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# Computer Vision in Flash Flood Forecasting: A Narrative Review of Applications, Integration Pathways, and Future Directions

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## Motivation

- Flash floods: rapid onset, severe local impacts; limited lead times.
- Traditional hydrologic/hydraulic models face uncertainty and latency constraints.
- CV extracts high-resolution, actionable signals from UAV, satellite, CCTV, crowdsourced imagery.

**Research Gap:** Limited synthesis on operational integration with forecasting workflows.

## Review Methodology

- Databases: ACM Digital Library, Wiley Online Library, IEEE Xplore.
- Search duration: 2010–2025
- Key search terms:
  - flash flood forecasting
  - flood extent mapping
  - river water segmentation
  - water level detection
  - flood debris detection
  - land use land cover classification
  - change detection
  - image compression
- Inclusion: peer-reviewed CV for flood-relevant tasks; preference for Europe.
- Extraction: region, data source, algorithm, metrics, integration pathways.

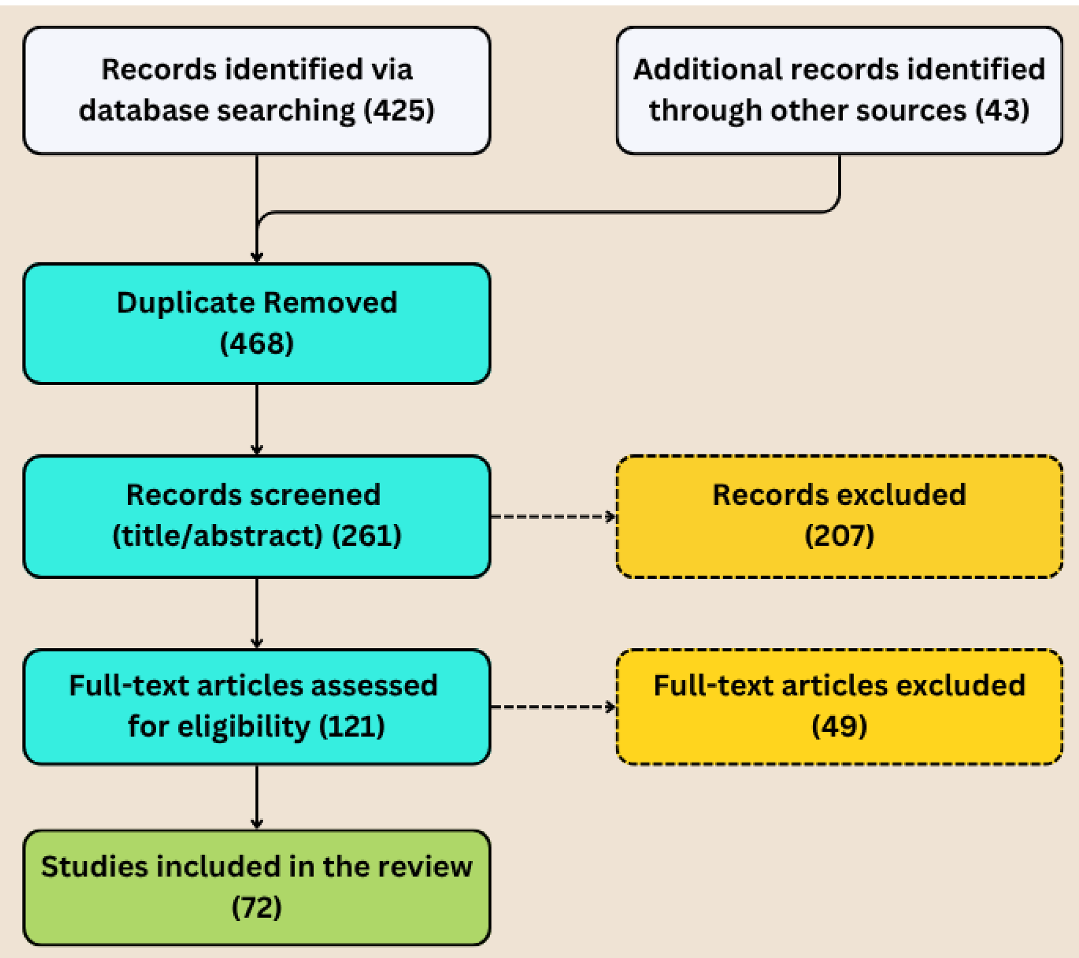



Figure 1: PRISMA-style flow diagram illustrating the identification, screening, eligibility, and inclusion process of studies

