

Earthquake damage mapping from Sentinel-1 modeling against coherence damage proxy

Mohamad El Moussawi

MSc Student, Geoinformatics Engineering, Politecnico di Milano, Milan, Italy

mohamad.elmoussawi@mail.polimi.it

ORCID: <https://orcid.org/0009-0002-7492-0654>

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Conflict of interest

None.

Data and code availability

Sentinel-1 SLC scenes are available from the Alaska Satellite Facility (<https://asf.alaska.edu/>). Damage grades are from the Copernicus Emergency Management Service (<https://emergency.copernicus.eu/>), activations EMSR884, EMSR648, EMSR412 and EMSR491. Building footprints are from OpenStreetMap (<https://www.openstreetmap.org/>) under the Open Database Licence. Processing code is available from the author on request.

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MSc Student, Geoinformatics Engineering, Politecnico di Milano, Milan, Italy – mohamad.elmoussawi@mail.polimi.it

ORCID: <https://orcid.org/0009-0002-7492-0654>

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Abstract

This paper tests whether a supervised model that uses the same Sentinel-1 signal as the coherence damage proxy can rank earthquake damage better than the proxy itself. Damage grades from Copernicus EMS for four earthquakes are joined to 783 635 OpenStreetMap footprints over 28 assessed areas, and the coherence drop is aggregated to buildings, morphological blocks and cells of 50 m to 400 m. A ladder of models, from a logistic regression to gradient boosting, a random forest and an RBF SVM, is compared with the proxy on identical folds, using the held-out area as the replicate. Under leave-one-area-out validation, modeling improves on the proxy for blocks, where the two boosting models beat it in 13 and 15 of 15 areas, significant after correction for multiple testing. For buildings the best model gains in 12 of 15 areas, which is not significant after correction, and for cells no model improves on the proxy, with the flexible models tending to perform worse. The logistic model is the most reliable one. It is never significantly worse than the proxy and its gain changes little between validation schemes. Only 2 % to 7 % of its weight is on the mean coherence drop used by the proxy, while 79 % to 87 % is on the distribution of the drop inside the unit and on its neighbourhood. These results hold within one event. The cross-event gains depend on assumed negatives and should be read as upper bounds.

1. INTRODUCTION

Rapid assessment of earthquake damage is needed for rescue, shelter planning and loss estimation. The most accurate remote sensing approach is still the manual comparison of pre- and post-event high-resolution optical images, which depends on daylight and cloud-free acquisitions. Synthetic Aperture Radar (SAR) does not have these limitations. When several SAR acquisitions are processed interferometrically, the loss of coherence between them reflects structural changes on the ground and can be used as a damage signal. A map of this signal is known as a Damage Proxy Map (DPM) (Yonezawa and Takeuchi, 2001, Yun et al., 2015). This paper studies whether a supervised model trained on the same signal can extract more information about damage than the proxy, and at which spatial unit (building, block or grid cell) it does so.

2. RELATED WORK

The decorrelation of repeat-pass interferometric pairs over damaged urban areas was first reported for the 1995 Hyogoken-Nanbu earthquake (Yonezawa and Takeuchi, 2001), and the multi-temporal SAR damage-assessment literature that followed is reviewed by (Plank, 2014). The operational form of this idea is the damage proxy map (Yun et al., 2015), which compares a pre-event coherence with a co-event pair. The same construction has been applied with Sentinel-1 to several natural and anthropogenic hazards in urban areas (Washaya et al., 2018), and multi-temporal coherence has been used to make the pre-event reference more stable (Hasanlou et al., 2021). Because the proxy is unsupervised, it is available on the day of the event without any training data, which makes it a strong baseline.

Supervised models have been trained on coherence time series (Stephenson et al., 2022) and on combinations of SAR and optical imagery (Adriano et al., 2021), and the transfer of a learned

building-damage model to new hazards and places has been studied by (Valentijn et al., 2020). Work at the level of individual buildings usually relies on metre-resolution SAR, where several resolution cells fall inside one footprint (Brunner et al., 2010). Sentinel-1 is much coarser, so it is not obvious that a building-level unit can carry its own signal. Learned models are also often reported without the unsupervised proxy scored on the same folds, which makes the gain due to learning hard to isolate.

The evaluation design follows the spatial cross-validation literature. When rows are spatially autocorrelated, a random split measures interpolation rather than prediction (Roberts et al., 2017), and spatial validation of published maps has shown much lower skill than their random-split scores suggested (Ploton et al., 2020, Meyer and Pebesma, 2022). This paper therefore scores every learner against the proxy on the same folds and uses the held-out area as the test unit.

3. THE SIGNAL

SLC (Single Look Complex) is the basic SAR product format, it stores $u = Ae^{i\phi}$ per pixel.

3.1 Interferogram and Coherence

The interferogram is the Hermitian product between two acquisitions:

$$v = u_1 u_2^* = A_1 A_2 e^{i(\phi_1 - \phi_2)}, \quad \phi_{\text{int}} = \arg v, \quad (1)$$

Complex interferometric coherence is the normalised cross-correlation of the two complex signals, estimated by replacing expectations with sums over a moving window W ,

$$\hat{\gamma} = \frac{|\sum_W u_1 u_2^*|}{\sqrt{\sum_W |u_1|^2 \cdot \sum_W |u_2|^2}}. \quad (2)$$

Enlarging W lowers both bias and variance but averages across genuine coherence boundaries.

3.2 The damage signal

Interferometric phase is preserved only where the arrangement of scatterers inside a resolution cell persists between acquisitions. Structural collapse rearranges those scatterers so γ drops and damage is observed as temporal decorrelation.

