GRVC Lab
Biweekly seminars

Abdalraheem Abdullah Yousef Ijieh
16 Enero 2026

grvc Robotics Vision Control

Universidad de Sevilla

TEMA

TRUSTED EXTREMELY PRECISE MAPPING AND PREDICTION FOR EMERGENCY MANAGEMENT

TEMA in a Nutshell

Consortium partners

TEMA at a glance

20 Partners   4 Years   11 M€

Mission

Deliver actionable situational awareness for disaster response by turning multi-source data into decision-ready information.

- Bring real-time situational data to responders and relevant end-users.
- Support operational decision-making during evolving incidents.
- Transferable across hazards (e.g., flood, wildfire) and geographic regions.

TEMA technologies

Trustworthy Federated Analytics

ID	**Technology**
TFA-tech-01	Concept discovery for latent space interpretability of deep neural networks
TFA-tech-02	Human-comprehensible presentation of concept-based explanations
TFA-tech-03	DNN robustness
TFA-tech-04	Explainability for transformer base neural networks
TFA-tech-05	Fire/smoke/flood/person detection
TFA-tech-06	Fire/flood/background segmentation
TFA-tech-07	Person re-identification
TFA-tech-08	Satellite-based flood detection and assessment
TFA-tech-09	Satellite-based Forest fire detection and assessment
TFA-tech-10	Privacy preservation during visual analysis
TFA-tech-11	Geo-social media analysis
TFA-tech-12	Sentiment analysis for short texts
TFA-tech-13	Contrastive image-language models
TFA-tech-14	Federated Learning
TFA-tech-15	Data scarcity, synthetic data generation pipeline

Phenomenon Prediction and Decision-Macking

ID	**Technology**
PDM-tech-01	Forest Fire Simulation
PDM-tech-02	3Di Hydrodynamic simulation
PDM-tech-03	Realistic 3D smoke modelling and fire detection
PDM-tech-04	**Drone planning**
PDM-tech-05	**Information fusion**
PDM-tech-06	Data-fusion-based decision support and process triggering

Simulation and Visualization

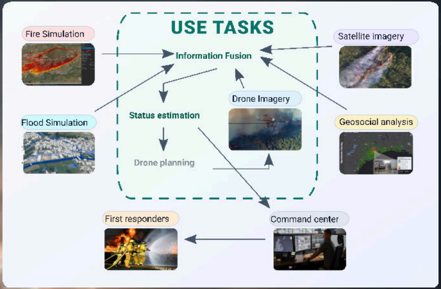
ID	**Technology**
SV-tech-01	**Drone-based image and data acquisition**
SV-tech-02	Digital Enabler
SV-tech-03	3D computer vision (SfM)/ Photogrammetry
SV-tech-04	Geovisual Analytics
SV-tech-05	Geospatial information retrieval
SV-tech-06	Extended Reality-based interactive visualisation system
SV-tech-07	Smartdesk

University of Seville (USE) technologies: SV-tech-01, PDM-tech-04, PDM-tech-05.

INFORMATION FUSION (PDM-TECH-05)

Motivation: why we need information fusion

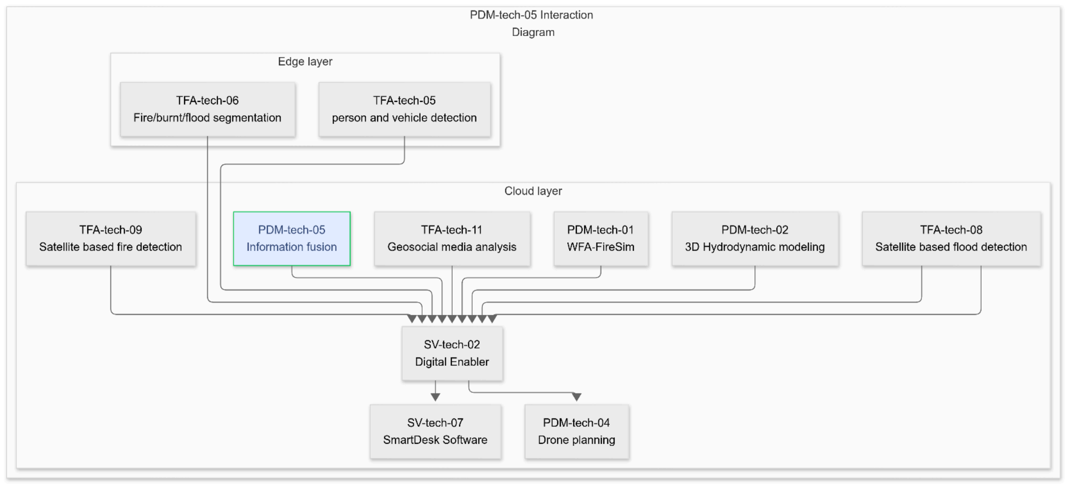
- In disasters, the bottleneck is not data availability, but **coherence**.
- UAV: detailed but local and intermittent.
- Satellite: wide-area but delayed and sometimes uncertain.
- Simulations: predictive but model-dependent.
- Geo-social: fast but noisy and biased.



Goal

Provide **one operational picture** that updates whenever new evidence arrives.