## Forecasting Workflow

- **Sources** → UAV, satellite (SAR/optical), CCTV, crowd images.
- **Transfer** → Compression, anomaly removal, prioritisation.
- **Features** → LULC, flood extent, debris, water level, changes.
- **Models** → ML/DL forecasting; (optionally) hydrodynamic DA.
- **Decisions** → Impact assessment and alerts.

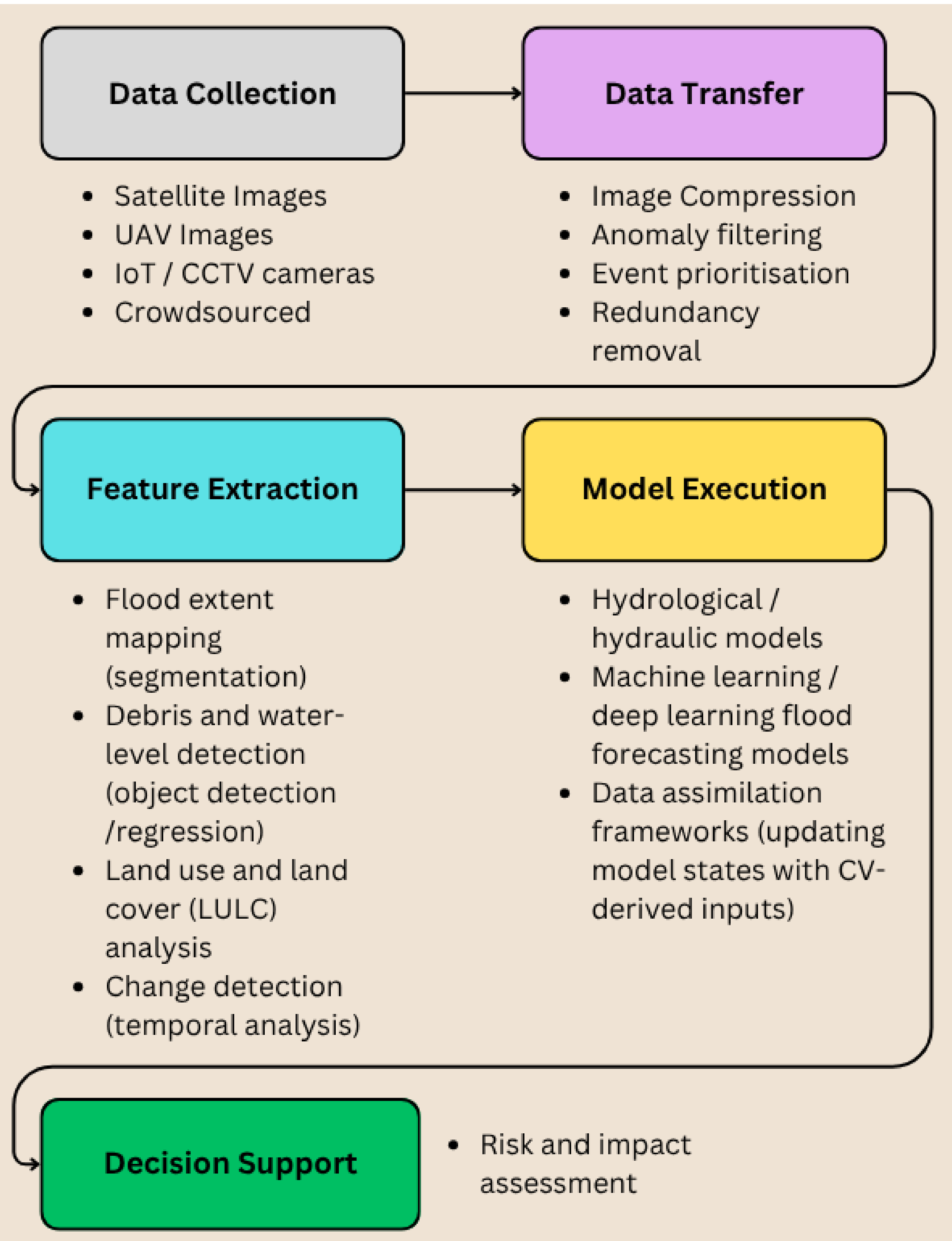



Figure 2: Workflow of computer vision in flash flood forecasting

## Image Sources

| Image Source | Resolution | Coverage Area | Cost & Efficiency |
|---|---|---|---|
| Satellite Imagery (Optical & Radar) | 10m - 250m (Sentinel-2: 10m, MODIS: 250m) | Large-scale (regional/global) | Free (Sentinel, Landsat) but costly for high-res (commercial satellites); moderate processing time |
| UAV (Drones) Imagery | cm-level | Small-scale (local/urban areas) | Expensive (drone purchase, operations); quick processing but limited scalability |
| Aerial Imagery (Manned Aircraft) | 10-50 cm | Large (city/state level) | Expensive (flight costs, data processing); slower than UAVs |
| Ground-Based Cameras | Varies (depends on camera type) | Point-based (specific locations) | Low-cost but limited spatial coverage |
| Crowdsourced Smartphone Images | Varies (depends on device) | Localised (urban areas) | Low-cost; requires validation for reliability |
| Weather Radar (Doppler Radar) | 1-2 km | Regional/National | Expensive infrastructure but automated data collection |
| LiDAR (Airborne/Terrestrial) | cm-level | Local to regional | Very expensive; data-heavy and slow processing |
| Street-Level & IoT Cameras | Varies (High to lower resolution) | Local (highways, urban streets) | Moderate cost; automated real-time monitoring |

## Flood Extent Mapping

**CNNs** (U-Net, SegNet, DeepLabV3+): strong edges, practical; U-Net data-efficient.
**Transformers**: long-range context; higher data/compute needs.
*Europe:* Sentinel-1/2 IoU often ∼0.70–0.85; UAV case studies high-detail but small datasets and occlusion challenges.
*Needs:* standard benchmarks, inference-time reporting, UAV datasets (NWE).