The coherence also responds to vegetation growth and wind, soil-moisture change, snow, surface water, landslides and liquefaction, and it cannot distinguish those from damage.

3.3 DPM

A Damage Proxy Map (DPM) flags damaged areas by detecting loss of interferometric coherence between a pre-event mean and a co-event pair, thresholded to produce a rapid map of probable damage extent,

$$\text{coh_diff} = \bar{\gamma}_{\text{pre}} - \gamma_{\text{co}}. \quad (3)$$

So damage gives a positive drop. The same drop means different things in different places, because the pre-event coherence baseline varies with land cover and season.

3.4 The standardised anomaly

To address this issue we introduce the predictor $z(p)$, where $x_{\text{co}}(p)$ is the co-event observation and $x_{\text{pre}}^{(k)}(p)$ the k -th pre-event observation of the n pairs falling entirely before the origin time. With pre-event mean $\mu_{\text{pre}}(p) = \frac{1}{n} \sum_{k=1}^n x_{\text{pre}}^{(k)}(p)$ and standard deviation $s_{\text{pre}}(p) = \sqrt{\frac{1}{n-1} \sum_{k=1}^n (x_{\text{pre}}^{(k)}(p) - \mu_{\text{pre}}(p))^2}$, the predictor is

$$z(p) = \frac{x_{\text{co}}(p) - \mu_{\text{pre}}(p)}{s_{\text{pre}}(p) + \varepsilon} \quad (4)$$

The sign is post minus pre, so damage gives a *negative* z . $n \geq 2$ is required per pixel, ε is a noise floor.

3.5 The observables

Three scalings of the same drop are carried side by side. cd is the classical drop of Eq. 3, averaged over a unit's pixels with no reference to spread. cz is $z[\gamma]$ of Eq. 4 averaged the same way, so a drop is compared with the usual variability of the same pixel instead of a single value for all land covers. czn re-centres cz a second time on the event's own built-up median and MAD, to remove effects common to a whole acquisition, such as a wetter pass or a different baseline. Within one event czn is an affine function of cz , so the two give the same ranking. czn is only meant to help when a model is moved *between* events.

The observables do not share a sign. cd is a loss of coherence, so a damaged unit has a large positive cd . cz and czn follow Eq. 4, post-event minus pre-event, so a damaged unit has a large negative value. The same holds for every feature built from them Sec. 9.3.

Table 1. The five stacks, one relative orbit and frame each. Δt in days.

Event	orbit/frame	scenes	co-event pair	Δt	areas
Albania 2019	153D/453	5	2019-11-19/12-01	12	5
Croatia 2020	124D/441	4	2020-12-23/2021-01-04	12	3
Türkiye 2023	021D/465	5	2023-01-29/02-10	12	8
Türkiye 2023	021D/471	5	2023-01-29/02-10	12	7
Venezuela 2026	033A/30	5	2026-06-18/06-25	7	5

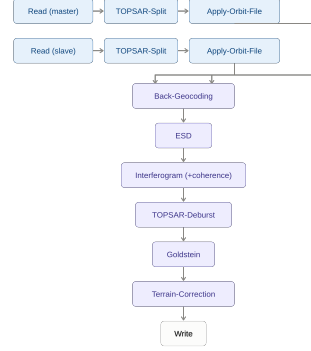


Figure 1. SNAP interferometric processing chain for Sentinel-1 IW SLC data.

4. SAR DATA PROCESSING

Sentinel-1 (Torres et al., 2012) IW SLC scenes, VV polarisation, are taken from the Alaska Satellite Facility archive: 24 scenes forming five stacks over the four events. A stack is a set of consecutive scenes sharing the same relative orbit, frame and pass direction (Table 1).

4.1 The interferometric chain

Each stack is processed with a fixed graph in ESA SNAP (European Space Agency, 2025) (Fig. 1). **TOPSAR-Split** cuts to one sub-swath and burst range, since each burst has its own coordinate system. **Apply-Orbit-File** replaces the predicted orbit with the precise one. **Back-Geocoding** co-registers the slave to the master geometrically. **ESD** corrects residual azimuth misregistration that back-geocoding cannot remove. **Interferogram** forms $v = u_1 u_2^*$, removes the geometric phase

$$\phi_{\text{geom}}(T) = -\frac{4\pi}{\lambda} (R_1^{\text{pred}}(T) - R_2^{\text{pred}}(T)), \quad (5)$$

where $R_i^{\text{pred}}(T) = |\mathbf{P}_i - T|$ is the predicted range from satellite position $\mathbf{P}_i$ to ground point T , and estimates $\hat{\gamma}$. **TOPSAR-Deburst** merges the separate bursts of a TOPS acquisition into one continuous image. **Goldstein** filtering suppresses phase noise. **Terrain-Correction** geocodes the result into a standard map projection.

Fig. 2 shows the co-event wrapped phase over each event's assessed areas.

5. DAMAGE LABELS

Labels are taken from Copernicus EMS damage grading (Copernicus Emergency Management Service, 2026) and the building inventory from OpenStreetMap (OpenStreetMap contributors, 2026). Four layers of a graded product are used:

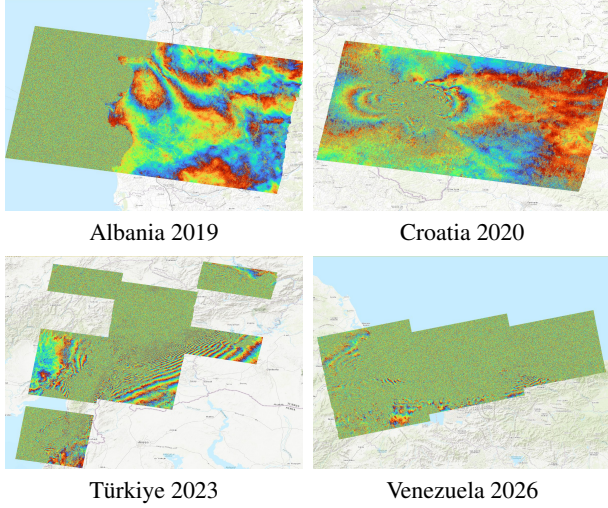


Figure 2. Co-event wrapped interferometric phase over each event’s assessed areas. One colour cycle is 2π radians. Contains modified Copernicus Sentinel data. Basemap: Esri.