How PDM-tech-05 connects to other TEMA technologies



Key challenges addressed by PDM-tech-05

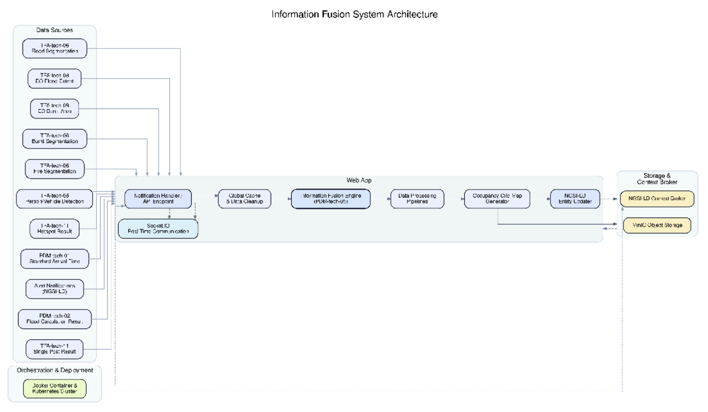
- **Heterogeneity:** mixing observations (UAV/satellite/geosocial) with model predictions
- **Asynchrony:** different refresh rates and latencies (seconds to hours).
- **Spatial mismatch:** different projections/resolutions $\rightarrow$ common reference grid
- **Uncertainty:** every source is imperfect; disagreement is normal.
- **Georeferencing:** UAV sensors + terrain $\Rightarrow$ spatial alignment is non-trivial.
- **Dynamics:** evolving hazard fronts and moving objects $\Rightarrow$ temporal consistency matters.

What the Information Fusion platform does

PDM-tech-05: multimodal fusion framework for NDM

- Select an Area of Interest (AOI) and a reference grid
- Ingest NGSI-LD entities (measurements + predictions) with timestamps and georeferencing metadata
- Fuse evidence probabilistically (event-driven updates).
- Maintain a persistent probabilistic state (**OGM** + **OPM**)
- Publish updated products to the Digital Enabler / SmartDesk and trigger workflows

Web app deployment view



Design principle

Same engine across hazards ⇒ Convert everything into consistent probabilities on a common spatial reference, then fuse.

Two primary outputs: OGM and OPM

Output 1: Occupancy Grid Map (OGM)

- Discretize the AOI into grid cells.
- Each cell stores a probability of occupancy:
  - **Flood OGM:** probability of water presence.
  - **Fire OGM:** probability of fire/smoke/burnt area presence.
- Updated asynchronously as new measurement & prediction arrives.

Output 2: Object Presence Map (OPM)

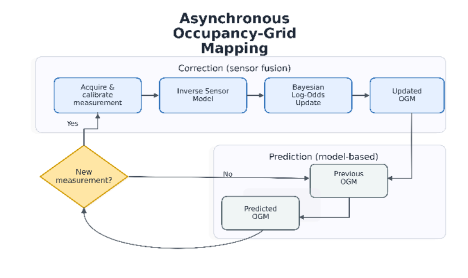
- Tracks persons/vehicles in geodetic coordinates.
- Data association (Hungarian) + state estimation (Kalman).
- Produces stable trajectories and uncertainty..

Operational view (web app)

OGM + OPM are served as the evolving operational picture to the command center.

Core engine: asynchronous occupancy-grid mapping

- Maintain a grid of **log-odds** values (numerically stable)
- **Correction (sensor fusion):** apply an update when a new measurement arrives
- **Prediction (model-based):** propagate using predictions when measurements are absent
- Asynchrony is handled naturally (no need to wait for all sources).



OGM update: Bayesian log-odds fusion (asynchronous sources)

Occupancy grid cell m_i (hazard present vs. absent)

Per-cell state

Posterior occupancy probability after fusing measurements up to time t:

$$p_i^t = P(m_i \mid z_{1:t}, x_{1:t}), \qquad \ell_i^t = \log \frac{p_i^t}{1 - p_i^t}, \qquad \ell_i^0 = \log \frac{p_i^0}{1 - p_i^0}.$$

Additive update (source s arriving at time t)

Let $p_{i,s}^t \in (0, 1)$ be the inverse-sensor-model output for cell i. Then:

$$\ell_i^t = \ell_i^{t-} + \left(\log \frac{p_{i,s}^t}{1 - p_{i,s}^t} - \ell_i^0 \right), \qquad p_i^t = \frac{1}{1 + e^{-\ell_i^t}}.$$

Fusion rule: measurements vs. predictions

Observational sources (UAV / satellite / geosocial)

- Convert raw outputs into a per-cell probability $p^t_{i,s} \in (0,1)$
- Add a log-odds increment $\delta\ell^t_{i,s} = \log \frac{p^t_{i,s}}{1-p^t_{i,s}}$
- Intuition: **high-confidence observations dominate locally**

Predictive sources (models)

- Predictions provide **structured early evidence** over large areas
- Fuse with the current OGM via **logit pooling** (weighted combination in log-odds space)
- Intuition: **predictions guide** until observations override

Flood measurement model: UAV flood segmentation

Aggregation from high-resolution UAV raster to the OGM grid

For cell i, let K_i be the set of georeferenced UAV pixels inside i and $n_i = |K_i|$.

$$\bar{s}_i^{\text{uav}} = \frac{1}{n_i} \sum_{k \in K_i} s_k^{\text{uav}} \in [0, 1].$$

Map the score to a measurement probability (clamp to $(\varepsilon, 1 - \varepsilon)$):

$$p_i^{\text{uav}} = p_{\min}^{\text{uav}} + \left(p_{\max}^{\text{uav}} - p_{\min}^{\text{uav}}\right) \bar{s}_i^{\text{uav}}, \qquad 0 < p_{\min}^{\text{uav}} < p_{\max}^{\text{uav}} < 1.$$

Log-odds increment and update

$$\delta\ell_{i,\text{uav}}^t = \log \frac{p_i^{\text{uav}}}{1 - p_i^{\text{uav}}} - \ell_i^0, \qquad \ell_i^t = \ell_i^{t-} + \delta\ell_{i,\text{uav}}^t.$$

Notes

$p_{\min}^{uav}, p_{\max}^{uav}$ encode trust in the segmentation (avoid overconfidence).

