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TERRA: Topological Extraction for Rapid Response Analysis – A Literature Survey

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Abstract: Up-to-date road networks are essential for rescue and relief operations after earthquakes, floods and wildfires, yet roads are often unmapped, occluded or damaged when they are needed most. This paper presents a literature survey carried out as the groundwork for TERRA (Topological Extraction for Rapid Response Analysis), a project on extracting road networks from satellite imagery for rapid response. Sixteen recent studies are reviewed and organised into five themes: encoder–decoder segmentation networks, graph- and topology-based road extraction, rural and emergency road mapping, disaster damage assessment, change detection and road condition monitoring, and disaster-aware path planning. For each study the methodology, reported results and limitations are summarised and compared. The survey shows that segmentation networks achieve good pixel-level accuracy but fragment narrow and occluded roads, that graph-based methods improve topological correctness at higher cost or with extra prerequisites, and that few works connect road extraction with damage-aware routing. Common research gaps are consolidated and a direction for TERRA is outlined.

Keywords: Road Extraction, Satellite Imagery, Deep Learning, Semantic Segmentation, Road Topology, Graph Neural Networks, Disaster Management, Emergency Response.

I. INTRODUCTION

Roads are the main physical lifeline through which rescue teams, medical services and relief supplies reach people affected by earthquakes, floods and wildfires. In many regions, however, road maps are incomplete, outdated or missing, particularly for rural and newly built roads, and a disaster can make parts of an existing network unusable. Digitising roads manually from satellite images is slow and labour-intensive [1], [2], which has motivated a large body of work on automatic road extraction from high-resolution remote sensing imagery using deep learning.

Early deep learning approaches treat road extraction as binary semantic segmentation, typically with U-Net style encoder–decoder networks [1]–[4]. Although these give good pixel-level accuracy, they are hampered by occlusions from trees, buildings and shadows, which fragment the predicted masks and break the connectivity that routing applications depend on [5]–[7]. More recent work therefore models roads directly as graphs [7]–[9] or regularises segmentation with graph neural networks [10]. In parallel, remote sensing and artificial intelligence have been applied to disaster scenarios, including rural road mapping for wildfire response [11], building damage assessment [12], change detection [13], road damage detection [14], hybrid disaster prediction [15] and reinforcement-learning-based rescue path planning [16].

This paper presents a literature survey carried out as the groundwork for TERRA (Topological Extraction for Rapid Response Analysis), a project that aims to extract topologically consistent road networks from satellite imagery to support rapid response analysis. Sixteen recent studies are reviewed and organised into five themes: encoder–decoder segmentation, graph- and topology-based extraction, rural and emergency road mapping, disaster damage assessment, change detection and road condition monitoring, and disaster-aware path planning. For each study the methodology, results and reported limitations are summarised, and the common research gaps are consolidated.

The rest of the paper is organised as follows. Section II reviews the literature, Section III compares the surveyed methods, Section IV discusses the research gaps, Section V outlines the direction proposed for TERRA, and Section VI concludes the paper.

II. LITERATURE REVIEW

The surveyed studies are grouped into the five themes shown in Fig. 1. The first two themes address how roads are extracted from imagery, the third addresses extraction in emergency settings, and the last two address how sensed and extracted information is used for disaster response.

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The survey covers sixteen studies: eleven on road extraction from satellite or aerial imagery [1]–[11], and five on damage assessment, change detection, disaster prediction and path planning [12]–[16], of which [13] is a review. All were published between 2018 and 2026, and all except [1], the foundational residual U-Net, appeared in 2022 or later. Datasets, metrics and baseline models named in the studies are cited to their original sources where they are first introduced.

These sixteen studies were chosen for three reasons. First, together they cover the whole chain on which TERRA depends, from extracting roads to using them in disaster response. Second, each represents a distinct approach within its theme: residual, pretrained, attention-based, dual-branch and high-resolution segmentation networks [1]–[6]; node-, keypoint-, foundation-model- and graph-attention-based extraction [7]–[10]; the only study aimed at wildfire-prone rural roads [11]; and damage, change, road-condition, prediction and planning studies [12]–[16]. Third, preference was given to recent peer-reviewed work that reports results on public benchmarks such as DeepGlobe, Massachusetts, CityScale and SpaceNet, and that states its limitations, since these limitations define the gaps discussed in Section IV. Study [1] is included because later encoder–decoder designs build on it.