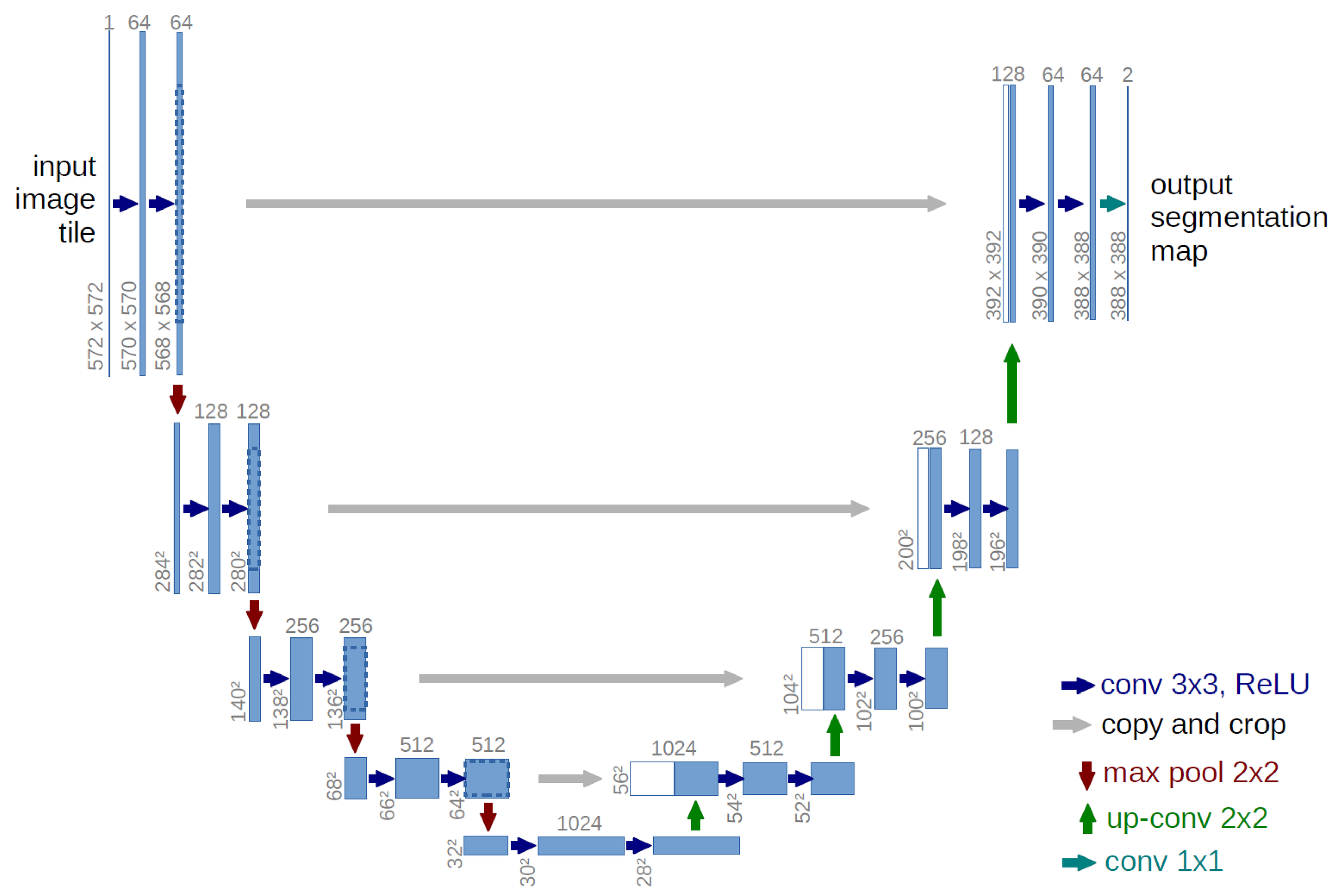



Figure 3: UNET architecture

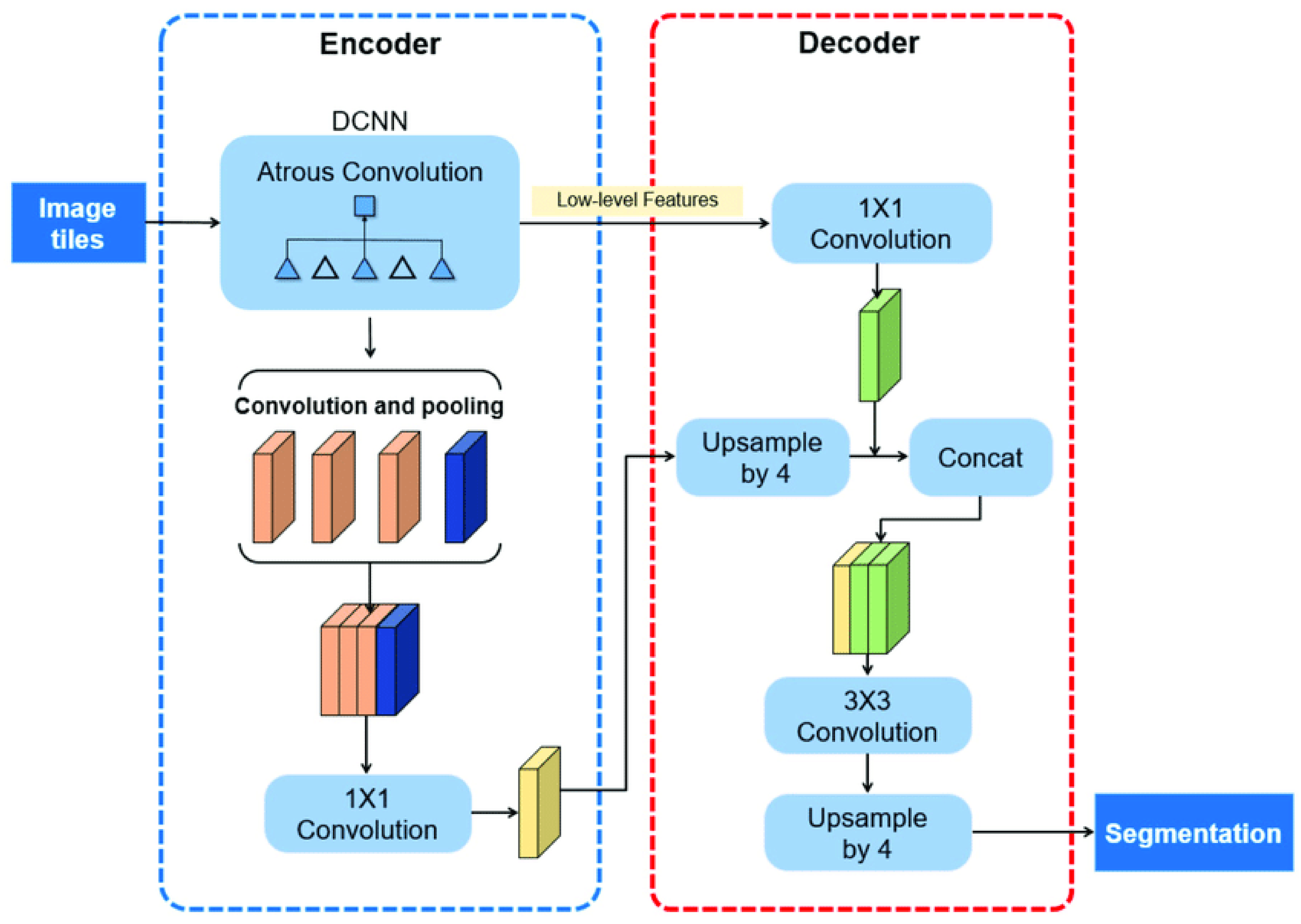


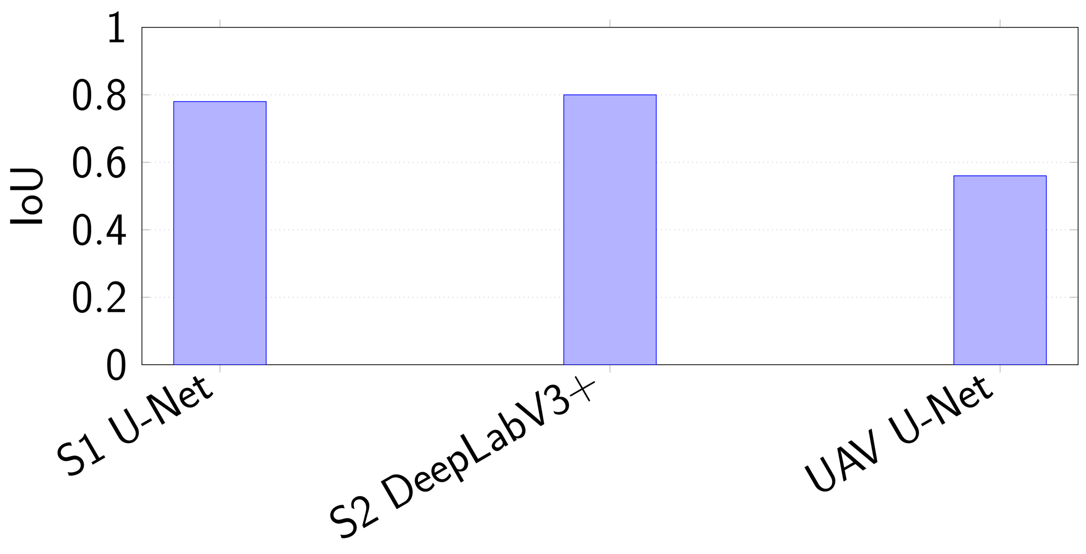

Figure 4: DeepLabV3+ architecture

**River water segmentation**: An application of Image segmentation

Actual Image | River Water Segmentation Mask

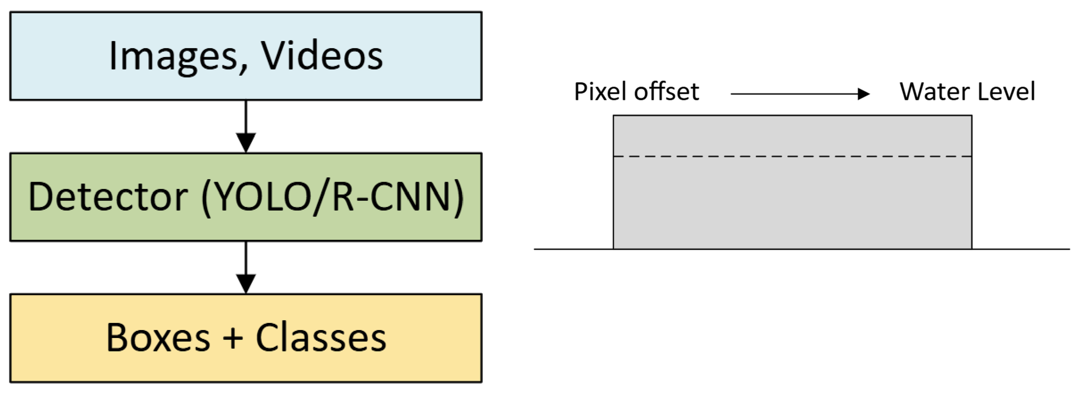
Figure 5: Segmented River water from the background, particularly useful in calculating water surface area

## Comparison between CNN architectures




## Debris and Water-Level Detection

**Debris:** YOLO / Faster/Mask R-CNN; UAV/CCTV video for real-time risk.
**Water level:** gauge reading (detection/segmentation), regression to stage.
*Trade-offs:* speed vs precision;view dependence;illumination/occlusion.