Flood measurement model: satellite flood extent

Per-cell probability from a resampled satellite mask

Let $m_i^{\text{sat}} \in [0, 1]$ be the resampled satellite mask value at cell i. For valid pixels:

$$p_i^{\text{sat}} = m_i^{\text{sat}} \in (0, 1), \qquad \delta\ell_{i,\text{sat}}^t = \log \frac{p_i^{\text{sat}}}{1 - p_i^{\text{sat}}}, \qquad \ell_i^t = \ell_i^{t-} + \delta\ell_{i,\text{sat}}^t$$

Cells outside the satellite swath (or invalid pixels) are not updated.

Notes

Probabilities are clamped to $[\epsilon, 1 - \epsilon]$ (e.g., $\epsilon \approx 10^{-6}$) to avoid infinite log-odds.

From counts/ratios to measurement probability

Let $\tilde{c}_t(i)$ and $\tilde{r}_t(i)$ be normalized post count and activity ratio, and $w_c + w_r = 1$. Define a hotspot score

$$s_t^{\mathrm{soc}}(i) = w_c\,\tilde{c}_t(i) + w_r\,\tilde{r}_t(i) \in [0,1],$$

then convert to a probability

$$p_t^{\mathrm{soc}}(i) = \epsilon + (1-2\epsilon)\,s_t^{\mathrm{soc}}(i), \qquad \delta\ell_{i,\mathrm{soc}}^t = \log\frac{p_t^{\mathrm{soc}}(i)}{1-p_t^{\mathrm{soc}}(i)}, \qquad \ell_i^t = \ell_i^{t-} + \delta\ell_{i,\mathrm{soc}}^t$$

Notes

Geosocial evidence is informative but noisy; weights are typically conservative compared to physical sources.

Flood prediction fusion: hydrodynamic depth (PDM-tech-02 / 3Di)

Depth-to-probability mapping (soft evidence)

For a predicted water depth $h_i \geq 0$, define

$$p_i^{\text{hyd}} = \epsilon + (1 - 2\epsilon)\,\frac{1}{1 + \exp\big(-(h_i - h_{50})/s\big)}.$$

Logit pooling with the current map state

Convert to log-odds $\ell_i^{\text{ogm}} = \log \frac{p_i^{\text{ogm}}}{1-p_i^{\text{ogm}}}$ and $\ell_i^{\text{hyd}} = \log \frac{p_i^{\text{hyd}}}{1-p_i^{\text{hyd}}}$, then fuse:

$$\ell_i^{\text{new}} = (1 - \alpha_{\text{hyd}})\,\ell_i^{\text{ogm}} + \alpha_{\text{hyd}}\,\ell_i^{\text{hyd}}, \qquad p_i^{\text{new}} = \sigma(\ell_i^{\text{new}}).$$

Fusing predictive outputs in a generic way

Prediction as probabilistic evidence (example: fire arrival / flood simulation)

For cell i, represent prediction as a pair of probabilities (hazard / no hazard):

$$p_i^{\text{pred}} = \frac{w_f\, p_f(i) + w_{nf}\, p_{nf}(i)}{w_f + w_{nf}}, \qquad w_f, w_{nf} > 0.$$

- **Flood:** $p_f(i)$ from model-derived inundation probability; $p_{nf}(i) = 1 - p_f(i)$.
- **Fire:** $p_f(i)$ from arrival-time evidence (e.g., within a forecast horizon); $p_{nf}(i) = 1 - p_f(i)$.

How it enters the OGM

Use the same update interface as observations: convert p_i^{pred} to log-odds and fuse; ; the same mechanism applies to floods and wildfires.

Extending beyond floods: fire occupancy grid map

Fire-related measurements

- UAV: *FireSegmentation* and *BurntSegmentation* (TFA-tech-06)
- Satellite: *EOBurntArea* (TFA-tech-09)
- Geosocial: *HotspotResult* (TFA-tech-11)
- Prediction: *StandardArrivalTime* (PDM-tech-01)

Example weighted combination (active fire vs. burnt evidence)

$$p_m(m_i) = w_{\text{fire}}\, p_{\text{fire}}(m_i) + w_{\text{burnt}}\, p_{\text{burnt}}(m_i), \qquad w_{\text{fire}} + w_{\text{burnt}} = 1.$$

This per-cell likelihood plugs into the same Bayesian occupancy update in log-odds space.

