjust to varying input resolutions and demonstrated the effectiveness of this approach. For further information, please refer to Section 3.5.1.2.
- **Architectural Design:** The design of the Information Fusion module was performed from an architectural perspective, defining the interactions with the rest of the modules of the TEMA platform, both inputs and outputs. For further information, please refer to Section 3.5.2.
- **Development of preliminary IF prototype:** The preliminary prototype of the Information Fusion system was developed to integrate diverse, heterogeneous inputs with varying temporal and spatial resolutions. This prototype demonstrated the effectiveness of employing Recursive Bayesian Filtering (RBF) alongside occupancy grid mapping for state estimation of the monitored natural disaster (ND). The primary objective was to showcase the RBF approach's capability to handle inputs with different temporal resolutions. For further information, please refer to Section 3.5.3.
- **Test of the IF prototype with Ahrtal historical data:** The test can be found in Section 3.5.3.

Fusing Information Derived by Social Media: Social media data provides very interesting data for a ND system. However, fusing it is very challenging. Section 3.6 summarizes the performed activities in this topic.

3.3 Information Fusion requirements and assumptions

3.3.1 Assumptions

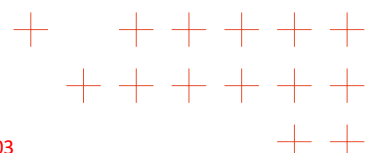
Information Fusion will not segment or process images or geosocial data. It will rely on the data analytics techniques developed in WP3 and will fuse the results of the processing of satellite images, drone images, and geosocial data to obtain the updated georeferenced state of the ND.

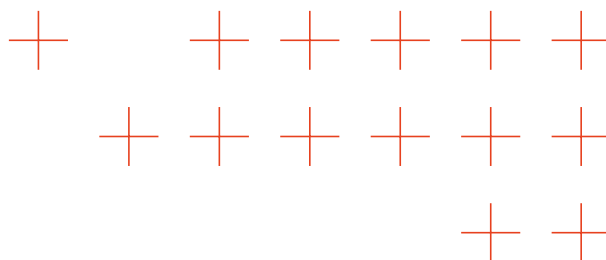
The input of Information Fusion is segmented satellite and drone images and geosocial data. The satellite images are assumed to be georeferenced. The geosocial data received by Information fusion is assumed georeferenced. The drone images will include (in the metadata) the position and orientation of the drone camera, as well as the camera optical parameters, so that the image can be georeferenced.

Information Fusion will include a component responsible for the georeferencing of the drone images. The georeferencing component requires a Digital Elevation Model (DEM) of the scenario.

Forest fires, floods, and the location of people and assets can vary along time. Information Fusion will assume that all the input data is timestamped and that there is one only time along the TEMA system.

Information fusion will require models that enable the prediction of the ND. Hence, it will use as input predictions of the ND status obtained from the forest fire model and the flood hydro-dynamic model (task T4.1).



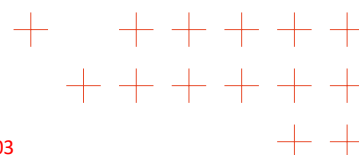


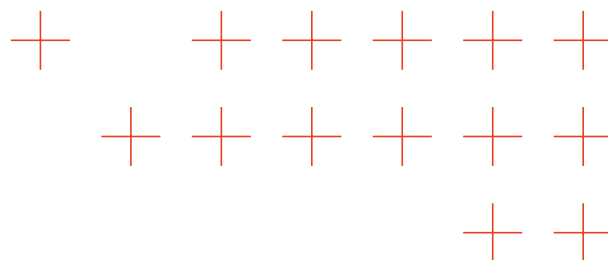
3.3.2 End-user requirements

Information fusion in TEMA will meet the defined requirements of the end-users analysed on deliverable “D2.1: Report on TEMA requirements. The main requirements involving the Information Fusion are summarized in Table 3.1. These requirements are classified into non-functional and functional categories. Both sets of requirements are used throughout TEMA to guide design, implementation, testing, and deployment activities.

Table 3.1. End-user requirements for Information Fusion.

Non-functional Req.	Description	Expected Fulfilment
EU-RQ-NF-04	Sharing information and data regarding ND	Information fusion will provide online-updated estimates of the state of the ND, which will enhance information and data sharing to facilitate coordination and collaboration among various agencies and organizations involved in disaster response.
EU-RQ-NF-08	Valid warnings	The Information Fusion will be able to be activated by alerts and warnings from upcoming NDs provided by end-users.
Functional Req.	Description	Fulfilment
EU-RQ-FUNC-02	Geo-Social Media Information	Information fusion incorporates as input geosocial media information for localizing and monitoring individuals in disaster-affected areas.
EU-RQ-FUNC-03	Monitor the development, the size of the affected area	Information fusion will continuously update maps with the state of the ND including the size and evolution of the affected area.
EU-RQ-FUNC-05	Reveal fires as they start	Information fusion will integrate data from inputs immediately with no delay. As soon as the fire has been segmented in a drone image or satellite image, it will be integrated by the information fusion module.

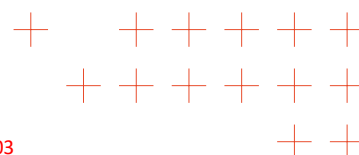


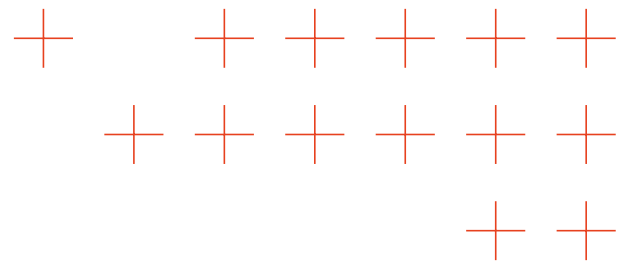


EU-RQ-FUNC-06	Teams involved	The information fusion system will integrate as input segmented images of people belonging to the teams involved, hence will online monitor the teams involved.
EU-RQ-FUNC-07	Geolocation of people who are in danger of life	Information fusion will integrate as input segmented images of people as well as geosocial information, hence enabling geolocation of people in danger in the affected area.
EU-RQ-FUNC-08	Model of fire propagation	Information fusion will provide the current status of the forest fire propagation and how it is spreading, which will be used to refine forest fire propagation models.
EU-RQ-FUNC-09	Monitor the area of interest for fire revival	If Information fusion receives as input segmented images of the area after fire extinguishing, it will monitor the status of burnt/fire-affected areas. If a fire reignites, the map will be promptly updated upon receiving the relevant data to reflect the presence of fire.
EU-RQ-FUNC-10	Response planning for extinguishing fires	Information fusion obtains updated state of the fire, which can be used for planning of the forest fire attack/extinguishing.
EU-RQ-FUNC-12	Flood propagation modelling	Information fusion will provide the current status of the flood, which will be used to refine flood propagation models.
EU-RQ-FUNC-13	Estimation of the damages	Information fusion can assist in damage estimation by providing the current status of the affected area.
EU-RQ-FUNC-15	Resource planning	Information fusion will show the location of the people present in the affected area, which helps in resources planning.

3.3.3 Additional design requirements

Integration of heterogeneous data modalities. Information Fusion will integrate results from analysing data from widely heterogeneous sources, including segmented satellite images, segmented drone visual and/or infrared images, and georeferenced geosocial information.





Integration of data with strong temporal-spatial heterogeneity. Satellite images are produced at a rate of 1/2 images per day, whereas drone images are generated at >10 Hz and geosocial information is generated asynchronously. Information fusion will be able to seamlessly integrate data with diverse temporal resolutions and asynchronous data.

Integration of data with strong spatial resolution heterogeneity. Satellite images have a low spatial resolution, while drone images have a high spatial resolution. Information fusion will be able to seamlessly integrate data with strongly diverse spatial resolutions.

High levels of uncertainty and noise. ND are scenarios prone to large uncertainty, error and noise levels. Information Fusion should be robust to uncertainty and provide reliable and accurate estimates.

Updated ND state estimation. Information Fusion will provide an updated georeferenced state of the ND, involved people, and vehicles (cars, boats, among others). In case of forest fire, it will provide the geolocated fire front location, fire front speed, and burnt area, among others. In case of a flood, it will provide the geolocated position of the flood, and the affected area, among others. It will also provide the location of people and vehicles (cars, boats, among others) involved in the affected area (as long they are detected from the input source data)

Reliability and robustness. Information Fusion will provide updated reliable and robust-to-uncertainty estimates of the ND status.

Computational efficiency. Information Fusion will operate online and provide updated and robust estimates of the ND status.

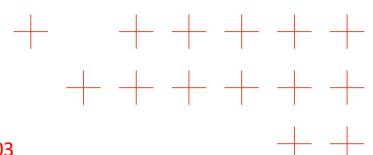
3.4 General design

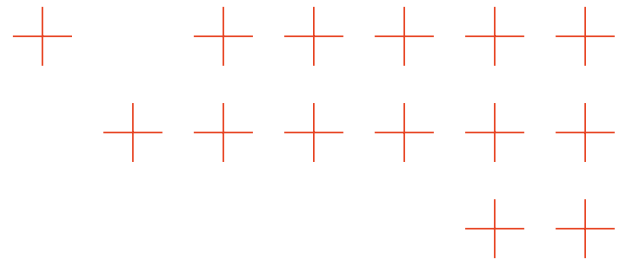
The Information Fusion module should fulfil the requirements and assumptions considered in Section 3.3. Accordingly, the following design decisions have been made.

3.4.1 Design decisions

3.4.1.1 Discrete Bayesian filtering

Information Fusion will be based on Recursive Bayesian Filters (RBF) as estimation tools. RBFs are robust and quasi-optimal estimation tools based on the Bayes Theorem. They have a strong mathematical foundation and assume that both observations (measurements) and models have noise. RBFs explicitly assume and model the uncertainty levels to consider within the estimation process to reduce the impact of noise and uncertainty on the estimate (Thrun et al., 2005). RBFs provide a comprehensive approach to naturally assimilating heterogeneous data sources and deriving actionable insights (Xinde et al., 2023, Ding et al., 2019). There is a wide variety of RBFs depending on the particularities of the problem, including Kalman Filters, Extended Kalman Filters, Unscented Kalman Filter, Information Filters, Particle Filters, Histogram Filters, and Occupancy Grids, among many others.





