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An Unsupervised Anomaly Detection Problem in Urban InSAR-PSP Long Time-series

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INTRODUCTION

Motivation

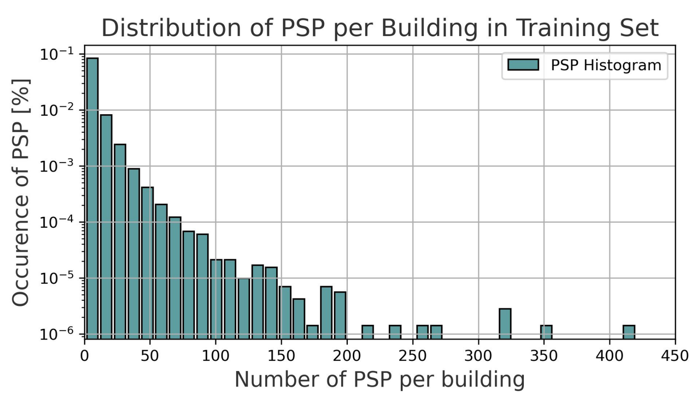
- Growing concern for building safety due to increasing urbanization
- Escalating demand for reliable infrastructure monitoring and management
- Evolving environmental factors impacting building displacements, e.g., climate change-induced natural disasters
- Challenges in detecting complex deformation patterns with traditional PS-InSAR

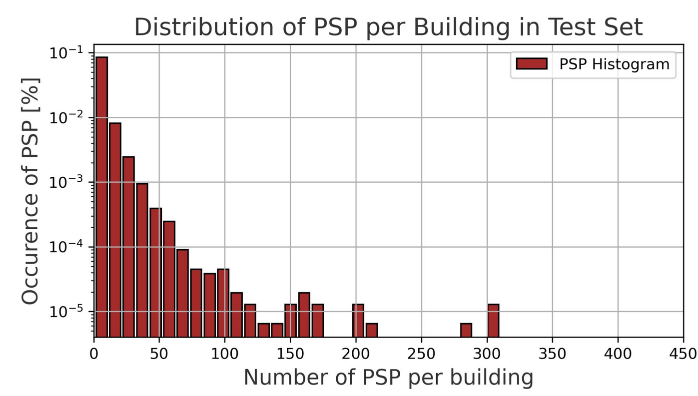
Proposed Solution

- Unsupervised learning method leveraging autoencoders and LSTM networks to address the lack of ground-truth data
- Innovative data preprocessing strategy and reconstruction loss function for enhanced anomaly detection performance
- Aim: Evaluate the effectiveness of the proposed method in accurately identifying diverse building displacement anomalies

DATABASE

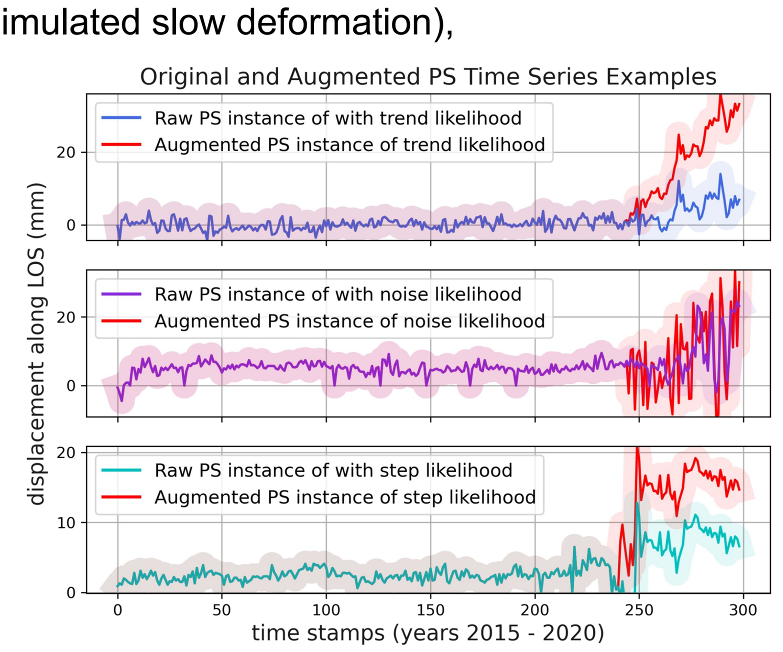
- Data from European Ground Motion Service (EGMS) covering a rectangular region around Rome, Italy
- 500,000 PS time-series with 300 timestamps each, indicating deformations in millimeter resolution along the line of sight (LOS)
- Measurements aggregated over 80,000 building footprints from 2015 to 2020