`areaOfInterestA`: the analysed extent, `notAnalysedA`: the uninterpreted holes within it, `builtUpP`: one point per graded building and `builtUpA`: one polygon per graded built-up block.

The areas of interest define the study area, delimiting both the ground available for scoring and the ground on which a negative may be declared. Where monitoring products grade the same ground repeatedly, the most recent grade is retained.

5.1 Grades and the target

The EMS grade strings are harmonised across events onto an ordinal scale: *Negligible to no damage* and *No visible damage* to $g = 0$, *Possibly damaged* to 1, *Damaged* to 2, and *Destroyed* to 3. The target is $y = 1 \iff g \in \{2, 3\}$. Grades 0 and 1 are treated as negatives.

5.2 Grades to Buildings

EMS delivers two geometry types that must be resolved to individual OSM footprints.

Block grades (Fig. 3a–b): a `builtUpA` polygon carries one grade for an entire city block. That grade is propagated to every OSM footprint inside the polygon.

Point grades (Fig. 3c–d): a `builtUpP` point is snapped to the OSM footprint that contains it, failing that, the nearest footprint within 10 m, failing both, a proxy square of 8 m half-width is created at the point location.

5.3 Inference of the negative class

A building is an *inferred negative* when two conditions hold: an OSM footprint records a building at that location, and the footprint lies inside an area-of-interest polygon, outside every not-analysed hole, and matches no EMS record.

Fig. 4 contrasts the graded footprints against the inferred negatives.

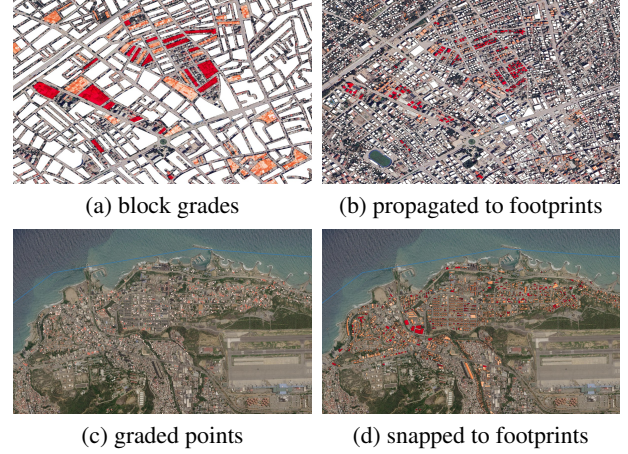


Figure 3. From EMS grades to OSM footprints. Block grades: `builtUpA` polygons (a) dissolved onto the footprints inside them (b). Point grades: `builtUpP` points (c) snapped to the containing or nearest footprint (d). Footprints © OpenStreetMap contributors. Background: Esri World Imagery.

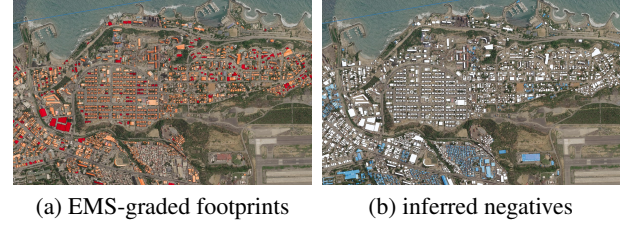


Figure 4. Negative class inference: EMS-graded buildings (a) alongside OSM footprints inside the area of interest that match no EMS record and are treated as undamaged (b). Footprints © OpenStreetMap contributors. Background: Esri World Imagery.

6. UNITS AND AGGREGATION

6.1 Three units

Three units are constructed and evaluated in parallel. A **building** is one OSM footprint, or one EMS geometry standing in for a footprint that does not exist. A **block** is a morphological closing of the footprint set at a fixed 5 m gap: grow every footprint by half the gap, union, take the connected pieces, shrink each back (Fig. 5a–b). A **cell** is a square of a fixed lattice, kept only if it holds a building pixel, swept at four sizes from 50 m to 400 m (Fig. 5c–f).

6.2 Aggregating the signal into a unit

Every statistic is computed over the pixels that belong to the unit, and the features are grouped into five families. **CHANGE** holds the damage observable (`cd`, `cz` or `czn`). **PRE** describes the pre-event state through the mean and standard deviation of the pre-event coherence (`coh_pre_mean`, `coh_pre_std`). **NBR** gives the neighbourhood context. For cells it is the mean observable over the 3×3 and 5×5 surrounding cells and their built fraction (`nbr_cd_3x3`, `nbr_cd_5x5`, `nbr_built_frac_3x3`). For buildings and blocks it is computed within a radius (`nbr_cd_r150`, `nbr_cd_r250`), with an extra built-fraction term for blocks (`nbr_built_frac_r150`). **DIST** describes how the drop is distributed inside the unit: `cd_std`, `cd_min`, `cd_max`, the 10th, 50th and 90th percentiles (`cd_p10/50/90`), and the fraction of pixels whose drop exceeds 0.2, 0.3 and 0.4 (`f20/f30/f40`). These nine