Recursive Discrete Bayesian Filtering (RBF) is a methodology for estimating the state of a dynamic system based on noisy observations. It relies on Bayes' theorem for probabilistic inference and recursion for iterative updates of the state estimate (Thrun et al., 2005). At the core of Recursive Discrete Bayesian Filtering is Bayes' theorem, which provides a principled way to update the belief about a system's state given new evidence. Mathematically, Bayes' theorem is represented as:

$$p(x|z) = \frac{p(z|x)p(x)}{p(z)},$$

where

- $p(x|z)$ is the posterior probability distribution over of the state x .
- $p(x)$ is the likelihood of the observation given the state x .
- $p(x)$ is the prior probability of the state x .
- $p(z)$ is the probability of the evidence.

Discrete Recursive Bayesian filtering (RBF) involves two main steps: Prediction and Update. The equations governing these steps are as follows:

- Prediction Step: The prediction step forecasts the system state based on the previous state and the system dynamics model before incorporating measurement z_t as:

$$\overline{bel}(x_t) = p(x_t|z_{1:t-1}, u_{1:t}) = \sum p(x_t|x_{t-1}, u_{t-1})p(x_{t-1}|z_{1:t-1}, u_{1:t-1}),$$

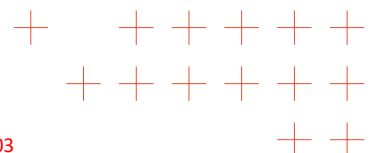
Where u_{t-1} is control input at previous time step, $p(z_{1:t-1}, u_{1:t-1})$ represents the posterior distribution from the previous time step denoted as $bel(x_{t-1})$, and $p(x_t|x_{t-1}, u_{t-1})$ represents the state transition model, which describes how the state evolves from previous time step ($t - 1$) to the current time step (t)

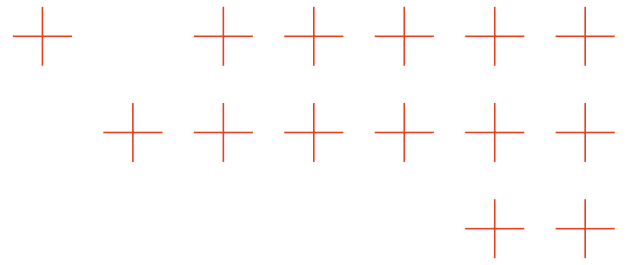
- Update Step: The update step refines the state estimate based on new observations. It is expressed as:

$$bel(x_t) = p(x_t|z_{1:t}, u_{1:t}) = \frac{p(z_t|x_t)p(x_t|z_{1:t-1}, u_{1:t})}{p(z_t|z_{1:t-1}, u_{1:t})},$$

Where $p(z_t|x_t)$ represents the observation model, which describes the likelihood of the observation given the stat, and $p(z_t|z_{1:t-1}, u_{1:t})$ is the normalizing constant.

The Bayes filter is recursive, in which, the belief $bel(x_t)$ at time t is calculated from the $bel(x_{t-1})$ along with the most recent control u_t and the most recent measurement z_t .





3.4.1.2 Occupancy Grids

Occupancy Grids are RBFs that operate in a spatial grid. Hence, it is suitable for providing georeferenced estimates of a phenomenon using observations (measurements) from the phenomenon and using models to predict the evolution of the phenomenon. Occupancy Grids can cope with strong spatially heterogeneous measurements if all the observations can be referred to the same georeferenced coordinates. As pointed out in Section 3.3, that is the case with Information Fusion. In addition, occupancy grid estimation can easily integrate observations with different temporal resolutions including asynchronous observations.

The occupancy grid mapping (OGM) algorithm discretizes the environment into a grid of cells, with each cell representing the probability of occupancy. The objective of the OGM is to calculate the posterior over maps given the data:

$$p(m | z_{1:t}, x_{1:t}),$$

where m is the map, $z_{1:t}$ is the set of all measurements up to time t and $x_{1:t}$ is the history of the state spaces.

Let m_i denote the grid cell index i . An occupancy grid partitions the space into finitely many grid cells:

$$m = \{m_i\},$$

The occupancy grid algorithm breaks down the problem of estimating the map into a collection of separate problems, namely that of estimating as:

$$p(m_i | z_{1:t}, x_{1:t}),$$

The posterior over maps is approximated as the product of its marginal:

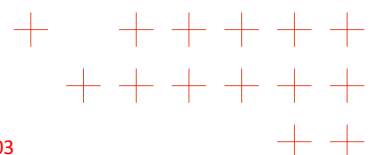
$$p(m | z_{1:t}, x_{1:t}) = \prod_i p(m_i | z_{1:t}, x_{1:t}),$$

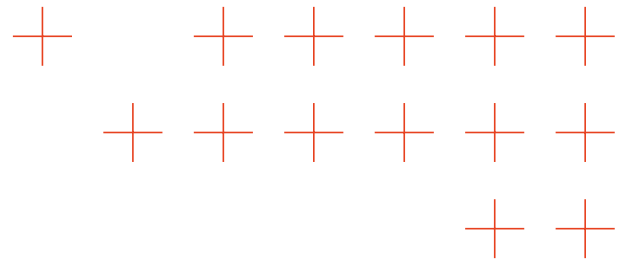
The environment is discretized into a grid, where each cell denotes a specific area of the space. The occupancy status of each cell is represented as either occupied or free. The notation $p(m_i = 1)$ or $p(m_i)$ refers to the probability that the grid cell is occupied.

As any other RBF, estimation using occupancy grids has two main stages: Prediction and Update. In the Prediction stage, the cells probabilities are changed following the prediction models of the phenomenon that is being estimated. For instance, in TEMA it is performed by using the forest fire propagation model and flood hydrodynamic model.

The Update stage makes use of the phenomenon observations (sensor measurements) to refine the probabilities of the grid cells. The sensor model, typically an inverse sensor model, computes the likelihood of a grid cell being occupied given observed sensor measurement:

$$p(m_i | z_t) = \eta * p(z_t | m_i) \overline{bel}(m_i),$$





where:

- $p(m_i | z_t)$ represents the posterior occupancy probability of cell (m_i) at time t .
- $p(z_t | m_i)$ represents the likelihood of the current measurement (z_t) given the state of the cell (m_i)
- $bel(m_i)$ is the predicted probability of a cell (m_i) at being occupied time t

Occupancy grid mapping employs probabilities to represent the likelihood of occupancy for each grid cell. To facilitate efficient updates, a log-odds formulation, known as occupancy log-odds (l), is often used:

$$l_{t,i} = \log \frac{p(m_i | z_t)}{1 - p(m_i | z_t)}$$

To recover the probabilities from the log odds ratio:

$$p(m_i | z_t) = 1 - \frac{1}{(1 + e^{l_{t,i}})}$$

Below, the main properties of occupancy grid estimation with respect to the requirements of Information fusion are summarized:

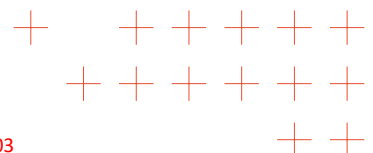
- Capable of integrating measurements from heterogeneous sensors as long as the sensor model is known,
- Capable of integrating measurements with strong spatial resolution heterogeneity as long as all measurements are georeferenced (i.e. referred to the same spatial coordinates),
- Capable of integrating measurements with strong temporal resolution heterogeneity as long as all measurements are timestamped with the same clock,
- Capable of coping with diverse levels of noise and uncertainty as long as the sensor measurement noise/uncertainty is known,
- Provides very high reliability and robustness due its quasi-optimal information fusion performance.

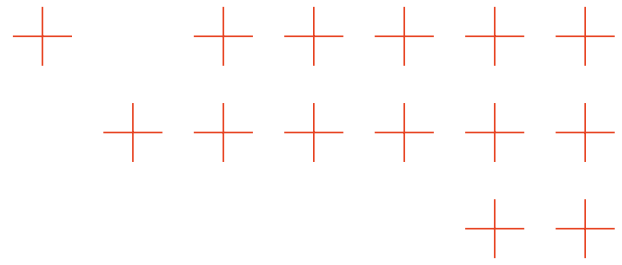
Hence, estimation using occupancy grids fulfils all requirements of the TEMA Information fusion module.

3.5 Occupancy grid mapping for TEMA

The proposed information fusion technology for TEMA will fuse various heterogeneous inputs that have different temporal and spatial resolutions to accurately estimate the status of the monitored natural disaster (wildfires/floods). Occupancy grid maps will be utilised to estimate the status of the monitored event, as OGM provides a structured representation of spatial information, dividing the disaster-affected area into a grid of cells. Each grid cell maintains a probability distribution representing the likelihood of occupancy by the disaster event, denoted as $p(m_i)$.

TEMA information fusion will be used for the updated estimation of:





- Forest fire status including georeferenced position and velocity of the fire front and the burnt areas. For such, it will fuse measurements: (i) fire segmented in satellite images and (ii) drone visual and infrared images.
- Flood status including georeferenced position and velocity of the flood. For such, it will fuse measurements: (i) flood segmented in satellite images and (ii) drone visual and infrared images.
- Status of people (both response teams’ personnel and citizens) and vehicles including the georeferenced position of people and vehicles. For such, it will fuse: (i) geosocial measurements and (ii) segmented people and vehicles in the drone images.

For that purpose, TEMA information fusion will use three independent probability grids. Figure 3.2 shows a general scheme of the Bayesian estimation tool for forest fire estimation. Similar schemes have been designed for flood estimation and people and vehicle estimation considering the above measurements.

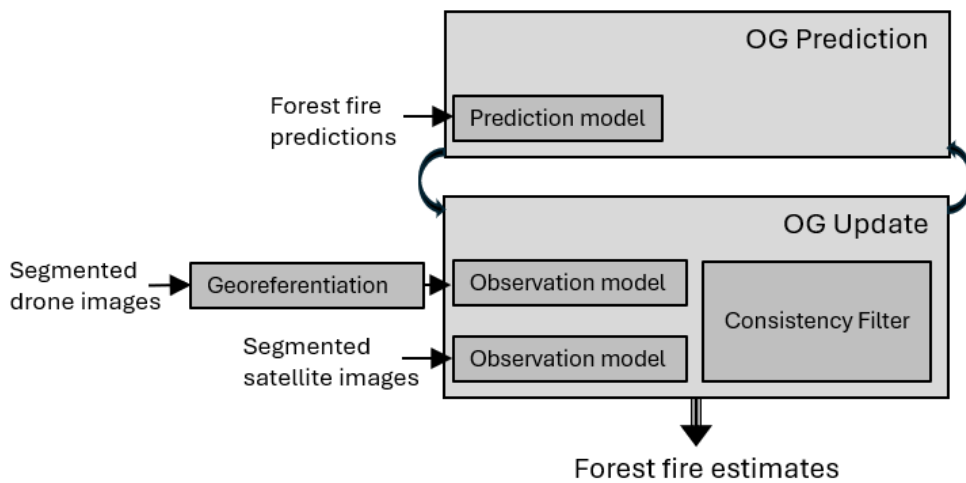
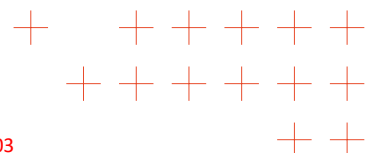
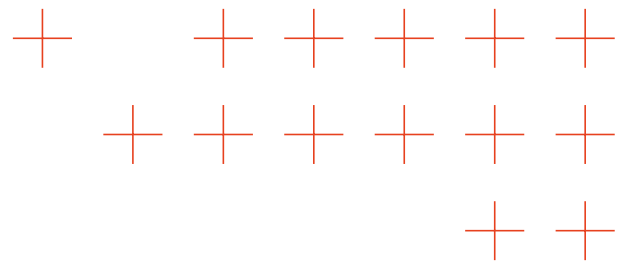


Figure 3.2 General scheme of the forest fire estimation tool designed for TEMA Information fusion.