Debris detection concept    Water-level proxy from calibrated gauge

## LULC Analysis

**Sentinel-2 + RF/CNN**: supports roughness/infiltration parameterisation; exposure mapping.
*Limits:* class confusion in complex urban terrain; update frequency.

## Change Detection

**Siamese CNNs, Transformers**: bi/tri-temporal morphology and flood progression.
*Note:* ViT excels at global changes; CNNs capture fine details with smaller data.

## Impact Assessment

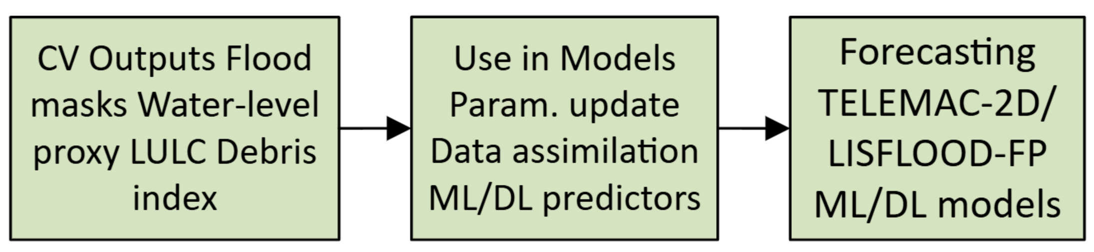
**Targets:** building/road damage, transport disruption, exposed assets.
**Inputs:** pre/post imagery + flood masks + ancillary GIS layers.
*Need:* harmonised labels, uncertainty reporting for decision support.