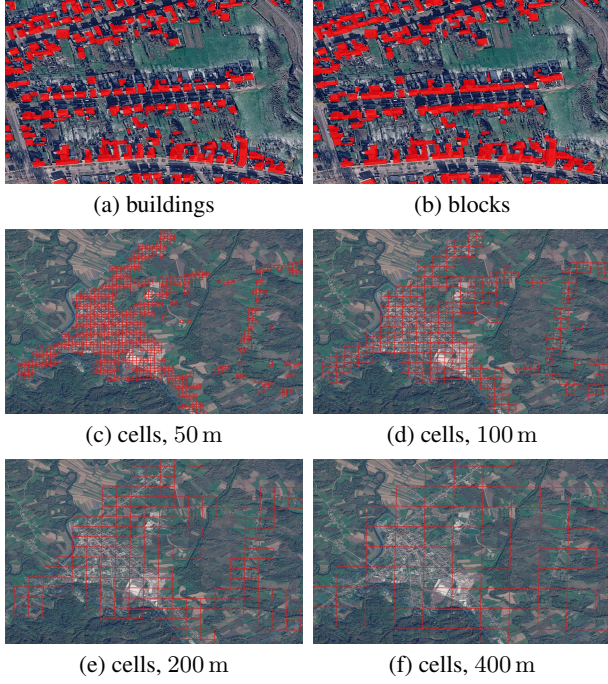


Figure 5. The three units over the same ground: OSM building footprints (a), morphological blocks (b), and the cell lattice at the four swept sizes (c–f). Footprints © OpenStreetMap contributors. Background: Esri World Imagery.

columns are the same for all three units. SHAPE describes the geometry of the unit: the built fraction `built_frac` for cells and blocks, and the footprint area `area_m2` for buildings and blocks.

The **core** set (CHANGE+PRE+NBR) is available for every unit and gives 5 features for buildings, 6 for cells and blocks. The **full** set adds DIST+SHAPE, giving 15 (buildings), 16 (cells) and 17 (blocks). Labels are aggregated at the same stage, each unit’s pixels counted by grade $n_{g0} \dots n_{g3}$.

7. CONFIGURATIONS

The result of one model on one setup could depend on that particular choice. For this reason the ladder is run over a grid of seven axes, and every result is reported per configuration instead of being averaged over the grid.

Unit selects the spatial object that carries a feature vector and a label: building, block, or cell. For cells, **cell size** is swept at 50, 100, 200 and 400 m.

Label basis controls how grades are turned into a binary target for cells. The damage fraction can be computed over all pixels in the cell (*area* basis) or over building pixels only (*footprint* basis), and in both cases the denominator can include inferred negatives (*assumed* variants) or not. For buildings and blocks the target is the unit’s own grade directly (*grade* basis). **Damage fraction threshold** (cells only) sets the minimum fraction at which a cell is called positive: 0.10, 0.25 or 0.50.

Scaling chooses which observable the CHANGE feature and all derived features are built from: `cd` (raw coherence drop), `cz` (drop normalised by per-pixel pre-event variability), or `czn` (`cz` further re-centred on the event’s built-up median and MAD).

Feature family selects *core* (CHANGE+PRE+NBR, 5–6 features) or *full* (*core*+DIST+SHAPE, 15–17 features).

Folding scheme is one of the five protocols described in Sec. 8.2: random rows, 2 km blocks, leave-one-AOI-out, transfer (one held-out area of another event), and transfer-event (one whole earthquake held out).

Training events: for transfer schemes two or more events are used for training, for all other schemes a single event (Türkiye 2023) provides both training and test folds.

One point in this grid is one *configuration*, and every number in Sec. 9 is either a mean over the admitted folds of one configuration or a count of configurations.

8. LADDER, FOLDS AND METRICS

8.1 The ladder

The models are organised as a *ladder* and evaluated on identical folds, so that every gain is a paired difference. Each rung is more flexible than the previous one.

Rung 0 is the published proxy: the mean coherence drop `cd_mean` over the unit’s pixels ranked directly, with no fitting. It is the baseline that every other rung is compared with.

Rung 1 fits an ℓ_2 -regularised logistic regression on that one column alone. Because it can only monotonically transform a single input, it cannot outrank rung 0 on a ranking metric. Its purpose is to check that the training pipeline works correctly before more features are added.

Rung 2 is the same ℓ_2 logistic model on the full feature set. It predicts $P(y = 1) = \sigma(\beta_0 + \beta^\top \mathbf{x})$ where $\sigma(z) = (1 + e^{-z})^{-1}$, the ℓ_2 penalty $\|\beta\|^2 / (2C)$ shrinks coefficients towards zero, with $C \in \{0.01, 0.1, 1, 10, 100\}$ selected by inner cross-validation.

Rungs 3 and 4 are histogram gradient boosting (HistGB): features are pre-binned into histograms so that split-point search is $O(B)$ in the number of bins rather than $O(n)$ in the rows. The boosting loop fits successive trees to the residuals of the current ensemble, updating the prediction by $\hat{y} \leftarrow \hat{y} + \eta \cdot h(\mathbf{x})$ where η is the learning rate and h the new tree. Rung 3 applies monotonic constraints on features whose physical direction is fixed by design (larger drop $\Rightarrow$ more likely damaged), rung 4 is unconstrained. Hyper-parameters are swept over three profiles (slow/medium, fast/wide, fast/narrow) with learning rates $\{0.05, 0.1, 0.1\}$, maximum leaf nodes $\{15, 31, 7\}$, minimum samples per leaf $\{20, 20, 40\}$, and maximum iterations $\{200, 150, 300\}$.