The estimation tools for these three occupancy grid maps:

1. **Prediction stage.** The next state of the estimated phenomenon is predicted by using the forest fire or flood prediction. In the TEMA platform architecture, they are provided by technologies:
 - a. Wildfire simulation (PDM-tech-01).
 - b. 3Di Hydrodynamic for flood modelling (PDM-tech-02).
2. **Update stage.** It incorporates sensors’ observations:
 - a. Forest fire or flood segmented georeferenced satellite images. In the TEMA platform architecture, they are provided by technologies TFA-tech-08 and TFA-tech-09. Satellite images





- are natively georeferenced and timestamped. They can be incorporated straightforward in the georeferenced occupancy grids.
- b. Drone images with segmented forest fire or flood or with detected people and vehicles. In the TEMA platform architecture, they are provided by technologies TFA-tech-06/05. Drone images are timestamped but not georeferenced. The metadata of each drone image contains the camera position, orientation, and optical parameters. Module *Georeferentiation* in Fig. 3.2 is responsible for georeferencing the drone images to enable their incorporation in the occupancy grids.
 - c. Geosocial media analysis with timestamped and georeferenced position of people (both team personnel and citizens). In the TEMA platform architecture are provided by TFA-tech-11. Geosocial media analysis is straightforward incorporated in the occupancy grids.

The likelihood of a grid cell being occupied is determined based on sensor measurements and the cell's spatial relationship to ND.

3.5.1 Dealing with challenges

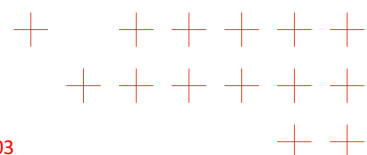
3.5.1.1 Spatial resolution heterogeneity

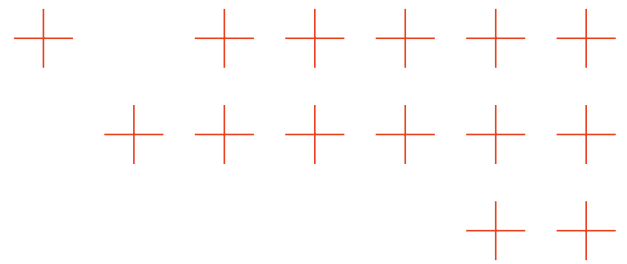
The information fusion incorporates various measurements with large spatial heterogeneity (from satellite images to drone images). To address this issue, the module is based on georeferenced occupancy grids, and it will unify their spatial resolutions to meet the developed OGM resolution by upscaling or downscaling the spatial resolutions of the input measurements. All measurements are natively georeferenced except the drone images, which will be georeferenced by module *Georeferentiation* using the drone camera pose and optical parameters that will be sent in the metadata of each individual image.

3.5.1.2 Temporal resolution heterogeneity

The input measurements of Information fusion have widely diverse temporal resolution (from satellite images at a rate of 1-2 images per day up to drone images at a frame rate of >10 Hz or the asynchronous geo-social data). To tackle this issue, Information fusion technology adopts an asynchronous approach. Assume x_k is the estimated map after the introduction of the last input measurement, which arrived at time k . Assume the following input measurement (either segmented satellite or drone image or geosocial data) z_{k1} arrives at time $k1 > k$. When z_{k1} arrives, the Prediction Stage is used to compute $x_{p_{k1}}$ from x_k , i.e. the ND state prediction at time $k1$ computed from x_k using the ND prediction model (i.e. forest fire prediction model or hydrodynamic model). Next, it will execute the Update stage with measurement z_{k1} , and as a result will obtain the ND state estimate at time $k1$. Hence, Information fusion waits until a new input measurement arrives to execute: first the Prediction stage and next the Update stage.

In this asynchronous approach, if no new measurement arrives, Information fusion does not perform neither the Prediction state nor the Update state. On the one hand, the approach is very efficient as it minimizes the number of executions of the Prediction and Update stages. On the other hand, the output of Information fusion does not





change if no measurement is received, being incapable of providing the updated ND state. To prevent this effect, if no measurement is received, Information fusion periodically performs the Prediction stage. When the time from the last execution of the Prediction stage exceeds a threshold, Information fusion performs a Prediction stage, which will modify the output hence providing an updated estimate of the ND. The threshold can be easily determined considering the ND state updating requirements. This asynchronous approach ensures adaptability to real-world scenarios where data availability might be intermittent or delayed, as in the processed satellite images (task T3.2) and the processed drone-based images (task T3.2). Figure 3.3 visually illustrates this asynchronous update mechanism, depicting how the system adapts the temporal dynamics of input data.

3.5.1.3 Computational cost

The Information fusion asynchronous approach is computationally efficient. However, its complexity scales when increasing the resolution of occupancy grid maps. Consequently, there exists a tradeoff between computational resources and the desired resolution of the occupancy grid: higher resolution necessitates greater computational power.

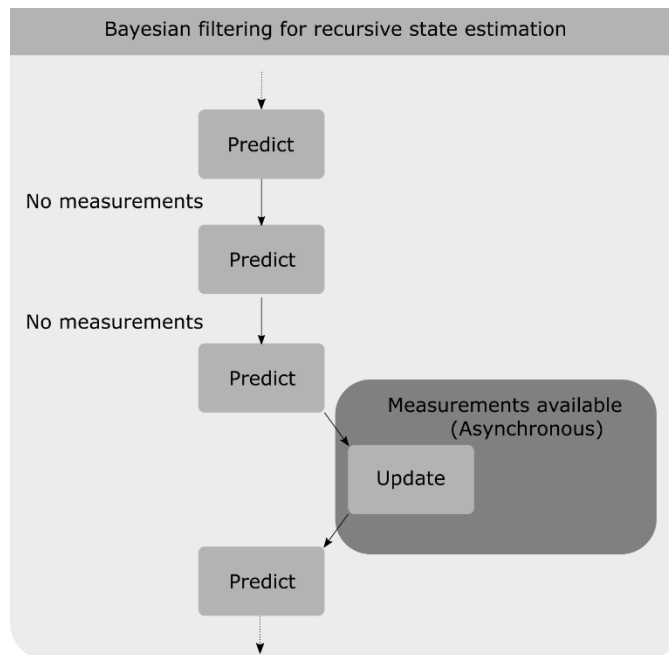
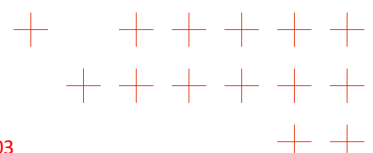
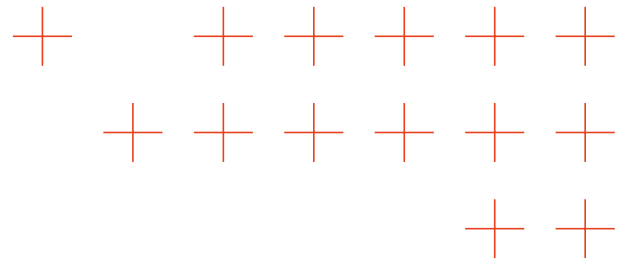


Figure 3.3. Asynchronous RBF approach.

3.5.2 Information Fusion within the TEMA Platform

Next, the interactions of the Information fusion module within the TEMA platform are summarized. In essence, it summarizes the key components of the technology PDM-tech-05: Information Fusion. Here, we recall the TEMA platform architecture specified in Deliverable D2.2: “Report on TEMA platform design, data models and architecture to stress the consistency of the design of the Information fusion module with the whole TEMA





architecture”. Information fusion module utilizes various inputs obtained from different technologies within the TEMA platform. The way of communicating with the other technologies is through the Digital Enabler (SV-tech-02) or via direct communications as follows:

- Through Digital Enabler (SV-tech-02):
 1. Results from processing of drone-based images:
 - a. Detection of Fire, Smoke, Flood, Persons or vehicles (TFA-tech-05), represented as images annotated with JSON.
 - b. Segmentation of Fire, Smoke, and Background (TFA-tech-06), represented as images annotated with JSON.
 2. Results from Sentiment and Geo-social Analysis:
 - a. Geo-social media analysis (TFA-tech-11) in GeoTiff, Shapefile, and KMZ formats.
 3. Results from Realistic Smoke Modelling and Fire Detection (PDM-tech-03) in various formats such as GeoTIFF, JSON, 3D voxels, and NetCDF.
 4. Results of flood prediction obtained by 3Di Hydrodynamic modelling (PDM-tech-02), the results are presented in GeoTIFF, TIFF, JSON, and CSV formats.
- Direct Communication:
 1. Results from processing satellite imagery:
 - a) Satellite-based Flood Detection and Assessment (TFA-tech-08) which shows flooded areas, permanent water, flood duration and frequency in GeoTIFF format, and detected objects (vehicles and building) in GeoJSON format.
 - b) Satellite-based Forest Fire Detection and Assessment (TFA-tech-09) which shows Burnt area extents, subdivided into regions with fire severity information in GPKG format

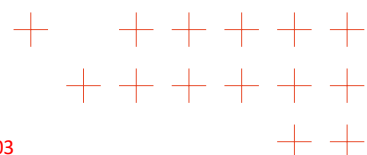
The Information Fusion estimates the updated georeferenced status of the ND as occupancy grid maps (of a flood, wildfires, and assets (e.g., persons, vehicles)) in GeoJSON and GeoTiff formats. Then, Information fusion publishes these estimated maps through the Digital Enabler (SV-tech-02). These outputs are then utilized for:

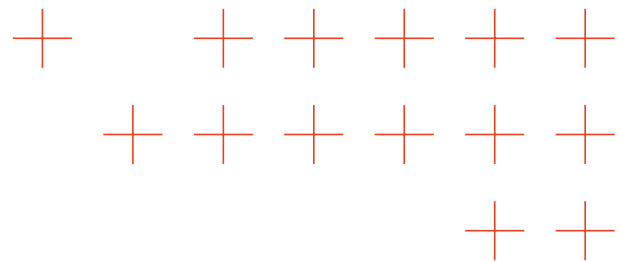
- Drone Planning (PDM-tech-04).
- Wildfire Simulator (PDM-tech-01) and Flood Simulator (PDM-tech-02) to refine simulation results.
- Visualization in Extended Reality-based Interactive Visualization System (SV-tech-06) and Smart Desk (SV-tech-07).