OPM: state, motion model, and asynchronous updates

Geodetic state for each tracked object k maintains a 6D state (geodetic position + velocity)

$$\mathbf{x}_{t,k} = \left[\lambda_{t,k} \;\; \phi_{t,k} \;\; h_{t,k} \;\; \dot{\lambda}_{t,k} \;\; \dot{\phi}_{t,k} \;\; \dot{h}_{t,k}\right]^\top.$$

Constant-velocity prediction transition:

$$x_{t+1,k} = Ax_{t,k} + w_t, \quad A = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Prediction step:

$$\hat{x}_{t|t-1,k} = A\hat{x}_{t-1|t-1,k}, \qquad P_{t|t-1,k} = AP_{t-1|t-1,k}A^\top + Q$$

OPM data association: gating and Hungarian assignment

For detection j at position $p_{t,j}$ and predicted track position $\hat{p}_{t|t-1,k}$:

$$d_{k,j} = d_{hav}(\hat{p}_{t|t-1,k}, p_{t,j})$$

Cost matrix for assignment:

$$C_{k,j} = \alpha \frac{d_{k,j}}{r_{gate}} + \beta \left(1 - c_{t,j}^{det}\right)$$

Association

Apply gating ($d_{k,j} < r_{gate}$) then solve the assignment with the Hungarian algorithm.

OPM state correction: confidence-aware Kalman update

Measurement model (position):

$$z_{t,j} = Hx_{t,k} + v_t, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Confidence-aware measurement noise:

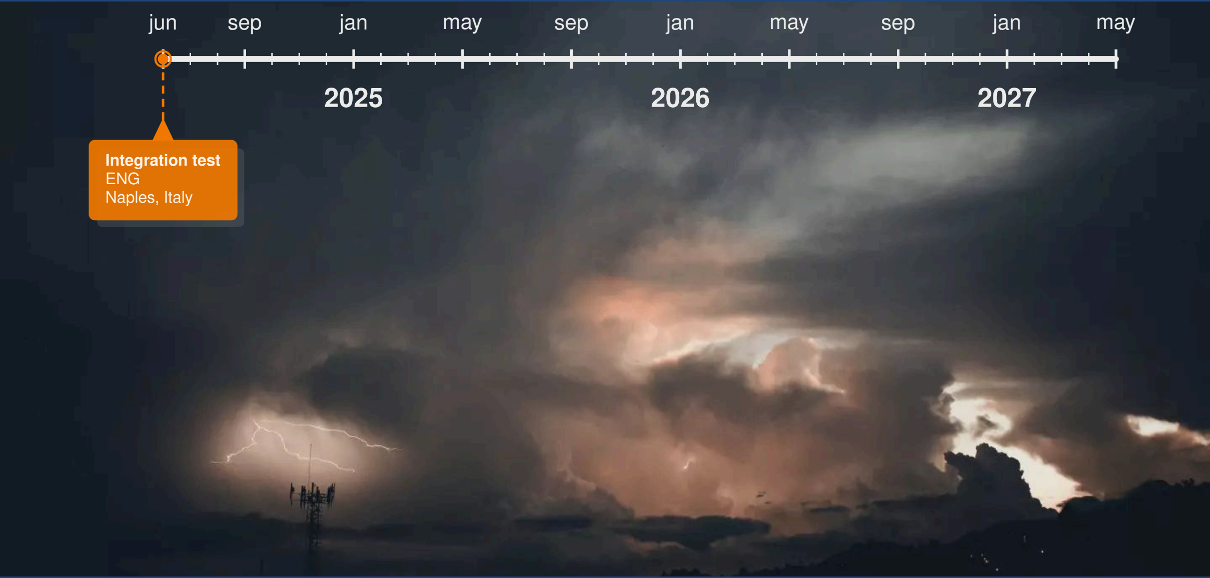
$$R_{t,j} = \frac{1}{\max(c_{t,j}^{det}, \varepsilon_c)} R_{base}$$

Kalman update:

$$S = HPH^\top + R, \quad K = PH^\top S^{-1}, \quad \hat{x}_{t|t} = \hat{x}_{t|t-1} + K(z - H\hat{x}_{t|t-1})$$