Rung 5 is a random forest. Each tree sees a random subset of features at each split (decorrelating the ensemble), *max features* is swept over $\{\sqrt{p}, \sqrt{p}, 0.5, 1\}$ and minimum samples per leaf over $\{1, 20, 20, 20\}$.

Rung 6 is an RBF-kernel SVM, restricted to cell scale because its training cost is $O(n^2) - O(n^3)$ in the number of rows. The kernel $K(\mathbf{x}, \mathbf{y}) = \exp(-\gamma \|\mathbf{x} - \mathbf{y}\|^2)$ implicitly lifts the data into a space where a linear margin can separate classes that are not separable in the original space, $\gamma \in \{\text{scale}, 0.01, 0.1\}$ and $C \in \{1, 10, 100\}$ are swept.

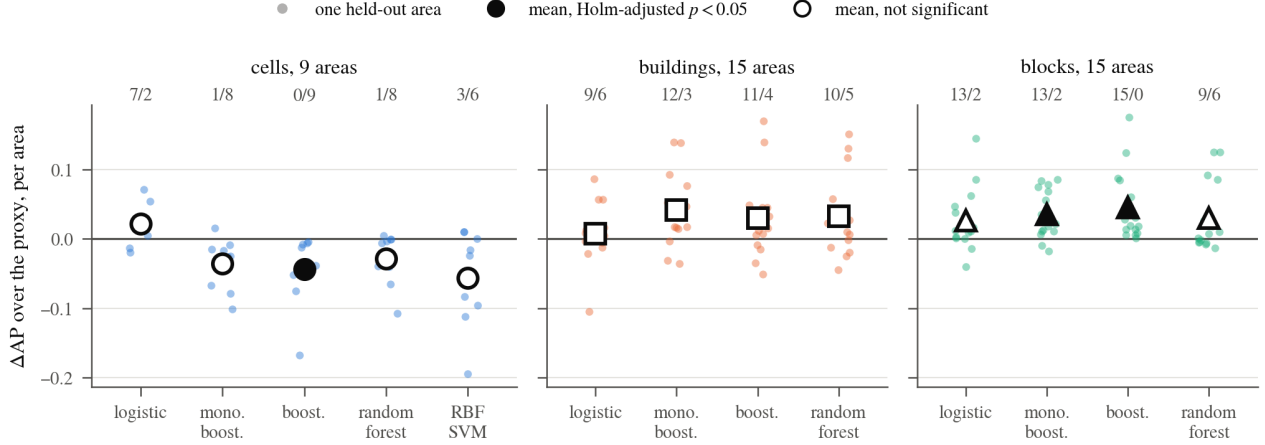


Figure 6. Gain in AP over the proxy, leave-one-AOI-out within Türkiye. A light point is one held-out area, its gain averaged over configurations, the large marker is the mean over areas, filled when the Wilcoxon signed-rank test over areas gives a Holm-adjusted $p < 0.05$ over the 13 tests. Above each learner: areas won/lost. The SVM ran at cell scale only.

8.2 Folds, admission and metrics

Leave-one-event-out would be the ideal protocol, but only one event has an observed undamaged class. The training event is therefore kept fixed and five splitting schemes are run side by side. *Leave-one-AOI-out* holds out one entire assessed area of the training event. *Blocked k-fold* groups on 2 km blocks and, on the training side only, drops every row within the *reach of a feature* of any test row. *Pooled k-fold* shuffles rows at random and is reported only to measure the inflation (Roberts et al., 2017). *Transfer* fits Türkiye and tests one held-out area of another event, and *transfer-event* holds out one whole earthquake. A fold is scored only if its test set contains at least ten positives and ten negatives.

The primary metric is **average precision** (AP), always reported as a *difference* against rung 0 on the same fold, because AP’s baseline is that fold’s prevalence. **ROC-AUC** is used wherever populations must be compared across different prevalence levels, its baseline being 0.5 regardless of class balance.

8.3 The budget

Rung 0 produces a ranking, not a probability, so a fixed threshold is meaningless. For confusion-matrix measures (accuracy, precision, recall, F_1 , Cohen’s κ) we instead fix a **top-10 % budget**: within each held-out fold of n units, the $k = \max(1, \lceil 0.1 n \rceil)$ highest-ranked units are declared positive. For example, with $k = 5$ folds of 50 held-out units each (e.g. 250 spatial blocks split into 200 training / 50 test), the budget flags the top 5 units per fold as the positive prediction. Confusion-matrix metrics are computed per fold and averaged over the 5 folds. The rule is the same for every rung, it reflects the operational limit of a fixed response capacity, and it is the convention used to compare hazard maps that share no common probability scale (Chung and Fabbri, 2003). For significance, the held-out area is used as the replicate instead of the fold. Under leave-one-AOI-out a fold is one area, held out once per configuration, so folds of the same area are not independent. Each area’s gain is first averaged over its configurations. Wins and losses are then counted over areas, and significance is tested with a two-sided Wilcoxon signed-rank test over areas. The learner comparisons of Sec. 9.2 form one family of 13 tests, so their p -values are Holm-adjusted (Holm, 1979), and a result is called

significant when the adjusted value is below 0.05. The additional tests in the Discussion are exploratory, and their p -values are not corrected.

