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)

Motivation and end-to-end workflow in TEMA

Why we need information fusion

In an evolving disaster, decisions are time-critical and data are imperfect. Sensors and models provide partial, asynchronous, and uncertain evidence. The command centre needs a single, continuously updated operational picture.

Typical inputs

- UAV imagery (flood/fire segmentation; person/vehicle detection)
- Satellite products (medium-resolution, large coverage)
- Simulations (hydrodynamic depth, fire spread / arrival time)
- Geosocial media analysis

Operational questions

- Where is the hazard now (and how confident are we)?
- Where will it be next (and when)?
- Where are people / vehicles at risk?
- Which areas should drones revisit?

End-to-end workflow in TEMA.

Key challenges addressed by PDM-tech-05

- **Heterogeneity:** mixing observations (UAV/satellite/geosocial) with model predictions
- **Asynchrony:** data arrive at different times and rates; some regions are intermittently observed
- **Spatial mismatch:** different projections/resolutions $\rightarrow$ common reference grid
- **Uncertainty:** probabilistic representation + numerically stable updates (log-odds)
- **Scalability:** update only where data overlap AOI; event-driven processing
- **Actionability:** expose products via APIs and a web app to decision-support tools

What the Information Fusion platform does

PDM-tech-05: generic fusion service for NDM

- Select an Area of Interest (AOI) and a reference grid
- Ingest multi-modal streams with timestamps and georeferencing metadata
- Apply source-specific measurement/prediction models
- Maintain a persistent probabilistic state (**OGM** + **OPM**)
- Serve updates to the Digital Enabler / SmartDesk and trigger workflows

Design principle

Convert everything into consistent probabilities on a common spatial reference, then fuse.

Two primary outputs: OGM and OPM

1) Occupancy Grid Map (OGM)

- Regular grid over AOI (e.g., 5 m cells)
- Each cell stores a hazard probability:
  - *Maps4Flood:* flood probability
  - *Maps4Fire:* fire/burnt probability
- Updated asynchronously as new evidence arrives

2) Object Presence Map (OPM)

- Tracks dynamic entities (persons / vehicles)
- Geodetic state with uncertainty (Kalman filtering)
- Data association (gating + Hungarian assignment)
- Supports responder-centric risk awareness

How PDM-tech-05 connects to other TEMA technologies

Web app and services architecture (deployment view)

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
- Event-driven: each source triggers only the relevant update on overlapping cells

OGM formalism: probability and log-odds

Occupancy grid cell m_i (hazard present vs. absent)

Posterior occupancy probability after fusing measurements up to time t:

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

With a prior $p_i^0 = P(m_i)$, the initial log-odds is

$$\ell_i^0 = \log \frac{p_i^0}{1 - p_i^0}.$$

Update in log-odds space (Bayesian occupancy update)

Each new, georeferenced measurement contributes an additive increment:

$$\ell_i^t = \ell_i^{t-} + \delta\ell_{i,s}^t, \qquad \delta\ell_{i,s}^t = \log \frac{p_{i,s}^t}{1 - p_{i,s}^t},$$

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 (TFA-tech-06)

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 $n_i = |K_i|$. The aggregated score is

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

Map the score to a measurement probability

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

then apply the additive log-odds update $\delta \ell_{i,\text{uav}}^t = \log \frac{p_i^{\text{uav}}}{1 - p_i^{\text{uav}}}$.

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

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:

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

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

Implementation note

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

Flood measurement model: geosocial hotspots (TFA-tech-11)

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

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

then convert to a probability

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

Interpretation

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 (typically via logit pooling to reflect its "prior-like" role).

Extending beyond floods: fire occupancy (Maps4Fire)

Fire-related measurements (examples)

- 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

$$\mathbf{x}_{t,k} = \begin{bmatrix} \lambda_{t,k} & \phi_{t,k} & h_{t,k} & \dot{\lambda}_{t,k} & \dot{\phi}_{t,k} & \dot{h}_{t,k} \end{bmatrix}^\top.$$

Constant-velocity prediction (discrete time)

$$\hat{\mathbf{x}}_{t|t-1,k} = A_t\, \hat{\mathbf{x}}_{t-1|t-1,k}, \qquad P_{t|t-1,k} = A_t\, P_{t-1|t-1,k}\, A_t^\top + R_t.$$

Rationale

Tracks persist even when detections are intermittent; uncertainty grows during prediction-only periods.

OPM: correction and data association

Kalman correction (when detection $z_{t,j}$ is assigned)

$$S_{t,j,k} = HP_{t|t-1,k}H^\top + R_{t,j}, \quad K_{t,j,k} = P_{t|t-1,k}H^\top S_{t,j,k}^{-1},$$

$$\hat{\mathbf{x}}_{t|t,k} = \hat{\mathbf{x}}_{t|t-1,k} + K_{t,j,k}\left(z_{t,j} - H\hat{\mathbf{x}}_{t|t-1,k}\right), \quad P_{t|t,k} = (I - K_{t,j,k}H)P_{t|t-1,k}.$$

Association: gating + Hungarian

- Gate candidates by geodetic distance (e.g., haversine) within r_{gate}
- Solve a minimum-cost assignment with cost

$$C_{k,j} = \alpha \frac{d_{\text{hav}}(\hat{p}_{t|t-1,k}, p_{t,j})}{r_{\text{gate}}} + \beta\,(1 - c_{t,j}^{\text{det}}).$$

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)

Key takeaways

- **Generic platform:** one fusion engine, multiple hazards (floods, wildfires, . . .)
- **Two operational products:** OGM for hazard status; OPM for dynamic entities
- **Robust fusion:** log-odds updates for observations + logit pooling for predictions
- **System-ready:** deployed as web services with APIs and a web app
- **USE contribution:** PDM-tech-05 (fusion) integrated with UAV acquisition and drone planning

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