GRVC Lab
Biweekly seminars

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Robotics
Vision
Control

Universidad
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Roadmap

1. TEMA context: partners and technologies (USE scope)
2. PDM-tech-05: Information Fusion platform (problem $\rightarrow$ approach $\rightarrow$ outputs)
3. Fusion methods: OGM (hazard occupancy) and OPM (multi-object tracking)
4. Flood case study (Ahrtal): inputs, fusion evolution, outputs and lessons learned

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

Phenomenon Prediction and Decision-Making

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-

TEMA

INFORMATION FUSION (PDM-TECH-05)

Information fusion: storyline

- Natural Disaster Management (NDM) produces many signals (UAV, satellite, models, geo-social), often **asynchronous** and sometimes **contradictory**.
- PDM-tech-05 turns these signals into a **single, continuously updated operational picture**.
- Two primary products:
  - **OGM (Occupancy Grid Map)**: disaster status as a probabilistic map (flood or fire).
  - **OPM (Object Presence Map)**: tracked people/vehicles with uncertainty.
- We validate the approach on a flood case study (Ahrtal), consistent 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

Hazard-agnostic engine; hazard-specificity enters via input models and OGM semantics (Flood/Fire)

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: bias or propagate 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 $p_t(i) = P(m_i \text{ occupied at time } t)$.

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

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

$$\ell_0(i) = \log \frac{P(m_i)}{1 - P(m_i)} \qquad \text{(prior; often } P(m_i) = 0.5\text{)}$$

Why log-odds?

Numerical stability and additive updates across asynchronous sources.

OGM fusion rule: Bayesian update in log-odds

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

$$\ell_t(i) = \ell_{t^-}(i) + \underbrace{\mathrm{logit}\big(P(m_i \mid z_t, x_t)\big)}_{\text{source evidence}} - \ell_0(i)$$

Interpretation

Each source produces a per-cell occupancy probability; we convert it to a log-odds increment and add it to the current map (subtracting the prior once to avoid double counting).

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 are fused conservatively:
  - as log-odds evidence, or
  - via **logit pooling** (weighted fusion 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 (TFA-tech-06

Segmentation provides per-pixel flood scores $s_k^{uav} \in [0, 1]$ for UAV pixels k projected into grid cell i.

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

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

$$\delta\ell^{uav}(i) = \mathrm{logit}(p_i^{uav}) - \ell_0(i), \qquad \ell_t(i) = \ell_{t^-}(i) + \delta\ell^{uav}(i)$$

Notes

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

Flood measurement model: satellite flood extent (TFA-tech-08)

Satellite products provide a per-cell probability (or a mask mapped to probability) $m_i^{sat} \in [0, 1]$.

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

$$\delta\ell^{sat}(i) = \mathrm{logit}(p_i^{sat}) - \ell_0(i), \qquad \ell_t(i) = \ell_{t^-}(i) + \delta\ell^{sat}(i)$$

Notes

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

Flood measurement model: geo-social hotspots (TFA-tech-11)

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

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

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

$$\delta\ell^{soc}(i) = \mathrm{logit}(p_t^{soc}(i)) - \ell_0(i), \qquad \ell_t(i) = \ell_{t-}(i) + \delta\ell^{soc}(i)$$

Notes

Geo-social is treated as uncertain evidence (conservative bounds and weights).

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

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

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

$$\ell_i^{hyd} = \mathrm{logit}(p_i^{hyd})$$

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

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

Notes

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

Extending beyond floods: fire occupancy (Maps4Fire)

- Same OGM formalism; semantics change to fire/smoke/burnt area occupancy.
- Example: combine active-fire 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 update / 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 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: AHRTAL FLOODS

Case study setup: AOI and common grid

- AOI defined as a polygon; discretized into an OGM grid.
- Initialization: $p_0(i) = 0.5$ (unknown) inside AOI.
- Asynchronous fusion as sources arrive: 3Di prediction, UAV segmentation, satellite extent, geo-social hotspots.
- Objective: progressively refine the flood probability map (FPM).

Asynchronous inputs: what arrives, and when

- Case study is driven by event arrivals, not a fixed fusion cycle.
- Predictions provide early structure; observations correct local errors and sharpen boundaries.
- Practical implication: the operational picture improves continuously, without waiting for a “complete” dataset.

3Di prediction: depth → flood probability prior

Predicted water depth (3Di)

Mapped flood probability p_i^{hyd}

- Prediction is fused conservatively (logit pooling) to avoid over-committing early.
- Sets the initial large-scale structure before high-resolution observations arrive.

UAV flood segmentation: image → mask → georeferenced eviden

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

Satellite flood extent: wide-area observational update

- Provides broader coverage than UAV but typically with latency.
- Converts extent/score into per-cell likelihood p_i^{sat}.
- Used to correct large-scale misalignment and fill gaps outside UAV footprint.

Geo-social hotspots: human-centric evidence (and limitations)

- Posts aggregated into hotspot cells (counts, activity, statistics).
- Converted into a measurement likelihood $p_t^{soc}(i)$.
- Ahrtal limitation: AOI falls mainly in a **single hotspot cell** $\rightarrow$ coarse spatial signal.

Qualitative evolution: the FPM sharpens as evidence arrives

- Prediction provides early structure; observations refine boundaries and correct local mismatches.
- Geosocial contributions are highly spatially heterogeneous, most abundant in the inner urban area, and absent in

Quantitative evolution: uncertainty reduction and change detectio

- Track the entropy of the flood probability map (FPM) to quantify confidence gains.
- Use map-to-map changes (Δ) to detect when new evidence meaningfully updates the picture.
- In Ahrtal, the strongest corrections coincide with UAV and satellite arrivals.

OPM case-study snapshot: tracking outputs

- OPM produces stable trajectories rather than flickering detections.
- Prediction fills gaps; corrections refine positions when detections arrive.
- Confidence-aware updates reduce overreaction to low-quality detections.

Key takeaways

- **Generic platform** for NDM: consistent handling of heterogeneous, asynchronous evidence.
- **Two operational products:** OGM (Flood/Fire status) and OPM (multi-object tracking).
- **Robust fusion:** Bayesian log-odds updates for measurements + logit pooling for predictions.
- **Operationalization:** event-driven services + web app cockpit + NGSI-LD interoperability.
- **USE loop:** Fusion $\rightarrow$ Drone planning $\rightarrow$ Drone acquisition $\rightarrow$ Fusion.

Q&A

Questions?