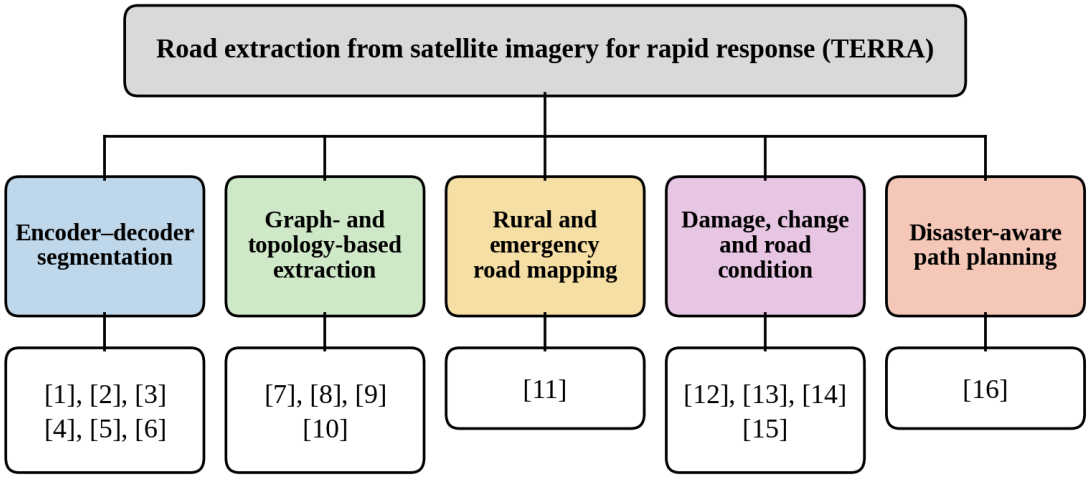


Fig. 1 Taxonomy of the surveyed literature

A. Encoder–Decoder Segmentation Networks for Road Extraction

Zhang et al. [1] proposed the Deep Residual U-Net (ResUnet), which combines deep residual learning with the U-Net architecture. It uses a 7-level encoder, bridge and decoder built from full pre-activation residual units, replaces pooling with stride-2 convolutions, and removes the cropping operation of the original U-Net, giving a 15-layer model with 7.8 M parameters compared with 30.6 M for U-Net. Trained with mean squared error loss and SGD on the Massachusetts roads dataset [17], it reached a breakeven point of 0.9187 against 0.9053 for U-Net, and separated narrow two-lane roads and roads under tree canopy more cleanly. The authors note the cost of fully hand-labelled images and suggest semi-supervised learning and additional map data such as GPS tracks or OpenStreetMap.

Daroch et al. [2] replaced the U-Net encoder with an ImageNet-pretrained ResNet-50 backbone, implemented in PyTorch with the timm library. Massachusetts masks were converted to road and background channels and cropped into 256×256×3 patches, augmented with rotations and flips, and the network was trained with the Adam optimiser (learning rate 0.00008, batch size 16) using a binary cross-entropy plus Dice loss. The model obtained a mean Dice coefficient of 0.782 and a mean IoU of 0.643, outperforming ResUNet and D-LinkNet [18] baselines, although it occasionally failed at the end points of road segments.

Akhtarmanesh et al. [3] addressed the strong class imbalance of remote sensing datasets, where background pixels far outnumber road pixels, by adding attention to U-Net. Hard attention is applied in pre-processing through image and mask patching, rotation and exclusion of background-only images, while soft attention is built into the decoder through attention blocks that merge up-sampled features with the matching encoder feature maps. On the DeepGlobe dataset [19] the model achieved an accuracy of 98.33%, a figure helped by the dominance of background pixels and therefore not comparable with the IoU and F1 values reported below. The authors report, however, that spatial information lost through repeated down-sampling can still fragment very narrow, low-contrast dirt roads.

