GRVC Lab
Biweekly seminars

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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.

TEMA

INFORMATION FUSION (PDM-TECH-05)

Information fusion: storyline

- Natural Disaster Management (NDM) produces **many signals** (UAV, satellite, models, geo-social), often **asynchronous** and **contradictory**.
- PDM-tech-05 turns these signals into a **single, continuously updated operational picture**.
- Two primary outputs:
  - **Occupancy Grid Map (OGM)**: disaster status (Flood & Fire) as a probabilistic map.
  - **Object Presence Map (OPM)**: multi-object tracking (people/vehicles) with uncertainty.
- Later: we demonstrate the platform with a **flood case study** (Ahrtal), aligned with the draft paper.

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.

Key challenges addressed by PDM-tech-05

- **Asynchrony:** different refresh rates and latencies (seconds to hours).
- **Heterogeneity:** masks, grids, point detections, text-derived signals, forecasts.
- **Uncertainty:** every source is imperfect; disagreement is normal.
- **Georeferencing:** mobile 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

1. **Ingest** NGSI-LD entities (measurements + predictions).
2. **Georeference** observations into a common map frame (AOI grid).
3. **Fuse** evidence probabilistically (event-driven updates).
4. **Track** objects over time (OPM).
5. **Publish** updated products to SmartDesk and downstream services.

Platform property

Same engine across hazards; hazard-specificity enters via input models and the OGM semantics (Flood/Fire)

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 from measurements & predictions using Bayesian log-odds.

Output 2: Object Presence Map (OPM)

- Tracks persons/vehicles in geodetic coordinates.
- Data association (Hungarian) + state estimation (Kalman).
- Produces stable trajectories and uncertainty, not flickering detections.

Operational view (web app)

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

Web app and services architecture (deployment view)

Core engine: asynchronous occupancy-grid mapping

- The OGM is updated **whenever** new evidence arrives.
- Measurements: update occupancy via inverse sensor models.
- Predictions: propagate or bias occupancy using forecast evidence.
- Asynchrony is handled naturally (no need to wait for all sources).

OGM formalism: probability and log-odds

Discretize the AOI into cells m_i and maintain an occupancy probability $p_t(i) = P(m_i \text{ occupied at time } t)$.

$$\ell_t(i) = \log \frac{p_t(i)}{1 - p_t(i)} \qquad \text{(log-odds)}$$

$$p_t(i) = \sigma(\ell_t(i)) = \frac{1}{1 + e^{-\ell_t(i)}} \qquad \text{(logistic)}$$

$$\ell_0(i) = \log \frac{P(m_i)}{1 - P(m_i)} \qquad \text{(prior, typically } P(m_i) = 0.5 \text{ inside AOI)}$$

Why log-odds?

Numerical stability and additive updates across asynchronous sources.

OGM fusion rule: Bayesian log-odds update

For an incoming observation z_t (from any source) and platform state x_t:

$$\begin{aligned}\ell_t(i) &= \ell_{t^-}(i) + \log \frac{P(m_i \mid z_t, x_t)}{1 - P(m_i \mid z_t, x_t)} - \ell_0(i) \\ &= \ell_{t^-}(i) + \underbrace{\log \frac{P(z_t \mid m_i, x_t)}{P(z_t \mid \neg m_i, x_t)}}_{\text{evidence from source}} - \ell_0(i)\end{aligned}$$

Interpretation

Each source provides a per-cell occupancy probability (or likelihood), which is converted into a log-odds increment and added to the current map.

Fusion of measurements vs. predictions

- **Measurements** (UAV/satellite/geo-social) update the current OGM via inverse sensor models.
- **Predictions** (e.g., hydrodynamics, fire simulation) encode forecast evidence and can be fused:
  - as additional log-odds evidence, or
  - via **logit pooling** (weighted combination in log-odds space).
- The platform remains generic: source-specificity enters only through the mapping from raw outputs to $p_t^{(s)}(i)$.