9. RESULTS

9.1 Folding Protocols Insights

Damage, coherence and labels are spatially autocorrelated, so a model tested on rows close to its training rows can score well by recognising the place rather than the damage (Roberts et al., 2017). A random split of the rows does not address this at all. 2 km blocks reduce it only partly, because a test block is still surrounded by training blocks from the same area. Within one event, leave-one-AOI-out is the split with the least spatial correlation between training and test data. The transfer splits separate the data further, but they rely on assumed negatives (Sec. 10.5). Leave-one-AOI-out is therefore used as the reference, and all results below use it unless stated otherwise.

Table 2 compares the same models on the same configurations under the three splits. Every model, the proxy included, has a higher ROC-AUC under random rows and 2 km blocks than under leave-one-AOI-out. Since the proxy is not trained, part of this gap is not leakage. It comes from the test sets of the random and blocked splits, which mix several areas, while a leave-one-AOI-out test set contains only one. The gap therefore overstates the leakage.

9.2 Modeling added value

Rung 1 ties the proxy exactly in AP and ROC-AUC on every fold where both were run, so the differences below come from the added features and the learner, not from the training pipeline.

With the held-out area as the replicate (Fig. 6), the result depends on the unit. The p -values below are Holm-adjusted over the 13 tests. For blocks, modeling improves on the proxy. Monotonic boosting gains 0.036 AP in 13 of 15 areas ($p = 0.018$) and unconstrained boosting 0.045 in all 15 ($p < 0.001$). The logistic model gains 0.027 in 13 of 15 areas, but this is not significant after correction ($p = 0.14$). For buildings, no model

Table 2. The same models under three splits, on the same configurations and, within a split, the same folds: mean held-out ROC-AUC of the proxy (r0), the logistic model (r2) and the random forest (RF). Their F_1 gains over the proxy are in Fig. 7. n : configurations, then folds per split in the order listed.

split	r0	r2	RF
<i>cells, n = 12; 60/60/76</i>			
random rows	0.684	0.711	0.730
2 km blocks	0.685	0.693	0.690
leave-one-AOI-out	0.658	0.670	0.613
<i>buildings, n = 2; 10/10/30</i>			
random rows	0.641	0.690	0.731
2 km blocks	0.642	0.688	0.694
leave-one-AOI-out	0.600	0.628	0.611
<i>blocks, n = 1; 5/5/15</i>			
random rows	0.666	0.716	0.738
2 km blocks	0.666	0.712	0.700
leave-one-AOI-out	0.595	0.635	0.599

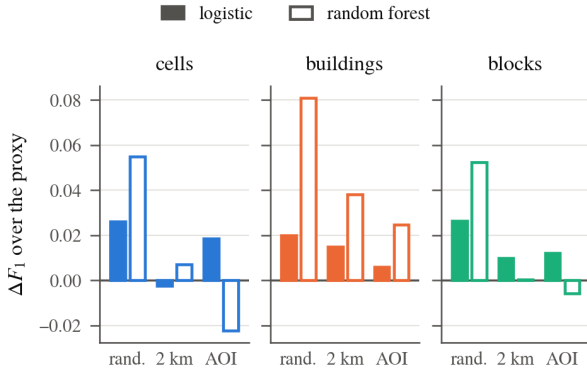


Figure 7. Gain in F_1 over the proxy at the top-10% budget, paired within each split: solid bars the logistic model, outlined bars the random forest, on the configurations run under all three splits (rand.: random rows, 2 km: blocked folds, AOI: leave-one-AOI-out).

improves on the proxy significantly. Monotonic boosting has the largest gain, 0.041 in 12 of 15 areas, but it does not survive the correction ($p = 0.067$). For cells, the flexible models tend to be worse than the proxy. Both boosting models and the random forest lose in 8 or 9 of the 9 areas, and the loss of unconstrained boosting is significant ($p = 0.043$). The logistic model gains 0.022 at cell scale, in 7 of 9 areas, which is not significant ($p = 0.33$).

This pattern can be explained by the number of pixels in each unit. A cell averages 25 to 1 600 pixels, so its mean drop is already a stable value. A building has a median of one pixel (Sec. 10.1), so its own drop is noisy and the neighbourhood carries more of the signal.

Overall, the logistic model is the most reliable learner. It is the only one that is never significantly worse than the proxy at any unit, and its F_1 gain changes by at most 0.028 between splits, compared with 0.056 to 0.077 for the random forest (Fig. 7). The next section therefore looks at the features the logistic model uses.

Table 3. Measured coherence pixels per unit: mean, standard deviation, median and 90th percentile, the share with at least ten pixels, and the median within-unit standard deviation of the drop (cd_std, defined from two pixels up).

unit	rows	mean	sd	med.	p90	≥ 10 (%)	cd_std
building	571 789	2.0	5.1	1	4	1.5	0.041
block	187 088	6.2	32.4	2	11	12.4	0.057
cell 50 m	186 755	24.9	1.5	25	25	99.7	0.094
cell 100 m	63 381	98.3	9.8	100	100	99.8	0.122
cell 200 m	20 333	382.4	63.3	400	400	99.9	0.136
cell 400 m	6 403	1421.1	386.5	1600	1600	100.0	0.141

9.3 What the logistic model uses

Fig. 8 shows how the standardised weight of the logistic model, $|\beta|$ as a share of the total of each fit and averaged over fits, is divided between its features and feature families. The mean drop used by the proxy (CHANGE) receives only 7% of the weight for cells, 3% for buildings and 2% for blocks. Most of the weight goes to the distribution of the drop inside the unit and to the neighbourhood. DIST and NBR together take 79% for cells and 87% for buildings and blocks. For buildings and blocks the neighbourhood alone takes 39% to 40%, mainly through the 150 m and 250 m means, followed by the within-unit maximum (positive) and minimum (negative). With the mean held fixed, these two signs mean that the model ranks higher a unit whose drop is uneven, with some strongly decorrelated pixels. For cells the weight is spread more evenly, with the 3×3 neighbourhood first. Because the features are correlated, these shares show where the fitted model puts its weight, not the value of each feature on its own.