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Babu et al. [4] proposed StripUNet-MCSA, which uses a pretrained ResNet50 encoder connected through skip connections to a five-stage dual-branch decoder. One branch applies standard 3×3 convolutions for local boundary detail while a parallel dilated branch enlarges the receptive field for thin, occluded roads, and Multi-Scale Channel Spatial Attention (MCSA) blocks suppress clutter such as buildings and shadows. With a hybrid Focal and Dice loss, the model reached an F1-score of 81.20% and an IoU of 68.35% on DeepGlobe, outperforming U-Net, DeepLabV3+, DLinkNet and UBR-Net. The work also adds a decision-support step that compares predicted road maps with GIS reference maps, using morphological filtering and confidence thresholding, to raise alerts for newly built roads.

Lin et al. [5] introduced a dual-task network with a mainline road-surface segmentation branch and an auxiliary road-centreline extraction branch. The segmentation decoder uses a multiscale and multidirection strip convolution module to capture strip-like road features, and the centreline features are fed back into the decoder to improve connectivity. On CHN6-CUG and DeepGlobe the network outperformed seven comparison methods and handled road coverings, complex intersections and small-sample training well. Chen et al. [6] proposed Hi-ResNet for general high-resolution remote sensing segmentation, combining a funnel module, multibranch information aggregation blocks and a class-agnostic edge-aware loss; it was evaluated on LoveDA, Potsdam and Vaihingen, reaching mIoU values of 52.6% on LoveDA and 87.6% on Potsdam, surpassing HRNet and DeepLabV3+, but the authors note that cluttered backgrounds and high computing cost remain open problems.

B. Graph- and Topology-Based Road Extraction

Segmentation followed by heuristic post-processing such as skeletonisation often fails to capture the true graph structure of a road network, which led to graph-based methods such as DeepRoadMapper [20], RoadTracer [21] and Sat2Graph [22]. Zhang et al. [7] proposed NodeConnect, which represents the network as an undirected graph G = (V, E) and trains a CNN jointly to predict node locations and a connectivity map, from which edges are inferred directly. On DeepGlobe and RoadTracer [21] it outperformed segmentation-based methods in both pixel-based and topological precision and recall. Its limitations are a markedly slower inference, difficulty with dense cities, flyovers and deep shadows, reliance on fixed human-defined thresholds, and the use of optical images only.

Zhang et al. [8] proposed kLCRNet, a non-iterative, end-to-end two-stage framework. Keypoint detection uses an HRNet-W32 backbone with heatmap (Focal loss), offset and segmentation heads, followed by non-maximum suppression and Hungarian matching with a decaying threshold. Local connectivity exploration then enumerates candidate pairs within a local radius of 12.0, samples K = 8 points along each candidate path, applies line pooling and classifies edges with a linear layer. On CityScale [22] it achieved a TOPO-F1 [23] of 78.27% and an APLS [24] of 68.96%, and an inference time of 2.56 s per 2048×2048 image, which is reported to be 25 times faster than TERNformer and 102 times faster than RNGDet. It was also evaluated on SpaceNet and Massachusetts. Performance drops under severe shadows and building occlusion, and multi-layered highway overpasses remain hard to separate in 2D imagery.

Yin et al. [9] tackled the scarcity of labelled graph data and the mismatch between training and inference in global road graph models. They introduced the Global-Scale dataset, about 20 times larger than existing public graph datasets and covering more than 13,800 km² across urban, rural and mountainous areas, built from 3,468 images of 2048×2048 pixels with OpenStreetMap graphs. Their SAM-Road++ model builds on the Segment Anything Model and adds node-guided resampling, which aligns training and inference node distributions, and an extended-line strategy, which supplies context across occluded segments. It reached F1 scores of 80.01 on CityScale and 81.57 on SpaceNet, and 62.33 / 48.34 F1 on the in-domain and out-of-domain Global-Scale test sets. The authors note noisy OpenStreetMap data, occlusion by trees and shadows, and multi-level roads as open problems.