TEMA
HISTORICAL AND REAL-TIME TRIALS

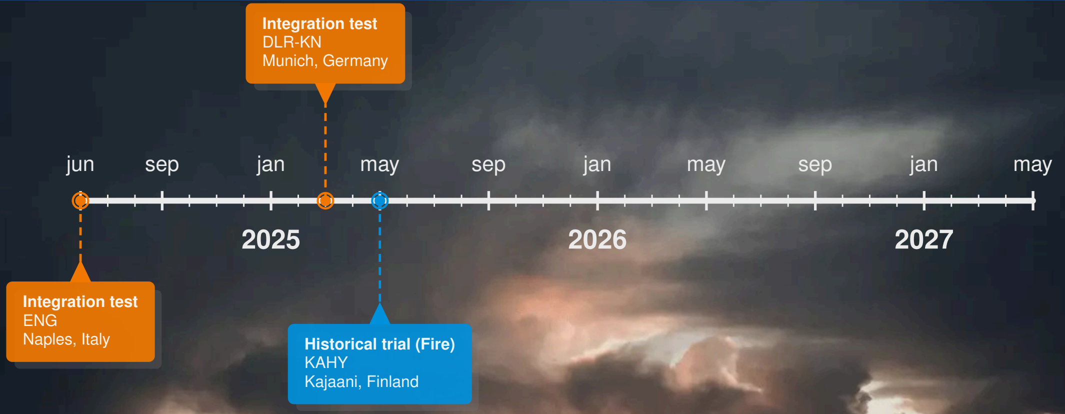
Trials timeline



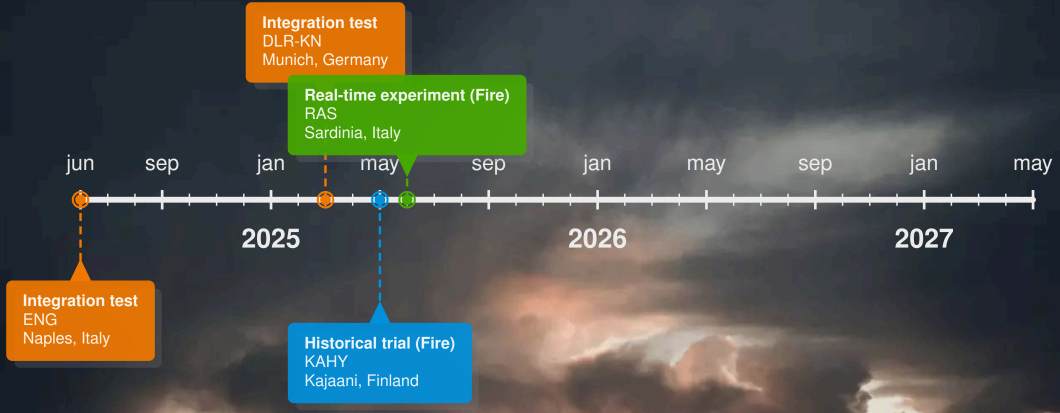
TEMA

Trials timeline

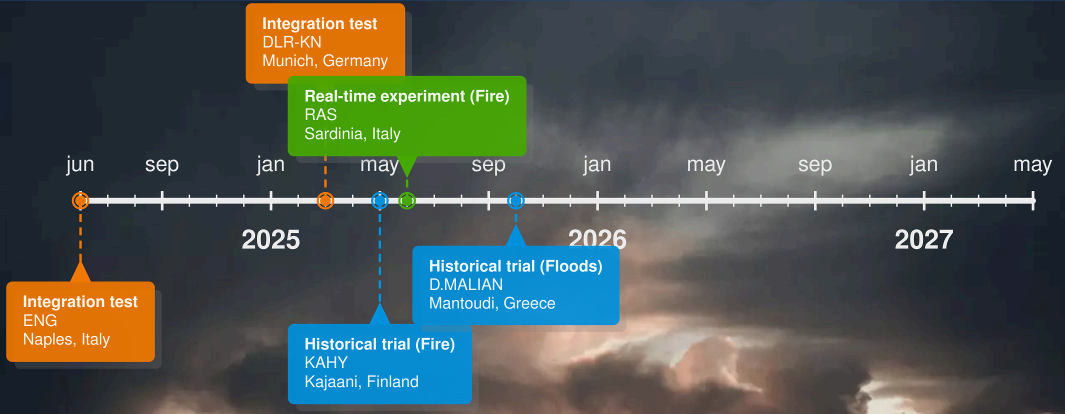
Trials timeline



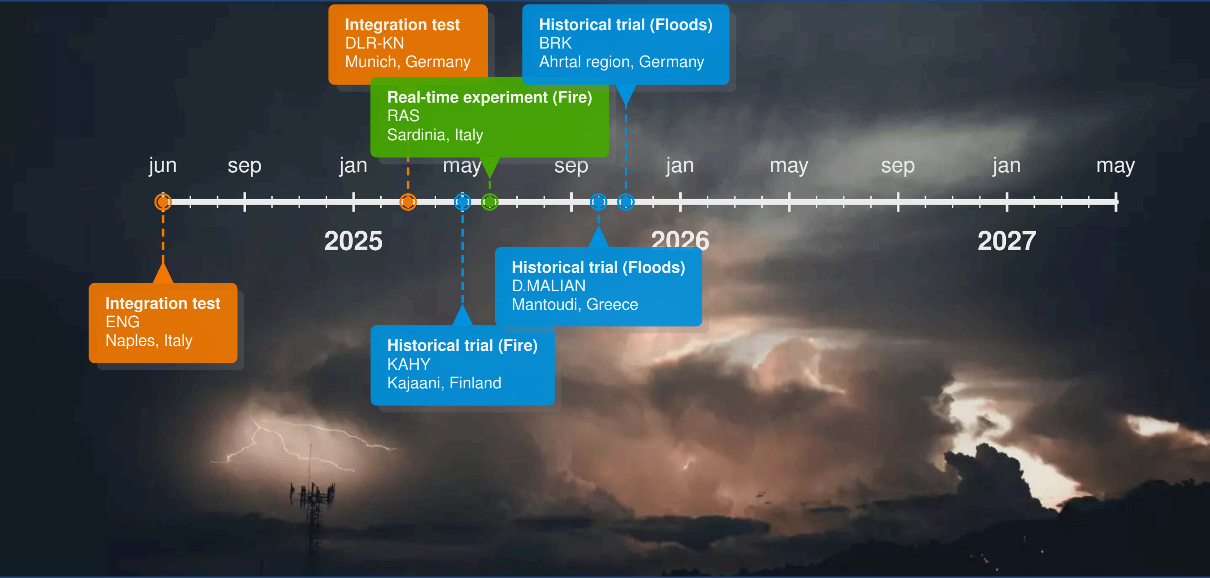
Trials timeline



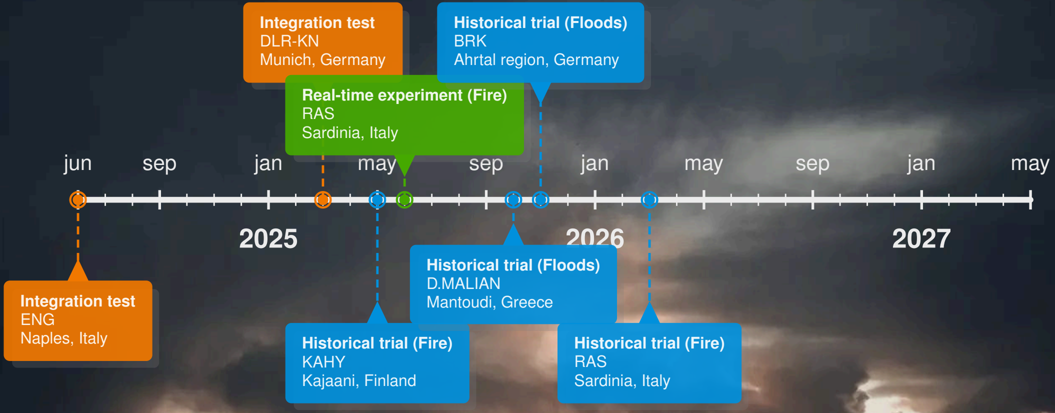
Trials timeline



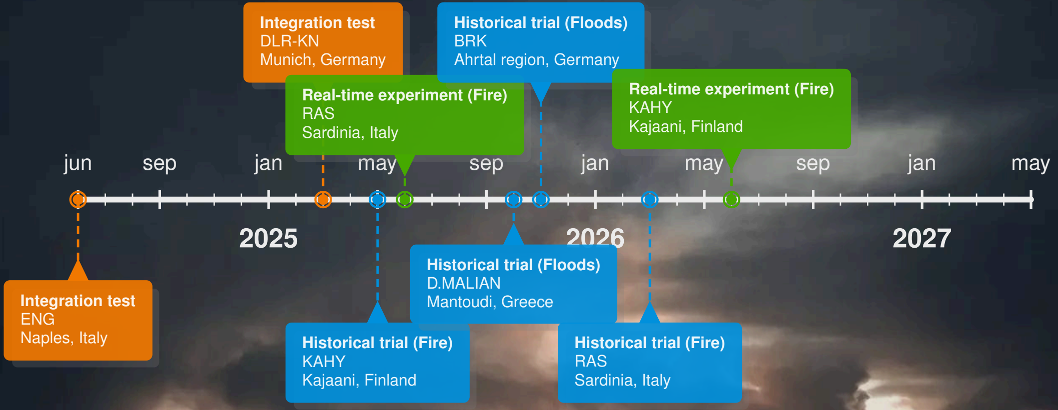
Trials timeline



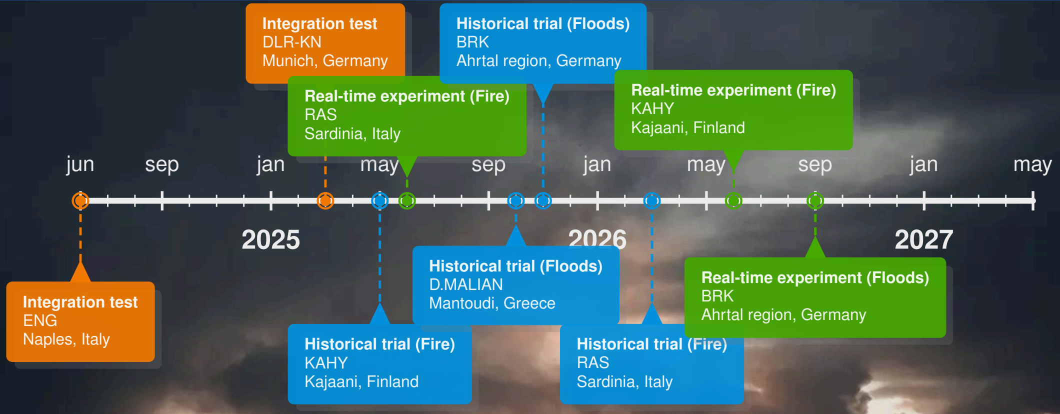
Trials timeline



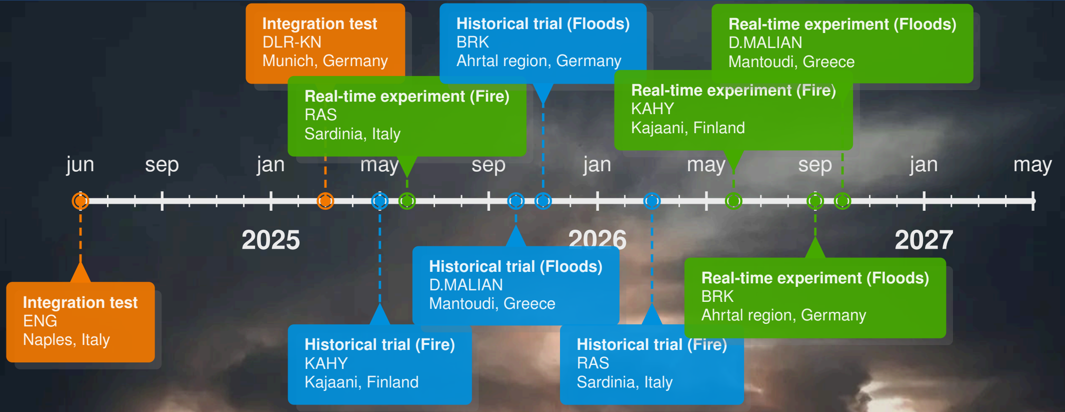
Trials timeline



Trials timeline



Trials timeline



CASE STUDY: HISTORICAL AHRTAL FLOODS, GERMANY

Case study focus: floods (Ahrtal) as a demonstrator

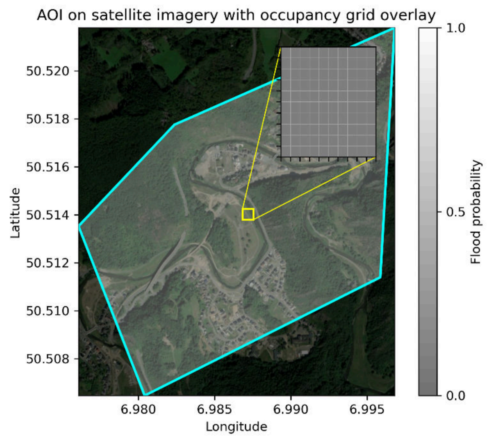
Why a flood case study?

The platform is hazard-agnostic, but floods provide a clear demonstration of fusing predictions (hydrodynamics) with heterogeneous observations (UAV, satellite, geosocial).

- AOI defined as a polygon; OGM grid initialised with $p_i = 0.5$ (unknown)
- Sources fused asynchronously upon arrival:
  - 3Di depth predictions $\rightarrow$ soft prior via logit pooling
  - UAV flood segmentation $\rightarrow$ high-resolution local corrections
  - Satellite flood extent $\rightarrow$ broader-area observational updates
  - Geosocial hotspots $\rightarrow$ human-centric weak evidence
- Outputs delivered to decision-support tools: OGM (flood status) + OPM (persons/vehicles)

AOI and OGM grid initialization

- AOI: $\sim$1.47 km^2 (urban river section).
- Grid: WGS84 (EPSG:4326), **5 m** resolution.
- Prior: $p = 0.5$ inside AOI (maximum uncertainty).



What gets fused in the OGM (inputs + roles)

Evidence roles (hazard-agnostic pattern)

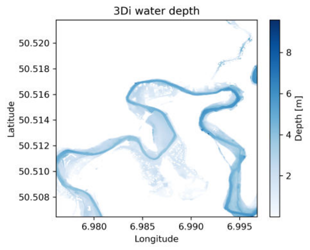
- **Hydrodynamics**: early spatial structure (physics-informed), but predictive uncertainty.
- **Satellite**: wide-area observational correction (coarser + time offsets).
- **UAV segmentation**: local, high-resolution refinement on demand (small footprint, high fidelity).
- **Geosocial**: additive human-centric confirmation; may be spatially coarse.