The complete interaction diagram for the information fusion technology (PDM-tech-04) with the other components is presented in Fig. 3.4.

Methodology

Since Information fusion is a central module of the TEMA platform, its development is deeply coupled with the development of the rest of the modules, and particularly those that provide inputs to Information fusion. To facilitate development, we adopt a methodology based on simulation. We will use simple simulators that will





provide Information fusion inputs such that the Information fusion can be developed independently of the rest of the modules.

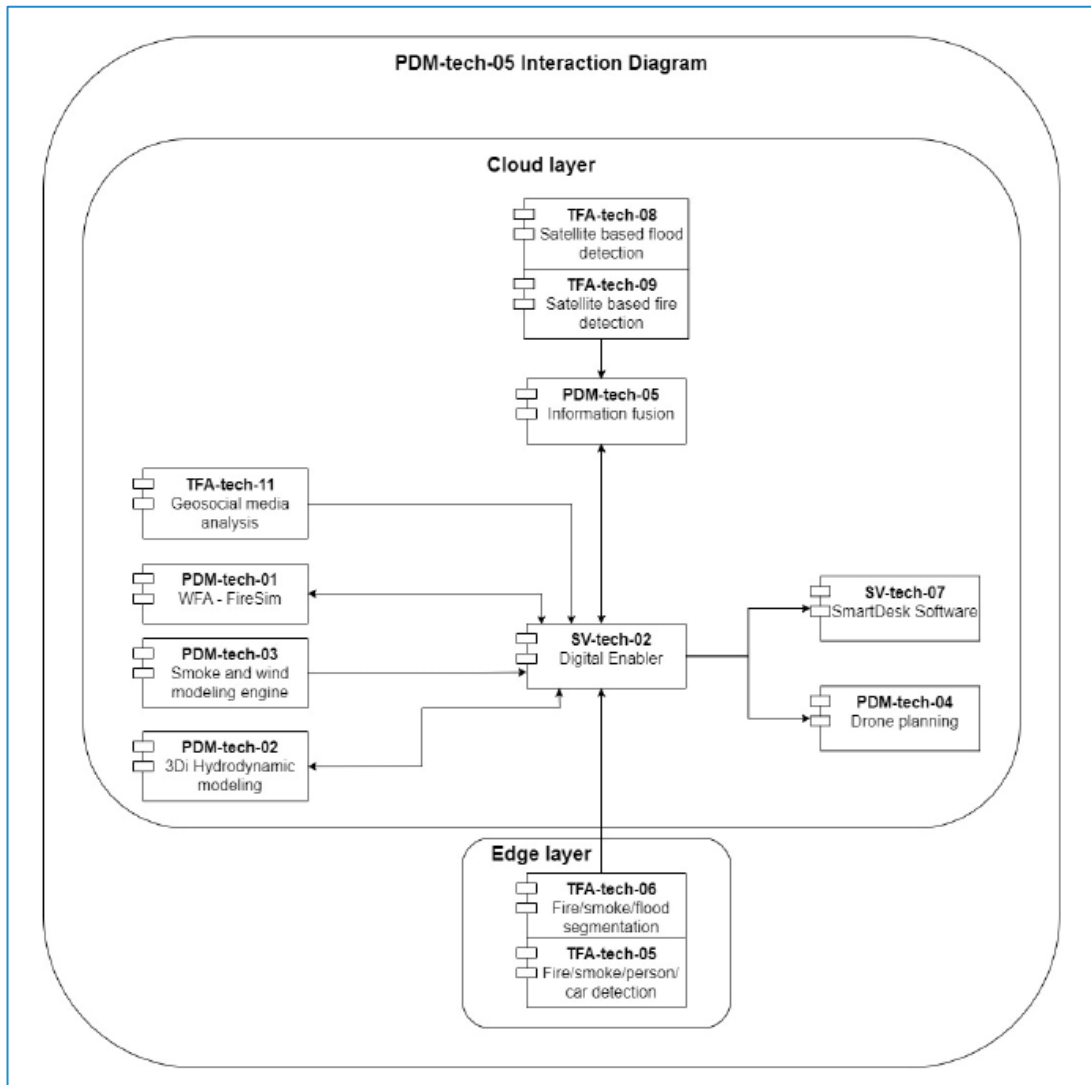
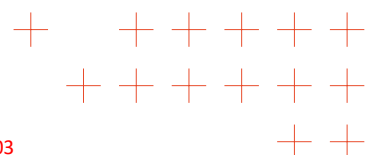
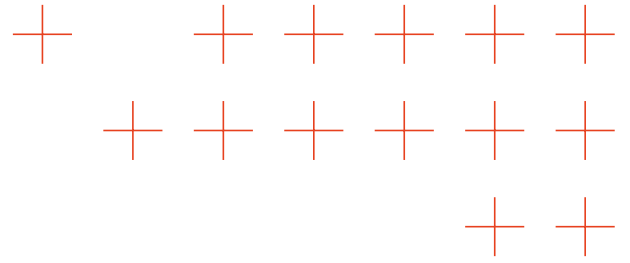


Figure 3.4. Interaction diagram of information fusion technology within the TEMA platform architecture.

3.5.3 First Information Fusion Prototype

The process for state estimation regarding NDs as floods and entities (e.g., people, vehicles, etc.) follows a similar framework as wildfire estimation. Consequently, in this prototype, we will focus exclusively on describing the state estimation process for NDs in the context of wildfires.





As all the inputs for the information fusion module are not yet ready, USE has started the development of the information fusion module for the TEMA framework (task T4.3) based on simulated data. Hence, a wildfire scenario has been simulated, mimicking the spread of real fire propagation. The module for information fusion was developed using occupancy grid mapping techniques, as previously discussed in Section 3.4.1. Accordingly, the developed occupancy grid map for front fire estimation is assumed to have a rectangular shape (representing the monitored area), in which each grid cell k represents two probabilities; one for indicating the fire probability in the cell $F_{k,t} \in \{0,1\}$, and the other represents the probability of the fuel being completely exhausted $Q_{k,t} \in \{0,1\}$. Hence, each cell k stores both probability values $\{f_k, q_k\}$. These two values correspond to probabilities $f_k = p(F_{k,t} = 1)$ (there is fire at a given cell), and $q_k = p(Q_{k,t} = 1)$ (the fuel in that cell is completely exhausted).

It is important to note that each cell is assumed to be georeferenced, as all the inputs to the information fusion are georeferenced, whether the segmented satellite images, drone-based images (georeferencing is performed through a module developed internally) or the geosocial media analysis results.

For incorporating the new measurements, the information fusion adopts the discrete RBF technique described earlier for updating each grid cell k in the occupancy map. Moreover, it is assumed that all inputs, whether utilized for predicting the status of the ND (priors) or for the updating step (likelihoods), have been preprocessed and segmented by the responsible TEMA partner.

3.5.3.1 The prediction step

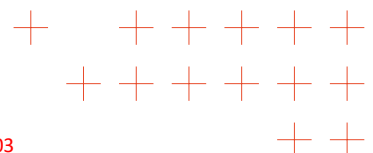
The adopted model for predicting wildfire propagation is simple, considering both temporal and spatial relations among cells. Its primary aim is to introduce a form of memory into the estimation process, thereby preventing the regression of fire propagation through areas previously traversed (this is the role of Q). Additionally, the model conducts spatial predictions to facilitate the smoothing of the estimated progression of the fire fronts.

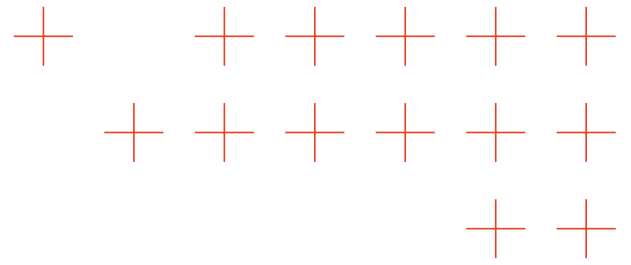
The temporal transition probability for each cell k is described as follows:

$$p(F_{k,t}|F_{k,t-1}) = \sum_{Q_{k,t-1}} p(F_{k,t} | F_{k,t-1}, Q_{k,t-1}) p(Q_{k,t-1}),$$

$$p(Q_{k,t}|Q_{k,t-1}) = \sum_{F_{k,t-1}} p(Q_{k,t} | F_{k,t-1}, Q_{k,t-1}) p(F_{k,t-1}),$$

The probability that a cell is completely exhausted if there was a fire in the previous time step is characterized by a parameter β , which is presented as follows:





$$p(Q_{k,t} = 1 | F_{k,t-1}, Q_{k,t-1}) = \begin{cases} 1 & \text{if } Q_{k,t-1} = 1 \\ 0 & \text{if } Q_{k,t-1} = 0 \text{ and } F_{k,t-1} = 0 \\ \beta & \text{if } Q_{k,t-1} = 0 \text{ and } F_{k,t-1} = 1 \end{cases}$$

The temporal evolution of the fire probability is given by:

$$p(F_{k,t} = 1 | F_{k,t-1}, Q_{k,t-1}) = \begin{cases} 0 & \text{if } Q_{k,t-1} = 1, \forall F_{k,t-1} \\ 0 & \text{if } F_{k,t-1} = 0, \forall Q_{k,t-1} \\ 1 & \text{if } Q_{k,t-1} = 0 \text{ and } F_{k,t-1} = 1 \end{cases}$$

The spatial relation in this simple prediction model assumes that the fire can propagate from one cell to its neighbours. Hence, the state of its neighbour cells $R(k)$ affects the current state of each cell k . This relation is modelled mainly by the parameter ω_j (whose value can depend on wind information if available), however, for the purpose of developing the information fusion module, ω_j is assumed to be constant in all directions (this assumption does not affect propagation to the neighbouring cells, as it assumes an even probability of fire propagation in all directions). The spatial relation is depicted as follows:

$$p(F_{k,t} = 1 | Q_{k,t-1}, F_{j,t-1}) = \begin{cases} 0 & \text{if } j \notin R(k) \\ \omega_j & \text{if } F_{j,t-1} = 1 \text{ and } j \in R(k) \text{ and } Q_{k,t-1} = 0 \\ 0 & \text{if } F_{j,t-1} = 0 \text{ or } Q_{k,t-1} = 1 \end{cases}$$

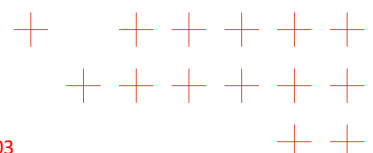
3.5.3.2 The update step

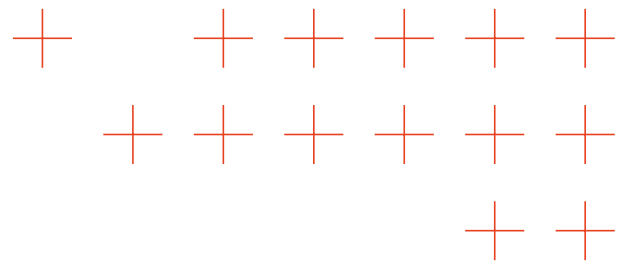
The update step is performed in an asynchronous way, which means whenever a new measurement data is received, the predicted probabilities for the grid cells are updated accordingly.