Yan et al. [10] formulated road surface extraction as a piecewise two-sided width regression problem on a road graph built from existing centreline data such as OpenStreetMap. An 11-layer CNN extracts 64-D features from rotated patches centred on graph vertices and an auxiliary boundary branch adds a 62-D boundary descriptor, giving a 128-D vertex descriptor, which a 3-layer Graph Attention Network aggregates over first-order neighbours under topological message-passing rules. Tested on Aerial KITTI, Bavaria, Wuhan and Shaoxing, it outperformed U-Net, D-LinkNet, NL-LinkNet, MRF baselines and RoadTagger, reaching a road smoothness index of up to 90.42% and reducing centreline offset to 1.4 pixels. Its main limitation is that it needs an initial rough centreline map and cannot extract roads from scratch.

C. Rural Road Mapping for Emergency Response

Rapid firefighting response needs accurate maps of rural roads, which are often unmapped or hidden by canopy and shadows. Lourenço et al. [11] annotated 1,044 high-resolution (0.25 m) aerial tiles from wildfire-prone regions of Portugal and expanded them to 4,700 samples through 90°, 180° and 270° rotations and vertical flips. Four U-Net variants with VGG16, VGG19, ResNet50 and MobileNet backbones were trained with pretrained weights, the Adam optimiser

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and cross-entropy loss. A two-step post-processing stage, morphological dilation–erosion with a 3×3 kernel to reconnect segments broken by vegetation followed by pixel-area thresholding to remove isolated noise, was applied. Augmentation raised the precision of ResNet50 U-Net from 29.4% to 70.9% and of MobileNet U-Net from 17.7% to 81.5%, and the best model, VGG16 U-Net, achieved 84.0% precision, 81.4% recall and a Jaccard index of 70.4%. Reconnecting fragments before removing outliers prevented valid occluded roads from being deleted. The authors identify labour-intensive annotation, pixel-wise metrics that over-penalise width variations which do not affect connectivity, and the lack of field validation with firefighting units as open issues.

D. Damage Assessment, Change Detection and Road Condition Monitoring

Żarski and Miszczak [12] proposed a Multi-Step Feature Fusion framework that classifies building damage from pre- and post-disaster image pairs. Images are cropped, resized to 224×224, normalised and augmented, and a Fuse Module performs horizontal and vertical feature fusion; a weighted mean squared error loss handles class imbalance. On the IDABD and xView2 datasets the Fuse_HV model improved the accuracy and F1-score of CNN and Vision Transformer models with fewer parameters, increasing Vision Transformer accuracy by more than 3%. Class imbalance, domain shift, occlusion and perspective variation remain open.

Yu et al. [13] reviewed deep learning-based change detection in remote sensing across SAR, multispectral, hyperspectral and multimodal data, covering CNNs, Transformers, GANs, RNNs, autoencoders and Mamba architectures and categorising methods as single-stream or dual-stream and as pixel-, object- or scene-level. CNN-based models remain widely used for feature extraction, while Transformer and Mamba models provide better global context and improved detection accuracy. Limited labelled data, class imbalance, multimodal fusion, image misregistration, noise and computational cost are identified as challenges, with foundation models, automated annotation, lightweight architectures and real-time datasets as future directions.

Silva et al. [14] studied automated road damage detection from UAV images. Using a combination of the Spain Road Dataset and RDD2022 with resizing, auto-orientation and augmentation, they compared YOLOv4, YOLOv5, YOLOv7 and YOLOv5 with a Transformer Prediction Head. YOLOv7 achieved the highest mAP@0.5 of 73.20%, against 59.9% for YOLOv5 and 26.8% for YOLOv4, while YOLOv5 with the Transformer Prediction Head reached 65.7% with reduced training time. Potholes and alligator cracks are still hard to distinguish, and the authors suggest multispectral imaging, LiDAR and better feature fusion.

Saleem et al. [15] presented a hybrid disaster management framework that uses Random Forest, SVM and Gradient Boosting models on historical records (EM-DAT) and NASA EOSDIS data for disaster prediction, CNNs on satellite imagery for damage assessment, and an optimisation model for allocating emergency resources by severity. It reported 90% accuracy for flood prediction, 92% for earthquake damage assessment and 88% for wildfire prediction, with reduced response time compared with conventional approaches. Rare events, imbalanced datasets and noisy geospatial data limit its robustness.