10. DISCUSSION

10.1 The Neighbourhood and Distribution Terms

The median building owns one measured coherence pixel and only 1.5% own ten or more (Table 3).

Blocks are barely better, with a median of two pixels and 12.4% at ten or more, and a heavy tail (standard deviation 32.4 pixels against a mean of 6.2).

Cells are fixed by construction, 25 to 1 600 pixels, short of the nominal count only at AOI edges.

This limits what a per-building feature can capture. The within-unit standard deviation of the drop grows from a median of 0.041 for buildings to 0.141 at 400 m. A building's spread is small because it is estimated from one or two pixels, so the DIST family is nearly empty at building scale.

Coherence is also estimated over a multi-look window several tens of metres across, so a building's own pixel already mixes in its neighbours. This helps explain why the neighbourhood features receive a large share of the weight when a unit is smaller than the estimation window.

10.2 Block and point propagation

Most positives were never graded as buildings: 66% inherited a block grade, 69.7% in Türkiye and 83.2% in Venezuela (Table 4). A block takes the worst grade among its assessed members, so one destroyed building makes every footprint in

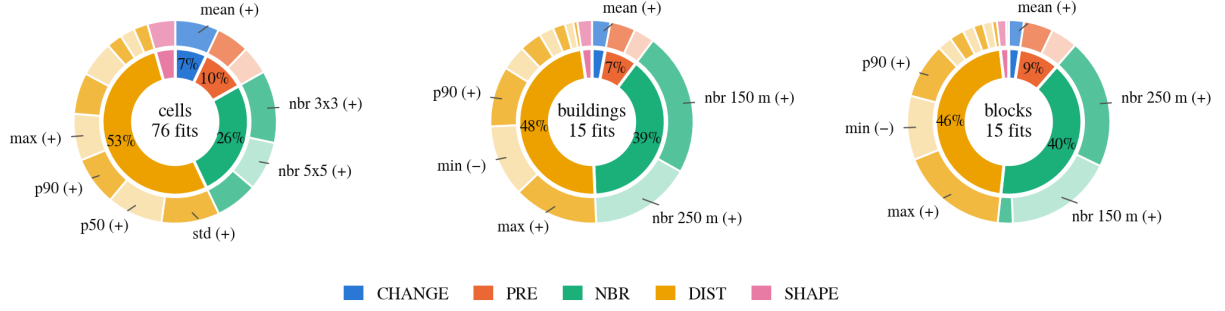


Figure 8. Where the logistic model puts its weight, leave-one-AOI-out within Türkiye, full feature set. Inner ring: each feature family's share of the standardised $|\beta|$, per fit then averaged over fits, outer ring: its columns, in the family's hue, with the coefficient's sign. Columns per family: CHANGE 1, PRE 2, DIST 9, NBR 3 for cells and blocks, 2 for buildings, SHAPE 1, and 2 for blocks.

Table 4. How each footprint got its grade: from an EMS point, from an EMS block, or graded in its own right because no OSM footprint existed. *Inherited* is the share of the positive class reached through a block.

event	EMS records		footprints from			
	points	blocks	point	block	own	inherited
Albania 2019	267	0	249	0	13	0.0 %
Croatia 2020	2 957	0	2 544	0	114	0.0 %
Türkiye 2023	25 451	10 728	23 492	94 141	2 340	69.7 %
Venezuela 2026	3 119	352	1 553	11 585	314	83.2 %

the block positive. This extends the positive class beyond the damaged buildings themselves. It favours block-scale and neighbourhood features, and at building scale the score partly measures how well a block-scale label is predicted. Albania and Croatia were graded by points only, so their positives are individual buildings. Point propagation introduces a smaller error. A point falls in its own footprint or in a neighbour within 10 m, one pixel at most, and the 4 % to 9 % of points with no footprint become 8 m squares.

10.3 Observable scaling: cd against cz

The tests in this and the next section are exploratory, and their p -values are not corrected for multiple testing. Standardising the drop does not help within an event (Fig. 9a). Used directly as a ranking, cz performs worse than cd for buildings and blocks, with a lower ROC-AUC in 13 and 12 of 15 areas ($p = 0.035$ and 0.048). For cells it is lower in 7 of 9 areas, which is not significant ($p = 0.164$). Once a model is fitted, the difference disappears at every unit ($p \geq 0.39$). The pre-event spread s_{pre} is estimated from only two to four pairs, so dividing by it adds noise to the ranking. A fitted model already has coh_pre_std as a feature and can learn any useful rescaling by itself. czn gives exactly the same results as cz here, because re-centring on one event's median and MAD is affine within that event. Its possible benefit can only be tested across events.