Because TEMA technologies interacting with Information fusion haven't provided any measurements yet, it is assumed that the measurements (likelihoods) would be similar to the data generated from the prediction step, with the addition of Gaussian noise to simulate real measurements. It is important to clarify that the purpose of this prototype for information fusion is not to generate or simulate data for either prediction or update steps but rather to highlight the primary objective of integrating inputs from diverse sources.

3.5.3.3 Simulated results

In the following, we present the results of the state estimation of fire front shape evolution with time. The fire is assumed to be initially ignited at the centre of the occupancy grid, which indicates setting the probabilities f_k to one and q_k to zeros for all cells of the grid corresponding to the initial position of the fire. Furthermore, the predicted states and the measurements are assumed to be preprocessed and segmented. The developed





occupancy grid map is assumed to have a size of (100×100) pixels and a spatial resolution of 5 m , i.e. the scenario area is assumed to be $500 \times 500\text{ m}^2$. Moreover, the information fusion prototype integrates georeferenced inputs, ensuring that all data utilized corresponds to real-world coordinates, whether in the prediction or update phases. Additionally, all inputs to the information fusion prototype are timestamped; this is important to maintain the order of incoming measurement data that will be incorporated into the map.

Furthermore, the information fusion prototype for TEMA adopts an asynchronous approach for incorporating the measurements, as in real-life situations, measurement inputs will have various temporal resolutions. Hence, any new measurement will be used to update the occupancy grid map as soon as it arrives (considering its timestamp). The outcomes of employing the information fusion prototype within TEMA are illustrated as follows.

Figure 3.5 depicts the state estimation at $timestep=1$. Specifically, Figure 3.5 (a) illustrates the predicted state (prior) generated through the transition model, while Figure 3.5 (b) displays the noisy measurement (likelihood)

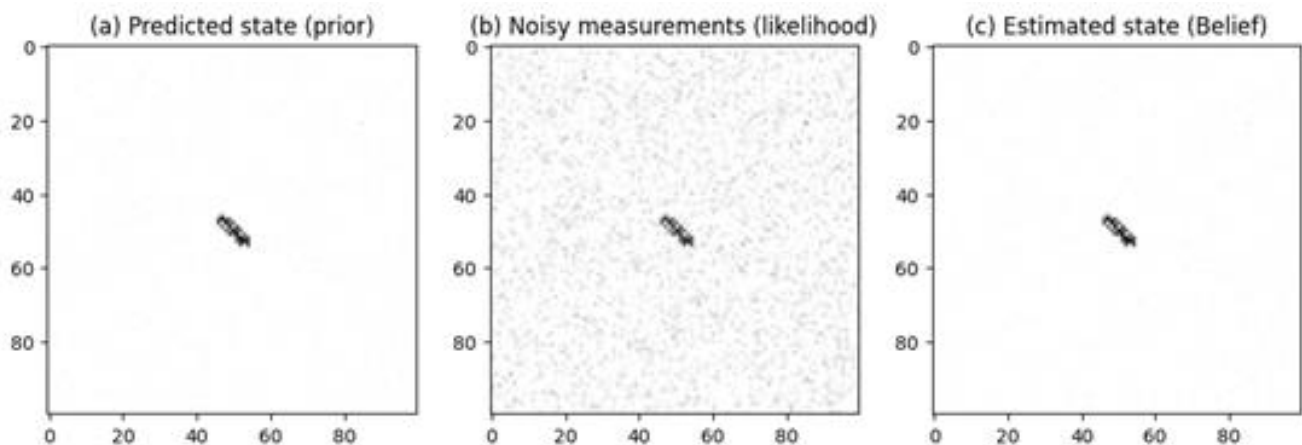
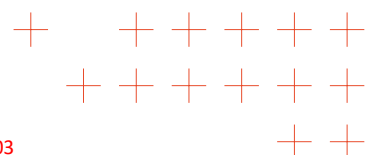


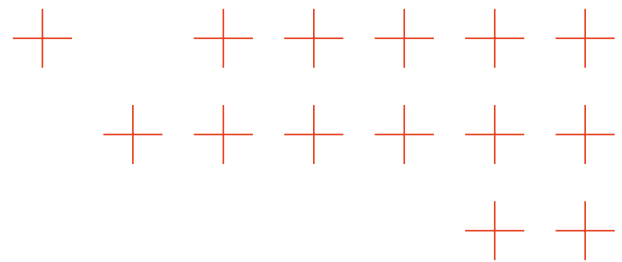
Figure 3.5. OGM at $timestep = 1$

available for incorporation. Finally, Figure 3.5 (c) shows the updated state after integrating the measurement with the prior utilizing the RBF.

In Figure 3.6, the state estimation at $timestep=2$ is presented. In this instance, the measurement is unavailable, prompting the occupancy grid map to update its estimation solely based on its current predicted state. This scenario highlights the capability of the occupancy grid map to adapt and refine its estimation even in the absence of new measurements.

Figure 3.7 shows the state estimation at $timestep=3$, in which the measurement data is available, shown in Figure 3.7 (b), and it is incorporated with the predicted state shown in Figure 3.7 (a) to estimate the state shown in Figure 3.7 (c). Figures 3.8 and 3.9 depict the scenario where measurement data is unavailable from $timesteps=6$ to 14. During this period, the state estimation is conducted solely by updating the occupancy grid map using the





predicted state (prior) and the previously estimated state. This process highlights the map's ability to adapt and refine its estimation even in the absence of new measurements, relying on iterative refinement to maintain accuracy. At *timestep*=14 the measurement is available, and it is used to estimate the state of the fire front shape.

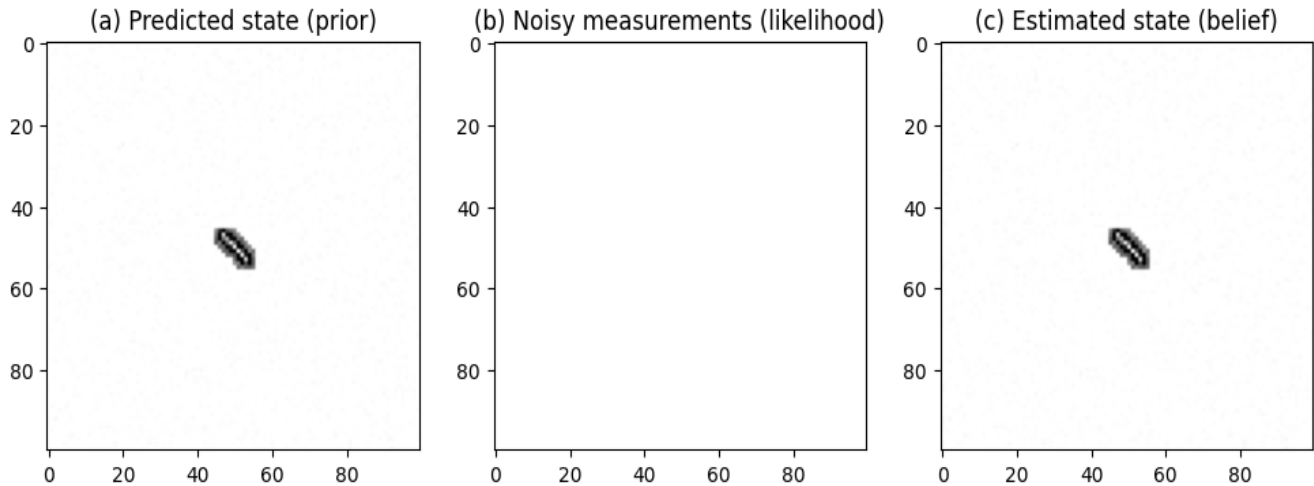


Figure 3.6. OGM at timestep = 2

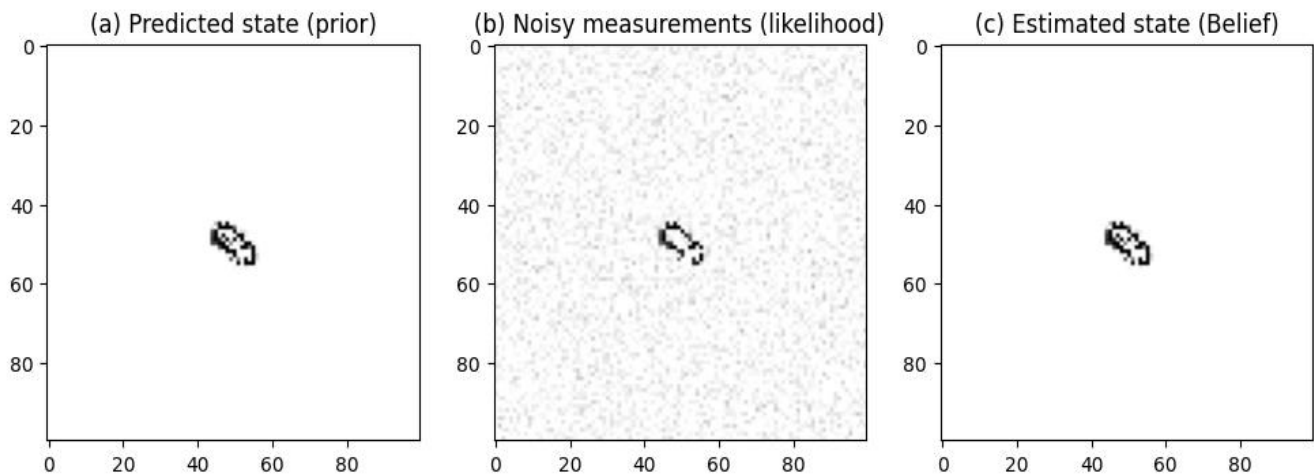
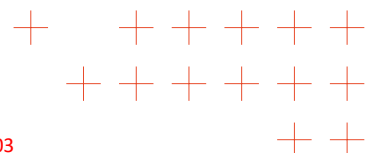