E. Disaster-Aware Path Planning

Guo et al. [16] proposed P2DARL, a reinforcement learning method for post-earthquake emergency response. Building damage is extracted with ChangeOS [25] and road networks with D-LinkNet [18] from dual-temporal high-resolution images, and the results are converted into a vector-based reinforcement learning environment in which disaster centres are identified by kernel density analysis. A deep neural network agent navigates this environment under a multiobjective reward that balances shortest path length, proximity to disaster centres, successful target reaching and dead-end avoidance. Evaluated on pre- and post-earthquake imagery of Mianzhu City from the 2008 Wenchuan earthquake, it outperformed Ant Colony Optimisation and basic reinforcement learning in medium- and short-distance scenarios. The authors criticise existing planners for idealised environments, little use of remote sensing and neglect of disaster severity.

III. COMPARATIVE ANALYSIS

Table I compares the road extraction methods and Table II summarises the disaster-oriented studies. The figures are those reported by the respective authors on different datasets and with different metrics, so they indicate the capability of each method rather than a ranking.

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TABLE I COMPARISON OF SURVEYED ROAD EXTRACTION METHODS

Ref.	Approach	Dataset(s)	Reported Result	Key Limitation
[1]	Deep residual U-Net with pre-activation units (7.8 M parameters)	Massachusetts	Breakeven point 0.9187 (U-Net 0.9053)	Needs fully hand-labelled images
[2]	U-Net with ImageNet-pretrained ResNet-50 encoder	Massachusetts	mDC 0.782, mIoU 0.643	Occasionally fails at road-segment end points
[3]	U-Net with hard and soft attention	DeepGlobe	Accuracy 98.33% (background-dominated; not comparable with IoU or F1)	Fragments very narrow, low-contrast dirt roads
[4]	ResNet50, dual-branch decoder, MCSA; new-road alerts	DeepGlobe	F1 81.20%, IoU 68.35%	Static single-frame optical input; lightweight deployment left as future work
[5]	Dual-task road surface and centreline network with strip convolution	CHN6-CUG, DeepGlobe	Outperformed seven compared methods	Not stated by the authors
[6]	Funnel module, IA blocks, edge-aware loss (general segmentation)	LoveDA, Potsdam, Vaihingen	mIoU 52.6% (LoveDA), 87.6% (Potsdam)	Cluttered backgrounds; high computing cost
[7]	NodeConnect: joint node and connectivity learning	DeepGlobe, RoadTracer	Improved pixel and topological precision and recall	Slow inference; dense cities, flyovers, deep shadows; fixed thresholds; optical only
[8]	HRNet-W32 keypoints with local connectivity classification	CityScale, SpaceNet, Massachusetts	TOPO-F1 78.27%, APLS 68.96% (CityScale); 2.56 s per 2048×2048 image	Severe shadows, building occlusion; multi-layer overpasses
[9]	SAM-Road++ with node-guided resampling and extended lines	CityScale, SpaceNet, Global-Scale	F1 80.01 (CityScale), 81.57 (SpaceNet)	Noisy OpenStreetMap data; occlusion; multi-level roads
[10]	CNN with Graph Attention Network for width regression on a road graph	Aerial KITTI, Bavaria, Wuhan, Shaoxing	Smoothness up to 90.42%; 1.4 px centreline offset	Needs an initial rough centreline map; cannot extract roads from scratch
[11]	U-Net backbones (VGG16 best) with morphological post-processing	1,044 aerial tiles, Portugal	Precision 84.0%, recall 81.4%, Jaccard 70.4%	Labour-intensive annotation; pixel metrics over-penalise width; no field validation

TABLE II SUMMARY OF DISASTER AND DAMAGE-ORIENTED STUDIES

Ref.	Task	Method	Reported Result	Key Limitation
[12]	Building damage classification	Multi-step Fuse Module on pre- and post-disaster pairs	Higher accuracy and F1; ViT accuracy up by over 3%	Class imbalance, domain shift, occlusion, perspective variation
[13]	Change detection (review)	CNN, Transformer, GAN, RNN, autoencoder, Mamba	Review; no experimental results	Limited labels, class imbalance, misregistration, computational cost
[14]	Road damage detection from UAV images	YOLOv4, YOLOv5, YOLOv7, YOLOv5 with Transformer head	YOLOv7 73.20% mAP@0.5	Potholes and alligator cracks hard to distinguish