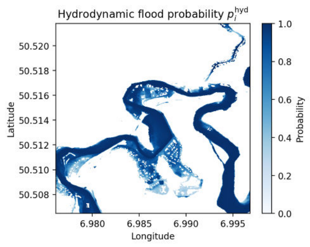
Key takeaway

OGM/FPM integrates all sources on a common grid using probabilistic updates; it does not treat any source as ground truth.

Hydrodynamic prediction as probabilistic evidence (3Di)

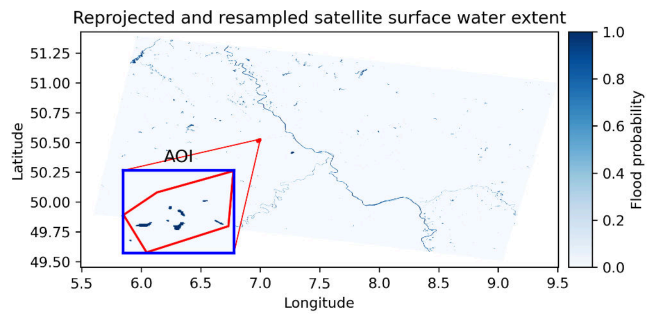
- Input: water depth field (3Di).
- Depth → probability via a **logistic mapping**.
- Provides **continuous early structure** when observations are sparse.



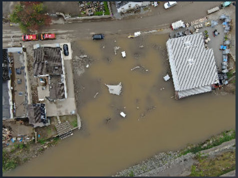


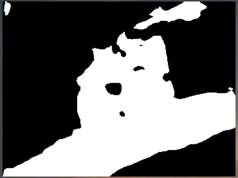
Satellite SWIM: wide-area observational layer

- Satellite surface-water extent product (probabilistic raster).
- Reprojected + resampled to the **5 m FPM grid**.
- Broad coverage complements UAV footprint; corrects regional mismatches.



UAV flood segmentation

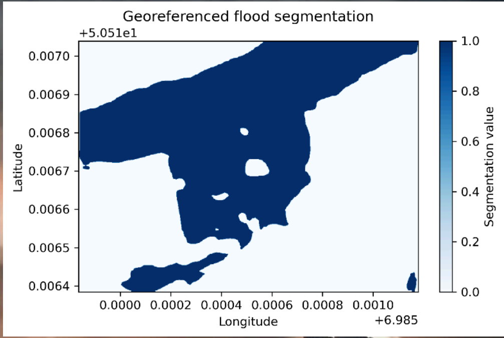




- UAV RGB imagery segmented into flood / non-flood.
- Mask is **georeferenced** onto the AOI (DEM + pose).
- Produces local, high-resolution observational evidence.