Figure 3.7. OGM at timestep = 3



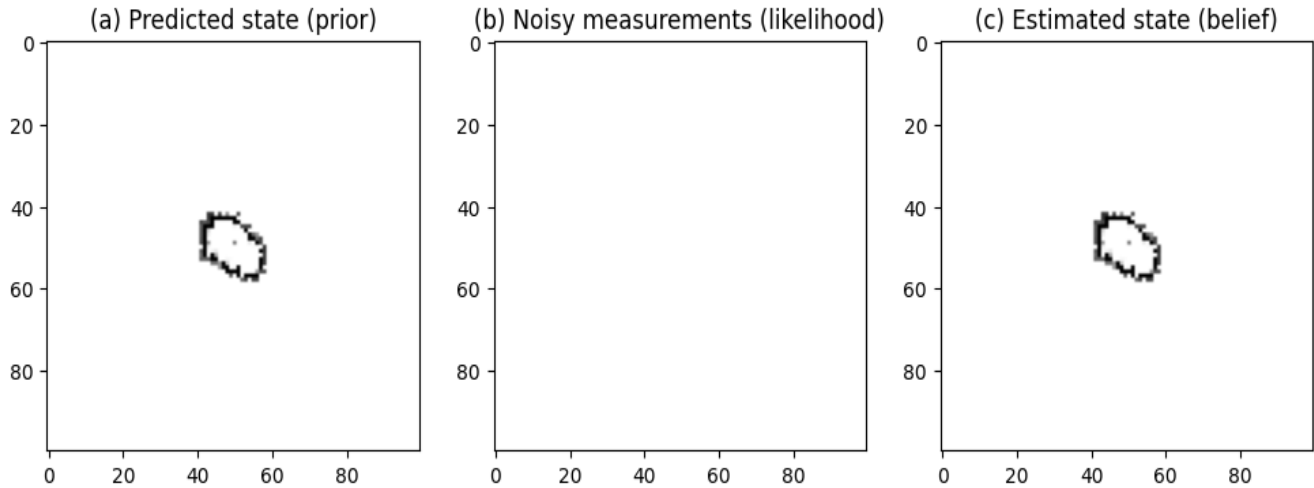
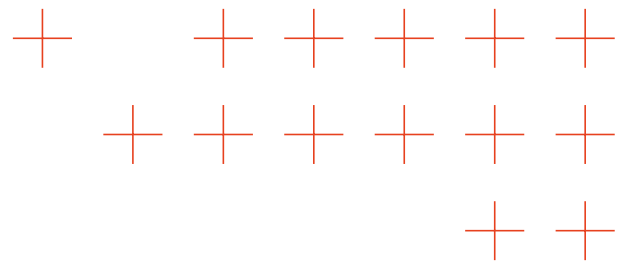


Figure 3.8. OGM at timestep = 6

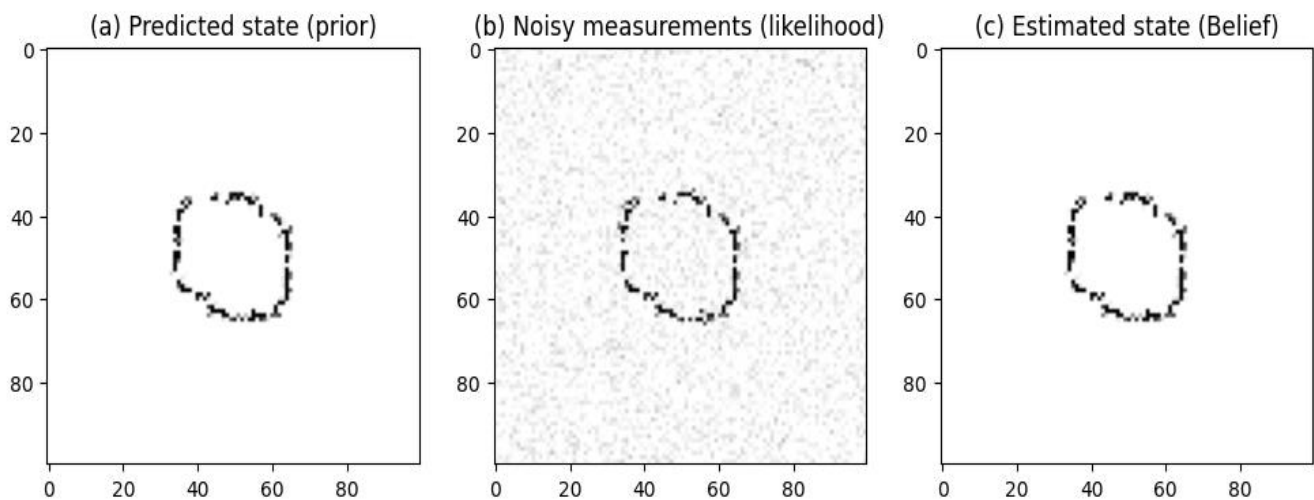
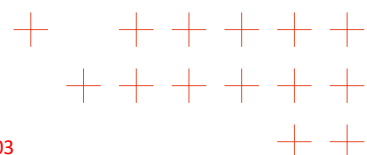
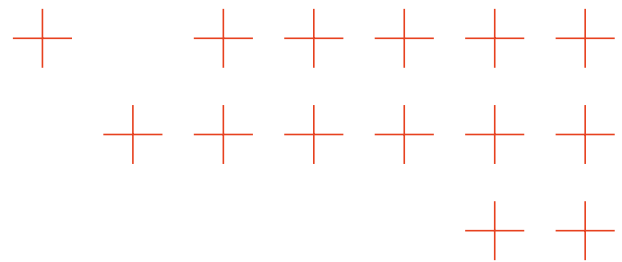


Figure 3.9. OGM at timestep = 14

3.6 Fusing Information Derived by Social Media

Linked to Task 3.3 (Social Media and Text Semantic Analysis), the development of methods for fusing multimodal information derived from social media is also part of Task 4.3 (Information Fusion).





3.6.1 State of the Art (SotA)

The integration of multimodal social media data for analysis has emerged as a crucial tool in disaster management, contributing across all phases of the disaster management cycle: mitigation, preparedness, response, and recovery. However, research has paid particular attention to the response and recovery phases due to the surge in social media activity during these periods (Phengsuwan et al., 2021). The multimodal nature of social media data—covering semantic content, sentiment, spatial, and temporal dimensions—offers enhanced situational awareness for emergency responders (Wang & Ye, 2018).

Despite the recognition of these dimensions, few existing frameworks simultaneously analyse all modalities. Recent studies have made progress by developing hypercube-based frameworks (e.g. Dunkel et al., 2019; Han et al., 2024), which capture spatiotemporal and semantic behaviour on social media during emergencies. Nevertheless, these approaches often rely on sequential workflows, where methods such as topic modelling and sentiment analysis are treated as independent pre-processing steps.

To some extent, semantics and sentiments have been merged into joint topic-sentiment models, which allow for simultaneous analysis of what a post is about and how the poster feels. However, the existing topic-sentiment models, such as the Joint Sentiment/Topic Model (JST) by Lin and He (2009), are still based on older bag-of-words techniques. These approaches have been substantially outperformed by newer neural network-based methods in pure topic modelling (Hanny & Resch, 2024), yielding much more coherent and diverse semantic topics. However, these advancements have not yet been applied to joint topic-sentiment modelling.

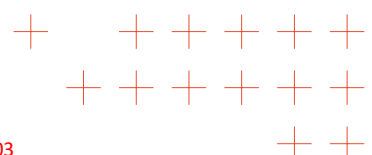
3.6.2 Planned Improvements within TEMA

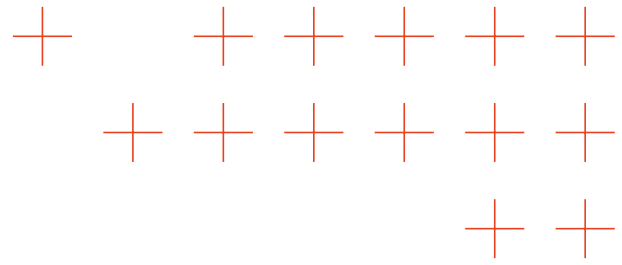
Building upon the state of the art, TEMA aims to advance multimodal social media analytics. We plan to move beyond bag-of-words approaches and present an integrated framework for multimodal information processing. As part of this, we will fuse semantic text embeddings, sentiment classification, spatial, and temporal data to extract useful information during emergencies. Additionally, we plan to integrate large-scale generative AI models like Llama-2-70B into the multimodal analysis workflow. This integration should allow for directly querying contextual information and summaries in natural language, offering emergency responders deeper insights in all stages of a disaster.

As part of this, we also plan to enhance the multilingual capabilities of such systems by leveraging multilingual language models. This is of particular importance within TEMA, given the large number of countries involved in the project. Finally, we also aim to explore the integration of external contextual information (e.g., mobile phone data) into the information fusion process.

3.6.3 Activities performed in the period M13-M18

Significant progress with respect to the planned improvements has already been made in the project. First, a joint neural, clustering-based topic-sentiment modelling method has been developed to improve upon existing techniques for uncovering sentiment-associated topics within large amounts of social media data. The model combines BERT-based semantic embedding generation and sentiment classification, fusing the outputs from the



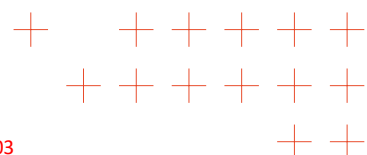


two into joint feature vectors. These feature vectors are then clustered, yielding coherent collections of posts regarding their semantic topic and sentiment. The approach was realized as a framework, allowing for the use of different language models and clustering methods. It is referred to as the Joint Topic-Sentiment (JTS) framework. Experimentally, it outperformed traditional approaches like JST and TSW in terms of semantic topic quality and sentiment classification accuracy. These results have been validated through various metrics, including Topic Coherence (TC), Topic Diversity (TD), and Sentiment-Exact Match Ratio (S-EMR), among others (as shown in Table 3.1).