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Ref.	Task	Method	Reported Result	Key Limitation
[15]	Disaster prediction and damage assessment	RF, SVM, GBM and CNN with resource optimisation	90% flood, 92% earthquake damage, 88% wildfire	Rare events, imbalanced and noisy data
[16]	Post-earthquake path planning	D-LinkNet and ChangeOS with a reinforcement learning agent	Outperformed ACO and basic RL	Gains shown for medium- and short-distance scenarios only

Three observations follow from the comparison. First, segmentation-based models [1]–[5] report good pixel-level scores, although IoU stays at about 64–68% where it is reported [2], [4], and the 98.33% accuracy of [3] is inflated by background pixels. The sequence of designs, from plain residual U-Nets to attention and strip-convolution decoders, shows a consistent effort to preserve thin and occluded roads, but because the datasets and metrics differ it is a trend in design rather than a measured improvement. Second, graph-based methods [7]–[10] are evaluated with topological metrics such as TOPO-F1 and APLS and address connectivity directly; kLCRNet shows that this can also be fast, whereas NodeConnect is slower than earlier methods and the method of Yan et al. depends on a prior centreline map. Third, evaluation is not uniform: pixel-wise metrics penalise width variations that do not alter connectivity [11], so connectivity-aware metrics are more meaningful for routing applications.

The datasets also show a bias. DeepGlobe, Massachusetts, CityScale and SpaceNet recur across most of the studies, whereas only Lourenço et al. [11] and Yin et al. [9] explicitly target wildfire-prone rural areas or globally distributed urban, rural and mountainous regions, which are the settings where emergency mapping is most needed.

IV. RESEARCH GAPS AND DISCUSSION

A. Occlusion and Topological Fragmentation

Occlusion by tree canopy, shadows and buildings is reported in more than half of the road extraction studies [3], [5], [7]–[9], [11]. Down-sampling in encoder–decoder networks loses spatial detail and fragments narrow, low-contrast roads [3], and keypoint detectors degrade in heavy shadow [8]. Multi-layered overpasses cannot be resolved reliably from a single top-down 2D image [7]–[9]. Post-processing can reconnect broken segments [11], but a learned, end-to-end treatment of connectivity is still missing.

B. Annotation Cost and Generalisation

Fully supervised models need large hand-labelled datasets [1], [11]. OpenStreetMap labels are not equally accurate everywhere and need manual filtering [9], and the method of Yan et al. cannot start without an initial centreline map [10]. Semi-supervised, self-supervised and weakly supervised learning are repeatedly suggested as remedies [1], [9], [11], along with stronger generalisation to unseen regions [9].

C. Computational Efficiency and Deployment

Accuracy gains often come at a computational price. NodeConnect is significantly slower than earlier methods [7] and Chen et al. note that methods addressing complex backgrounds demand too much processing power for high-resolution imagery [6], whereas kLCRNet shows that fast graph extraction is possible [8]. Lightweight attention or Transformer structures suitable for edge deployment are proposed as future work [4].

D. Temporal and Multi-Source Data

Current road extraction models rely on static single-frame optical images, which limits tracking of ongoing construction or disaster-induced changes [4], [7]. Future work points to temporal satellite series [4], GPS trajectories and SAR [1], [7], [9], and LiDAR or multispectral data [14], together with efficient multimodal fusion [13].

E. Linking Extraction to Emergency Decisions

Road extraction and disaster response are largely studied in isolation. Guo et al. [16] come closest: they combine D-LinkNet [18] road extraction with ChangeOS [25] building damage assessment and a reinforcement learning planner. However, the roads come from a segmentation network without a connectivity-oriented extraction step, the gains are shown for medium- and short-distance scenarios, and none of the surveyed works examines which road segments are critical to network connectivity. Guo et al. also observe that existing planners assume idealised conditions and underuse remote sensing, while damage and prediction frameworks [12], [15] do not model road connectivity. None of the surveyed

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works provides a unified pipeline that extracts a topologically correct road graph, identifies its critical segments, detects changes or damage after an event, and uses the updated graph for damage-aware routing, which is the gap that TERRA targets.