**LULC** Sentinel-2 + RF/CNNs → roughness, infiltration, exposure.
**Change** Siamese/Transformer → morphology and progression.
**Impact** Damage to roads/buildings; pre/post + masks + GIS overlays.

## Image Compression

**Autoencoders, VAEs, GANs, Transformers**: enable UAV→ground transfer with low latency.
*Note:* quantify impact of compression on downstream CV accuracy.

## Integration into Forecasting Models




**Hydrodynamic DA (Europe):** SAR flood products assimilated into TELEMAC-2D, LISFLOOD-FP, hydrologic–hydraulic chains; improved event forecasts but latency/compute costs.

**ML/DL coupling:** use flood masks, water-level proxies, LULC features as predictors to reduce runtime while preserving physical signals.

| Example (EU) | Integration Insight |
|---|---|
| SAR → TELEMAC-2D | EnKF dual state–parameter updates improve skill. |
| SAR → LISFLOOD-FP | Particle filter with probabilistic flood masks. |
| LULC → Rainfall–runoff | Parameterisation of roughness/infiltration. |

## Key Insights & Future Directions

- CNN segmentation remains most practical; transformers promising with data.
- SAR reliable under cloud; revisit and preprocessing latency constrain NRT.
- UAV provides on-demand high-res; limited benchmarks/coverage.
- Hybrid CV–ML/DL workflows for near-real-time forecasting.
- Priorities: lightweight models, open benchmarks (esp. NWE), reproducible pipelines.

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