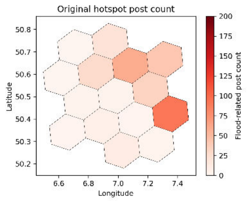
UAV evidence on the map: local probabilities

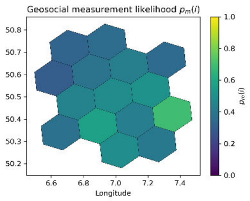
- UAV flood segmentation converted to per-cell likelihoods.
- Interpreted as **local flood probabilities** on the FPM grid.
- Key role: **boundary sharpening** and local corrections.



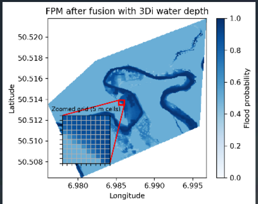
Geosocial hotspots: human-centric evidence (and limitations)

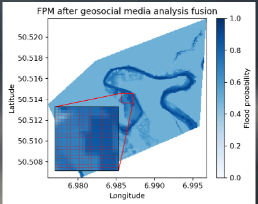
- Posts aggregated into hotspot cells (counts, activity, stats).
- Converted into a measurement likelihood $p_m(i)$.
- Ahrtal limitation: AOI falls in a **single hotspot cell** $\Rightarrow$ coarse spatial signal.

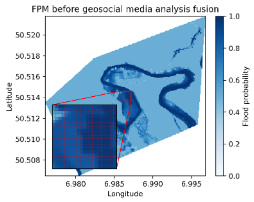


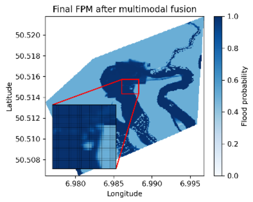


Qualitative evolution: the FPM sharpens as evidence arrives





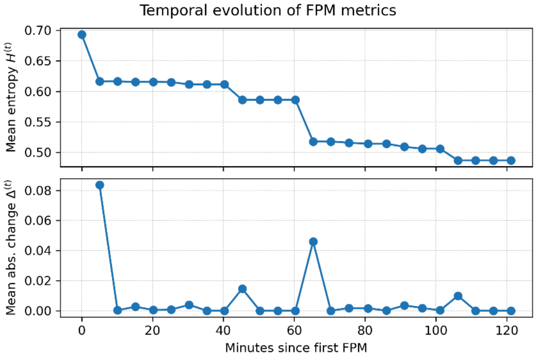




- Predictions provide early structure; observations refine boundaries and correct local mismatches.
- Geosocial contribution is deliberately moderate but visible in the inset.

Temporal behavior: responsiveness + stability

- Metrics computed over published FPMs (5-min intervals).
- $\Delta(t)$ spikes when strong evidence arrives, then $\rightarrow 0$ (convergence).
- $H(t)$ decreases as uncertainty reduces.



Cross-modality consistency (internal agreement with final FPM)

Why this metric?

Dense external ground truth is limited; we quantify how the fused FPM aligns with each modality on its support.

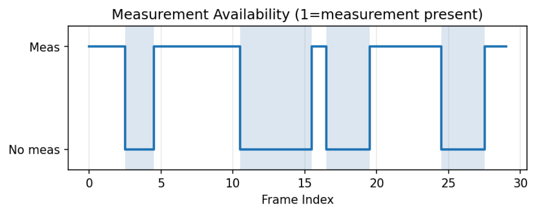
Source s	$\lvert I_s \rvert$ [cells]	D_s	A_s [%]
UAV segmentation	326	0.05	97
Satellite SWIM product	58,789	0.12	90
Hydrodynamic (3Di)	58,789	0.18	85
Geosocial hotspots	58,789	0.35	52

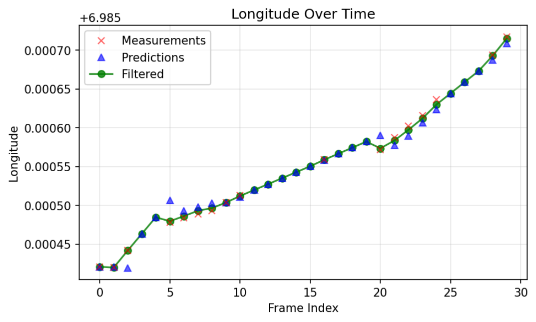
- UAV aligns best (high local fidelity on its footprint).
- Satellite moderate (observational but coarser / time offset).
- Hydrodynamics lower (predictive uncertainty).
- Geosocial lowest (coarse spatial support in Ahrtal).

OPM setup: detections $\to$ georeferenced observations $\to$ tracker

- UAV person/vehicle detections are georeferenced to (λ, ϕ, h) with confidence.
- Multi-object mode: **gating + Hungarian assignment** for association.
- State estimation: **6D geodetic Kalman filter** (prediction-only during detection gaps).
- Discontinuity rule: reject updates when prediction–measurement discrepancy exceeds $r_{\mathrm{FPM}} = 5$ **m** (aligned with OGM resolution).

Tracking under missed detections: gaps and continuity





- During gaps: prediction-only propagation; filtered state remains continuous.
- When detections return: correction pulls the trajectory back toward measurements.

grvc

THANK YOU FOR ATTENDING, QUESTIONS?