V. PROPOSED DIRECTION FOR TERRA

Based on the gaps identified above, the following directions are proposed for the TERRA project. They are derived from the surveyed literature and the TERRA project plan, and are not evaluated in this paper. The planned pipeline is shown in Fig. 2.

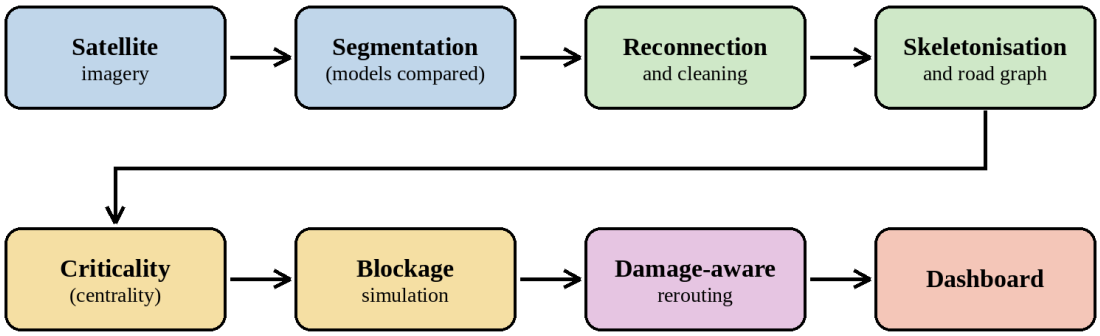


Fig. 2 Planned TERRA pipeline

1) *Topology-Aware Road Extraction:* Several segmentation models will be trained and compared on DeepGlobe [19], and the best-suited one retained. Backbones with attention and strip or dilated convolutions [4], [5] can be combined with connectivity-oriented outputs such as centrelines or graph representations [7], [8] so that narrow and occluded roads remain connected.
2) *Reconnection and Cleaning:* Morphological reconnection followed by removal of isolated false positives [11] offers a simple step to repair fragmented predictions before graph construction.
3) *Graph Construction and Criticality Analysis:* The cleaned mask is skeletonised and converted into a road graph, and centrality measures rank the segments and junctions whose loss would most reduce network connectivity. None of the surveyed works addresses this criticality step.
4) *Connectivity-Aware Evaluation:* Models should be assessed with pixel metrics (IoU, F1) together with topological metrics (TOPO-F1, APLS) [8], [9], since both matter for routing.
5) *Change and Damage Awareness:* Comparing predicted roads against reference maps [4] and using pre- and post-event imagery [13], [16] can identify new, missing or damaged roads.
6) *Blockage Simulation and Damage-Aware Routing:* Blocked or damaged segments are simulated on the updated graph and routes are recomputed so that access to affected areas is preserved, accounting for disaster severity [16]. The results are presented on a dashboard for responders.
These directions lead to three research questions. RQ1: which segmentation model gives the best connectivity-aware score (TOPO-F1, APLS) after reconnection? RQ2: do centrality-based criticality rankings identify the segments whose blockage most degrades access? RQ3: does rerouting on the updated graph keep affected areas reachable better than static shortest-path routing under simulated blockages?

VI. CONCLUSION

This paper surveyed sixteen recent studies on road extraction from satellite imagery and its use in disaster response. Encoder–decoder segmentation networks achieve good pixel-level accuracy but fragment thin and occluded roads; graph-based methods give more faithful topology at the cost of speed, prerequisites or manual rules; rural mapping and damage-oriented studies show the need for datasets and metrics that reflect emergency conditions; and path planning work demonstrates the value of coupling extracted roads with damage information. The main open problems are occlusion and overpasses, dependence on manual labels, computational cost, the use of single-frame optical data, and the lack of an integrated pipeline that runs from topology-aware extraction through criticality analysis to damage-aware routing. These findings define the research direction for TERRA.

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