Flood measurement model: UAV flood segmentation

Let the segmentation provide per-pixel flood scores $s_k^{uav} \in [0, 1]$ for pixels k projected into grid cell i.

$$\bar{s}_i^{uav} = \frac{1}{n_i} \sum_{k \in K_i} s_k^{uav}$$

$$p_i^{uav} = p_{\min}^{uav} + \left(p_{\max}^{uav} - p_{\min}^{uav}\right) \bar{s}_i^{uav}$$

$$\delta \ell^{uav}(i) = \log \frac{p_i^{uav}}{1 - p_i^{uav}}, \qquad \ell_t(i) = \ell_{t-}(i) + \delta \ell^{uav}(i)$$

Notes

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

Flood measurement model: satellite flood extent

Satellite products provide a per-cell flood probability (or a mask mapped to probability) m_i^{sat}.

$$p_i^{sat} = \text{clip}\left(m_i^{sat}, \varepsilon, 1-\varepsilon\right)$$

$$\delta\ell^{sat}(i) = \log\frac{p_i^{sat}}{1-p_i^{sat}}, \qquad \ell_t(i) = \ell_{t^-}(i) + \delta\ell^{sat}(i)$$

Notes

ε prevents infinite log-odds; confidence can be source-dependent (clouds, resolution, latency).

Flood measurement model: geo-social hotspots

Geo-social analytics yields a spatial score from activity and relevance signals (normalized per AOI):

$$s_t^{soc}(i) = w_c\,\tilde{c}_t(i) + w_r\,\tilde{r}_t(i), \qquad w_c + w_r = 1$$

$$p_t^{soc}(i) = \varepsilon + (1 - 2\varepsilon)\,s_t^{soc}(i)$$

$$\delta\ell^{soc}(i) = \log\frac{p_t^{soc}(i)}{1 - p_t^{soc}(i)}, \qquad \ell_t(i) = \ell_{t-}(i) + \delta\ell^{soc}(i)$$

Notes

Geo-social is treated as **uncertain evidence** (use conservative bounds).

Flood prediction fusion: hydrodynamic depth (3Di)

Convert predicted water depth h_i into occupancy probability via a logistic mapping:

$$p_i^{hyd} = \varepsilon + (1 - 2\varepsilon)\,\frac{1}{1 + \exp\left(-\frac{h_i - h_{50}}{s}\right)}$$

$$\ell_i^{hyd} = \log \frac{p_i^{hyd}}{1 - p_i^{hyd}}$$

Logit pooling (weighted fusion in log-odds space):

$$\ell_i^{new} = (1 - \alpha_{hyd})\,\ell_i^{ogm} + \alpha_{hyd}\,\ell_i^{hyd}$$

Notes

$\alpha_{hyd} \in [0, 1]$ controls reliance on prediction vs. accumulated evidence.

Fusing predictive outputs in a generic way

Prediction sources provide p_i^{pred} on the same grid (e.g., fire arrival time, binary forecast, propagation probability).

$$p_i^{pred} \to \ell_i^{pred} = \log \frac{p_i^{pred}}{1 - p_i^{pred}}$$

$$\ell_i^{new} = (1 - \alpha_{pred})\, \ell_i^{ogm} + \alpha_{pred}\, \ell_i^{pred} \quad \text{(logit pooling)}$$

Key point

Predictions are fused as **evidence**, not as immutable truth; the same mechanism applies to floods and wildfires.

Extending beyond floods: fire occupancy (Maps4Fire)

- Same OGM formalism; semantics change to **fire/smoke/burnt area occupancy**.
- Example: combine fire front and burnt-area evidence:

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

- Update $\ell_t(i)$ using the same log-odds / pooling rules.

OPM: state, motion model, and prediction

Track k maintains a 6D state (geodetic position + velocity):

$$x_{t,k} = \begin{bmatrix} \lambda & \phi & h & \dot{\lambda} & \dot{\phi} & \dot{h} \end{bmatrix}^\top$$

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 (example):

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

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:

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

Case study focus: floods as a demonstrator (Ahrtal)

- The platform is generic (Flood & Fire); we demonstrate end-to-end behavior on a flood event.
- Floods stress-test multimodality: UAV segmentation, satellite extent, geo-social signals, hydrodynamic prediction.
- Narrative to show: **uncertain initialization** $\rightarrow$ **progressive refinement** as evidence arrives.

Key takeaways

- **Generic platform** for NDM: consistent handling of heterogeneous, asynchronous evidence.
- **Two primary outputs:** OGM (Flood/Fire status) and OPM (multi-object tracking).
- **Operationalization:** event-driven service + web app operator cockpit + NGSI-LD interoperability.
- **USE loop:** Fusion $\rightarrow$ Drone planning $\rightarrow$ Drone acquisition $\rightarrow$ Fusion.