	<i>k</i> = 10			<i>k</i> = 25			S-EMR	SU	SC	DBI
	TC	TD	TQ	TC	TD	TQ				
JST	0.22	0.58	0.12	0.15	0.48	0.07	0.35	1.00	-	-
TSWE	0.22	0.50	0.11	0.16	0.40	0.07	0.35	1.00	-	-
BERTopic	0.18	0.69	0.12	0.12	0.46	0.05	0.72 *	0.56 *	-	-
JTS(<i>k</i> -means)	0.31	0.58	0.18	0.22	0.48	0.11	0.72	0.89	0.33	1.02
JTS(GSOM)	0.31	0.56	0.17	0.21	0.48	0.10	0.72	0.90	0.31	1.02
JTS(HDBSCAN)	0.32	0.73	0.23	0.19	0.60	0.11	0.72	0.77	-0.09	1.32

Table 3.1. Comparison of Topic Coherence (TC), Topic Diversity (TD), Topic Quality (TQ) for different numbers of keywords along with the Sentiment-Exact Match Ratio (S-EMR), Sentiment Uniformity (SU), Silhouette Coefficient (SC) and the Davies-Bouldin Index (DBI).

Building upon the JTS approach, an approach for joint spatio-temporal topic-sentiment modelling has also been developed. By extending the feature vectors with normalized projected coordinates and a normalized representation of time based on Unix time, additional modalities were integrated into the method. However, with spatial coordinates in the feature vectors, a spatially coherent clustering approach was required. For this reason, a Geographic Growing Self-Organizing Map (Geo-GSOM) for dynamic learning in the multimodal feature space was developed. It preserves the geographic coherence of clusters using a hierarchical update procedure: first searching for the geographically closest neuron and then identifying the Best Matching Unit (BMU) in its vicinity. Moreover, the neuron grid grows dynamically over time, not restricting it to a predefined shape as in a regular SOM. The Geo-GSOM is used to cluster the multimodal feature vectors.



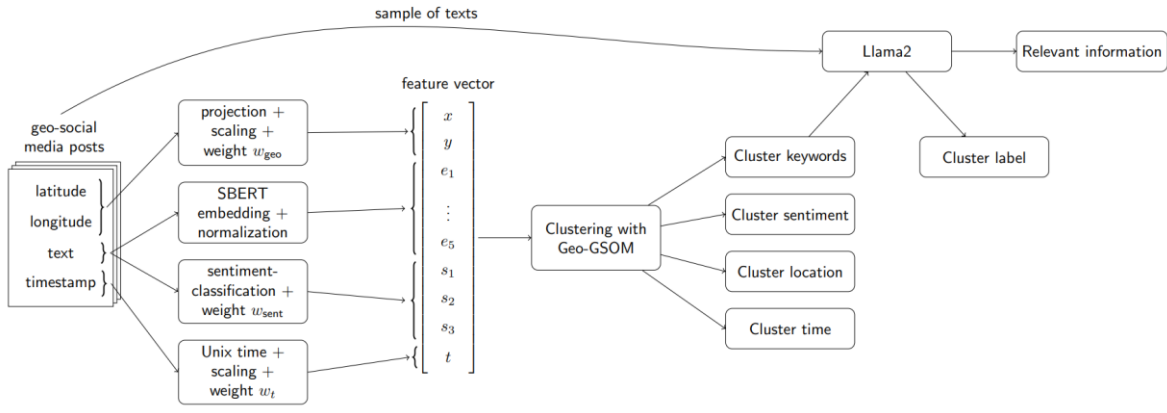
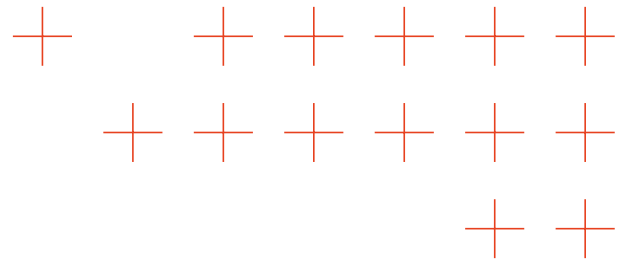


Figure 3.10. Workflow diagram of the developed approach to joint spatio-temporal topic-sentiment modelling which fuses social media information from multiple modalities.

The output consists of locally delineated clusters, from which information can be extracted using statistics and generative AI. While the output of the generative model is currently still restricted to predefined outputs, it already allows for the extraction of contextual information like summaries and emergency-related details. Using this workflow, it is possible to reduce thousands of social media posts to a few actionable, interpretable clusters, providing high-level insights into social media discussions for emergency responders. The model has already been applied to real-world events, such as the 2021 Ahr Valley flood in Germany, as depicted in Figure 3.11.

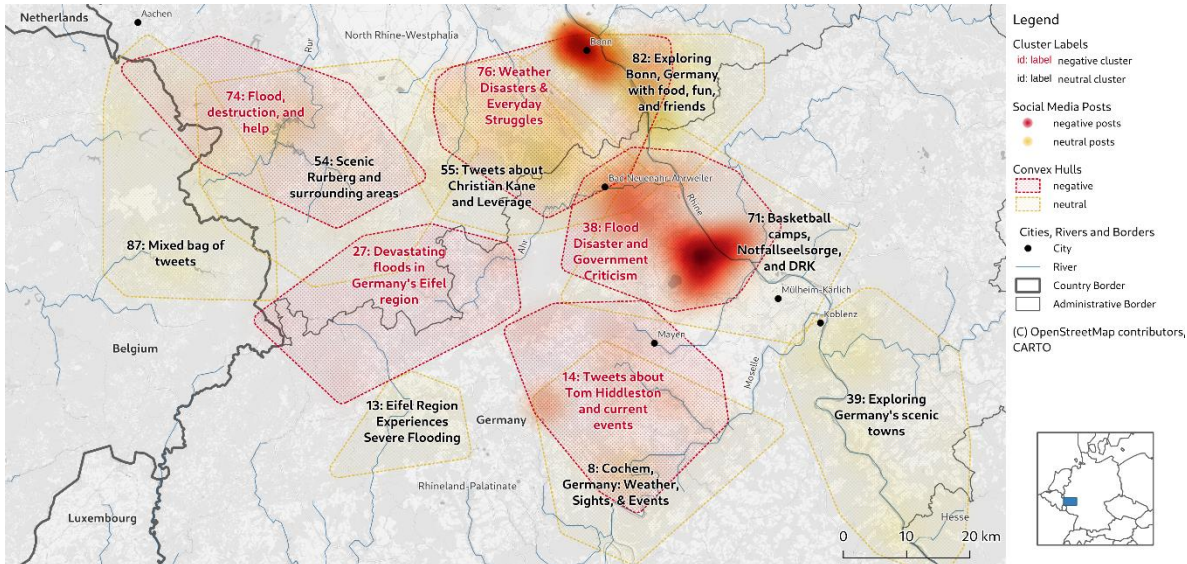
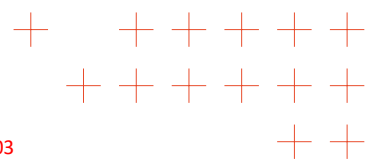
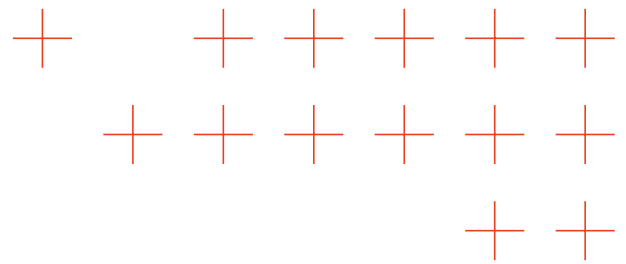
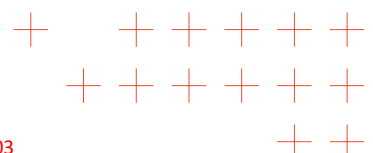


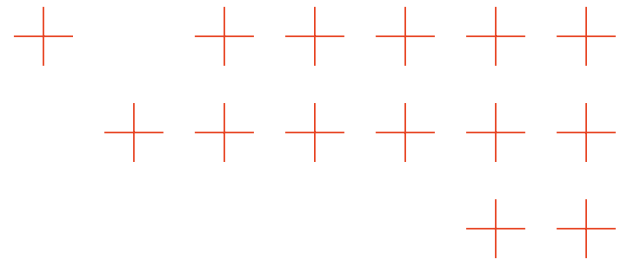
Figure 3.11. Exemplary output map of our multimodal approach for joint spatio-temporal topic-sentiment modelling.





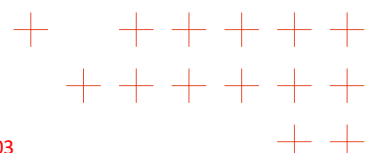
To date, the JTS method has been published in a journal paper, and the multimodal approach has been published in a conference paper at AGILE 2024. Additionally, another journal paper is under revision, where we systematically examined the parametrization effects of our developed methods.

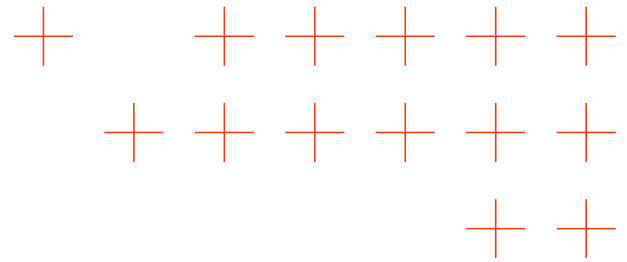




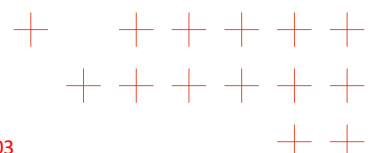
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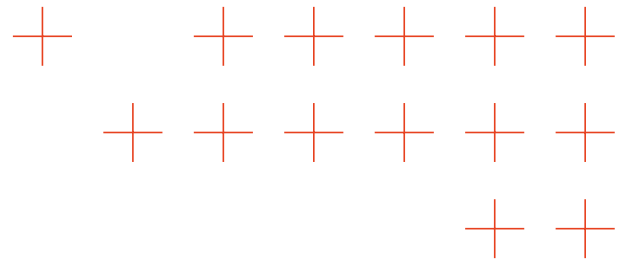
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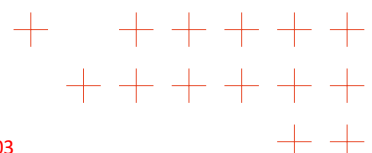