10.4 Graded negatives against assumed ones

Adding every ungraded OSM building as a negative reduces the prevalence by a factor of four to five, for buildings from 0.206 to 0.041, and changes the proxy's ROC-AUC by at most 0.013. The logistic model's gain for blocks does not depend on the choice of negatives: 0.027 AP in 13 of 15 areas with graded negatives and 0.024 in 12 with assumed ones (Fig. 9b). For buildings the gain is nominally significant only with assumed

Table 5. Türkiye buildings: ROC-AUC of the coherence drop by distance to the nearest graded building. Damaged against assumed negatives climbs with distance, damaged against confirmed ones much less, and the two negative classes separate from each other as they move apart.

band	damaged vs		assumed vs
	assumed	confirmed	confirmed
0–200 m	0.545	0.573	0.528
200–400 m	0.603	0.617	0.515
400–800 m	0.706	0.643	0.432
800–1600 m	0.837	0.670	0.308
1.6–3.2 km	0.884	0.691	0.275
>3.2 km	0.809	0.840	0.534

negatives, 0.013 in 11 of 15 areas ($p = 0.035$), against 0.008 in 9 areas ($p = 0.28$) with graded ones, so it cannot be considered established. For cells the result is mixed, with 5 of 9 areas in both cases. Within Türkiye the assumed negatives lie among graded buildings in the same areas, so assuming them costs little. This is no longer the case when the test data come from another event (Sec. 10.5).

10.5 Transfer and the assumed negatives

The transfer protocols give the highest scores of all splits. Under the held-out event, the logistic model reaches a ROC-AUC of 0.829 at cell scale against 0.792 for the proxy. This result should be treated with caution. Outside Türkiye no event graded a building as undamaged, so all transfer negatives are assumed, and most of them are far from the damage. Table 5 shows the effect of distance. Damaged buildings are separated from assumed negatives with a ROC-AUC of 0.545 within 200 m and 0.884 at 1.6 km to 3.2 km, while the separation from confirmed negatives only rises to 0.691. The two negative classes also separate with distance (AUC 0.275 in the same band), because distant assumed negatives lose less coherence than confirmed ones. Part of the transfer skill therefore comes from distinguishing a damaged district from undamaged ground several kilometres away, rather than from detecting damage itself, and the transfer gains should be read as upper bounds.

11. CONCLUSION

This paper examined whether a supervised model can improve on the coherence damage proxy when both use the same Sentinel-1 signal. Under leave-one-AOI-out validation, with

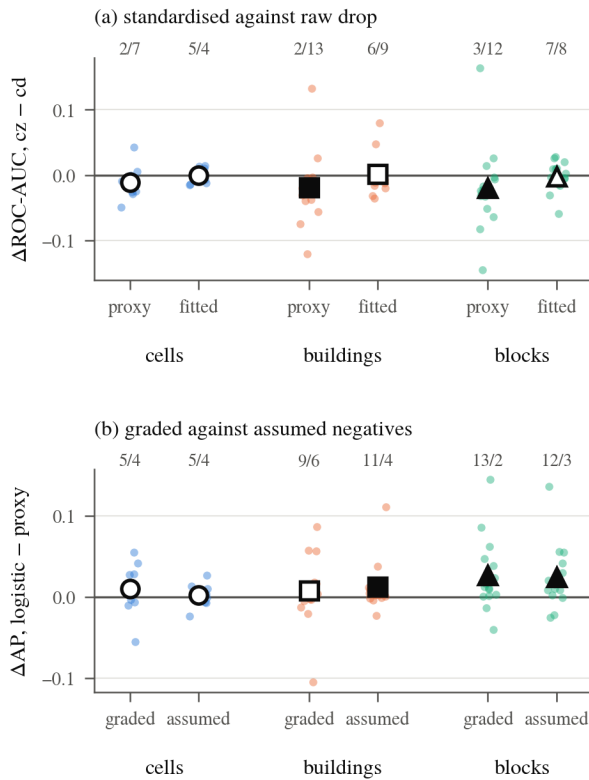


Figure 9. Does the answer survive a change of input? One light point per held-out area, large marker the mean over areas, filled when the uncorrected Wilcoxon test over areas gives $p < 0.05$, above, areas won/lost. (a) The standardised drop cz against the raw cd, as the proxy alone and pooled over the fitted rungs 2–4. (b) The logistic model's gain over the proxy with graded negatives only and with every ungraded OSM building added as an assumed negative, cells at 100 m.

the held-out area as the replicate and Holm-adjusted tests, the answer depends on the unit. For blocks, both boosting models beat the proxy significantly, in 13 and 15 of 15 areas, and the logistic model gains in 13 of 15. For buildings, monotonic boosting gains in 12 of 15 areas, but no model is significantly better than the proxy after correction. For cells no model improves on the proxy, and the flexible models lose in 8 or 9 of 9 areas.

The logistic model is the most reliable learner. It is never significantly worse than the proxy, and its gain varies much less between validation schemes than that of the random forest. It gives 2% to 7% of its weight to the mean drop used by the proxy and 79% to 87% to the distribution of the drop inside the unit and to its neighbourhood. The added value of modeling therefore comes mainly from how the drop is distributed within and around a unit.

These results have three main limitations. First, they are based on the only event with an observed undamaged class, so they hold within one event, and the cross-event gains, which rely on assumed negatives, are upper bounds. Second, most positives inherited a block grade, so the building and block gains partly reflect a block-scale label. Third, the choice of validation scheme changes the conclusions. Under random splits the random forest appears to be the best model, while under leave-one-AOI-out it is not the best at any unit. The validation scheme

should therefore always be reported together with the results.

DATA AND SOFTWARE

This work contains modified Copernicus Sentinel data (2019–2026), obtained from the Alaska Satellite Facility and processed with ESA SNAP (European Space Agency, 2025). Damage grades are from the Copernicus Emergency Management Service, activations EMSR884, EMSR648, EMSR412 and EMSR491 (Copernicus Emergency Management Service, 2026). Building footprints are © OpenStreetMap contributors and available under the Open Database Licence (OpenStreetMap contributors, 2026). The background imagery in Figs. 3–5 is Esri World Imagery (Esri, Maxar, Earthstar Geographics, and the GIS User Community), and the basemap in Fig. 2 is provided by Esri (Esri, 2026).

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