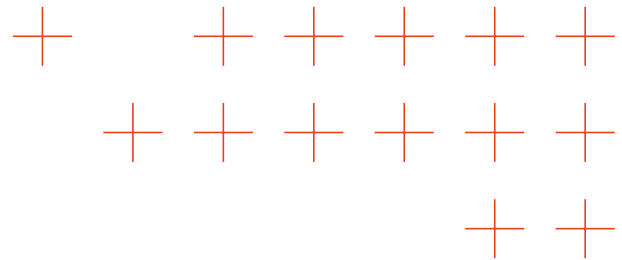
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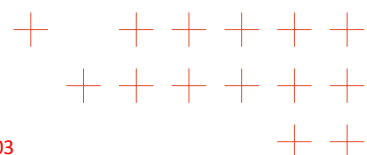
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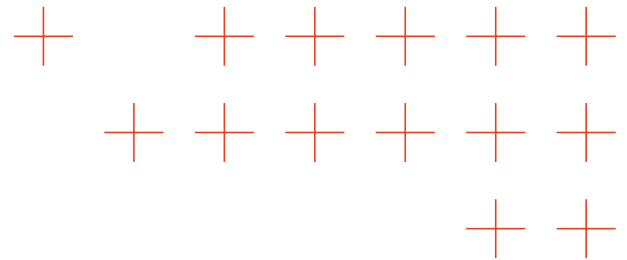
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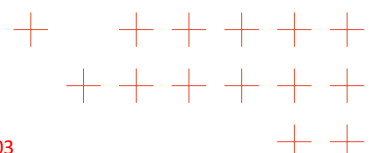
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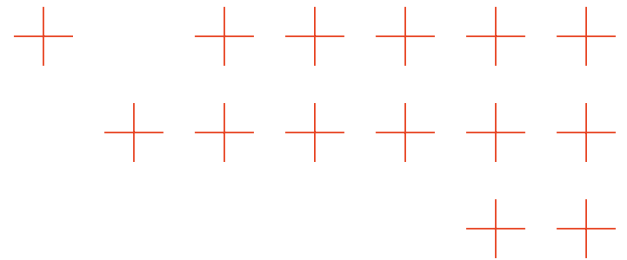
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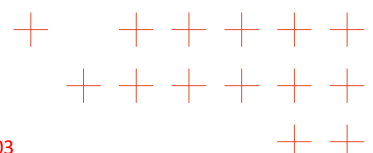


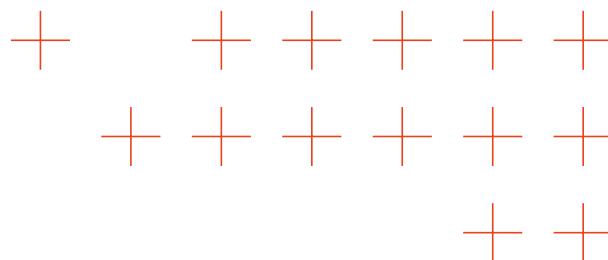
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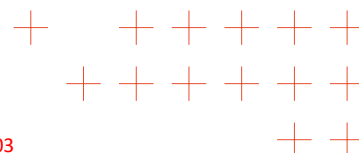


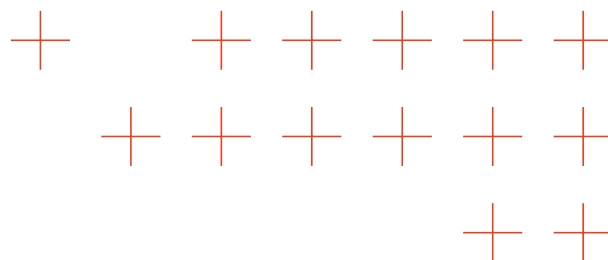
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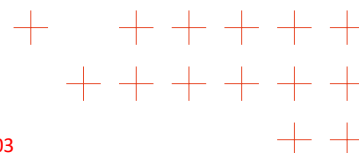


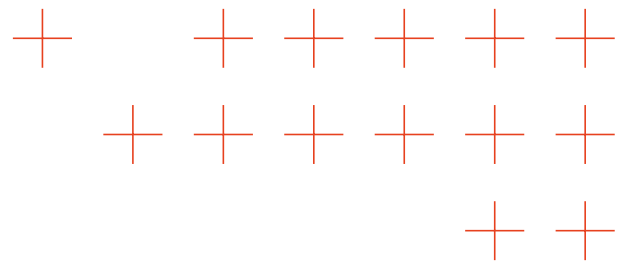
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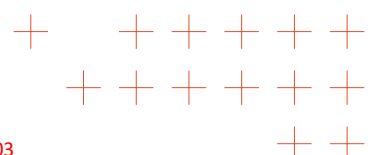
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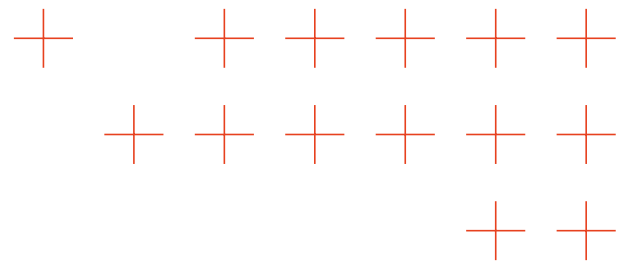




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5. Conclusion and Next Steps

In Section 2, we examined the foundational aspects of the Task 4.1 development, with a particular emphasis on the two central technologies designed for modelling forest fires and flood scenarios, and their seamless integration into the TEMA platforms. This section offered a comprehensive review of the latest advancements in the field, encompassing state-of-the-art methodologies employed in the applied modelling processes.

Additionally, we describe the underlying mathematical models used for simulating these events, including an analysis of input variables and the different types of output data generated. We also considered specific aspects of the processing algorithms, discussing key specifications and how they contribute to the accuracy and efficiency of the models.

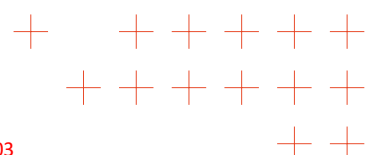
The next steps in the development of these modules will be conducted further within WP4 as well as within WP6. Some preliminary results have been recently published (see Appendix A).

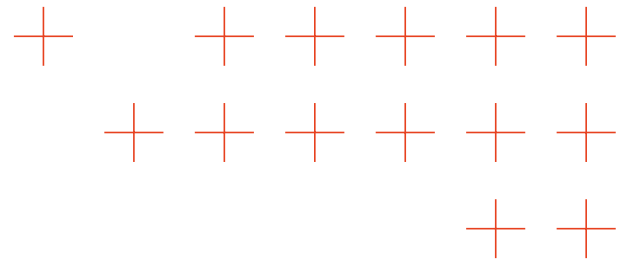
The further development will involve refining the modelling techniques, optimizing integration with the TEMA platforms, and ensuring that the modules are robust and scalable to meet the project's goals.

To this end, the project team will work on improving the precision of the simulations, enhancing the user interface for better visualization of results, and increasing the interoperability of the different components. The overall aim is to ensure that the Task 4.1 development aligns with project objectives and delivers high-quality outcomes. By addressing these key areas, we expect to contribute significantly to advancing the understanding and management of forest fire and flood scenarios within the TEMA platforms.

Section 3 summarized the design of the Information fusion module of the TEMA platform architecture. The end-users' requirements and challenges have been analysed to devise the design Information fusion. The design of the Information fusion module based on asynchronous georeferenced occupancy grid estimation addresses all requirements and challenges:

- Reliability and robustness with high levels of noise and uncertainty, through an RBF estimation tool that reasons on the measurement and model uncertainty,
- Multimodality of input measurements, through an RBF approach that considers the observation models of the used sensors,



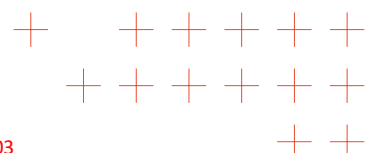


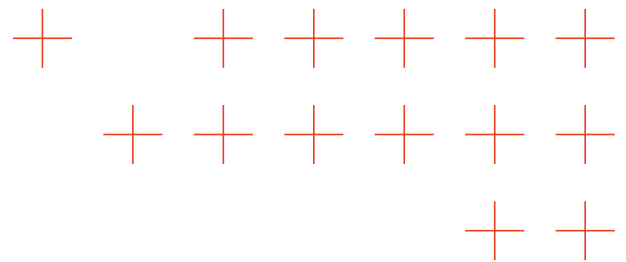
- Spatial resolution heterogeneity though using a georeferenced estimation tool and georeferenciation modules,
- Temporal resolution heterogeneity though using timestamped inputs and an asynchronous estimation approach,
- Computational efficient through an asynchronous approach and implementation in the cloud,

The design of the Information fusion has been also performed from an architectural perspective, by defining the interactions with the rest of the modules of the TEMA platform, both inputs and outputs.

Since Information fusion is a central module of the TEMA platform, to facilitate development, we adopt a development methodology based on simulation such that Information fusion can be developed independently of the rest of the modules.

The preliminary prototype of our Information Fusion system represents our initial attempt to integrate diverse heterogeneous inputs with varying temporal and spatial resolutions. This prototype serves to illustrate the effectiveness of employing RBF alongside occupancy grid mapping for the state estimation of the monitored ND. Our primary objective with this prototype is to demonstrate the effectiveness of the RBF approach within the context of occupancy grid mapping, demonstrating its capability to handle inputs with different temporal resolutions. By adopting an asynchronous RBF methodology for occupancy grid mapping, the proposed approach highlights its adaptability to adjust varying input resolutions. The developed Information Fusion prototype serves as the foundational milestone, functioning as the core module upon which subsequent improvements will be built. As we progress towards future milestones, further enhancements and refinements to amplify the functionality and performance of the Information fusion module will be performed.





6. Appendix

Below we add copies of the publications associated with this deliverable.

DLR-KN

During the first two quarters of Work Package 4, DLR-KN has submitted three conference papers under topics relating to the Task 4.1. Specifically, “Domain Knowledge Assisted Gas Tomography” addresses the challenging problem of Gas Tomography (GT) – a reconstruction technique for a spatial gas distribution based on measurements with an open-path sensor. Gas tomography could eventually prove useful to monitoring smoke plumes. In a publication “Gas Source Localization Using Physics-Guided Neural Networks” we proposed a novel method for estimating the location of a gas source based on spatially distributed concentration measurements taken, e.g., by a mobile robot flying platform. The proposed approach uses a Physics-Guided Neural Network to approximate the dispersion of the gas, and integrates it with an optimizer to solve a Gas Source Localization problem. In a further publication “Physics-Guided Neural Networks for Distributed Sparse Gas Source Localization Using Poisson's Equation and Green's Function Method” we looked into solving a gas source localization problem using Sparse Bayesian Learning. This gives a potential method to validate the locations of ignition in a forest fire.

PLUS

PLUS has published one paper relating to Task 4.3 regarding joint topic-sentiment analysis “Clustering-Based Joint Topic-Sentiment Modeling of Social Media Data: A Neural Networks Approach”. Another paper regarding spatiotemporal topic-sentiment modelling for disaster management was accepted for the AGILE 2024 conference: “Multimodal Geo-Information Extraction from Social Media for Supporting Decision-Making in Disaster Management”. A third paper examining the robustness of the methodology is currently under review.