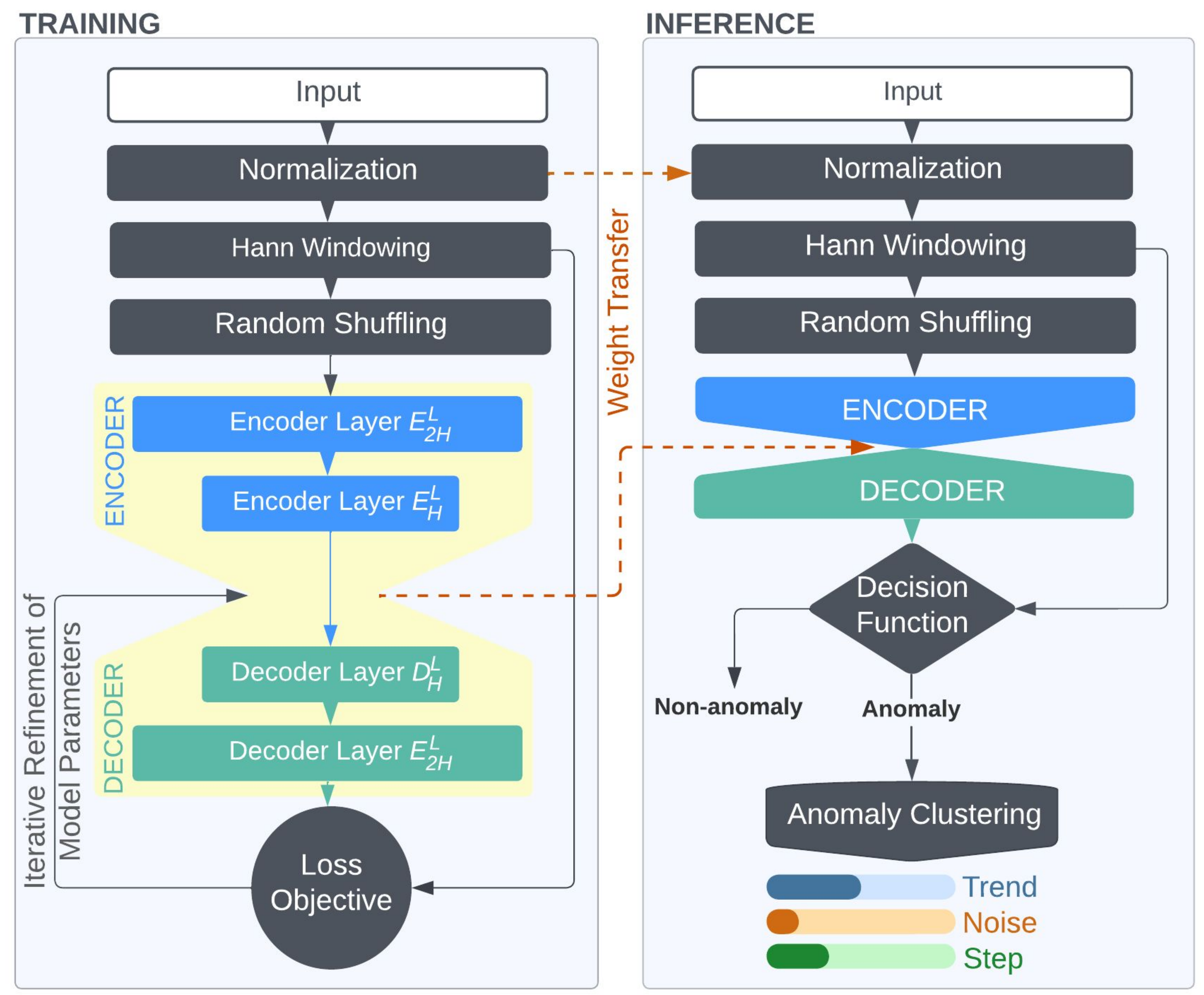
Ground-truth Generation

- Absence of ground truth anomalies leads to using synthetic deformation for training/validation
- Examples: Anantrasirichai et al. (simulated slow deformation), Lattari et al. (change points for slow deformation), Shakeel et al. (Gaussian peaks for earthquake deformations)
- Three synthetic deformation scenarios: trend anomaly, noise anomaly, and step anomaly
- Up to 25% anomaly rate to simulate varying proportions of anomaly presence in evaluation samples



METHODOLOGY

The proposed approach utilizes an LSTM-autoencoder to reconstruct randomly permuted input sequences, leveraging the Hann window for smoothing time series and a custom soft-DTW loss function for improved anomaly detection performance.



EXPERIMENTAL RESULTS

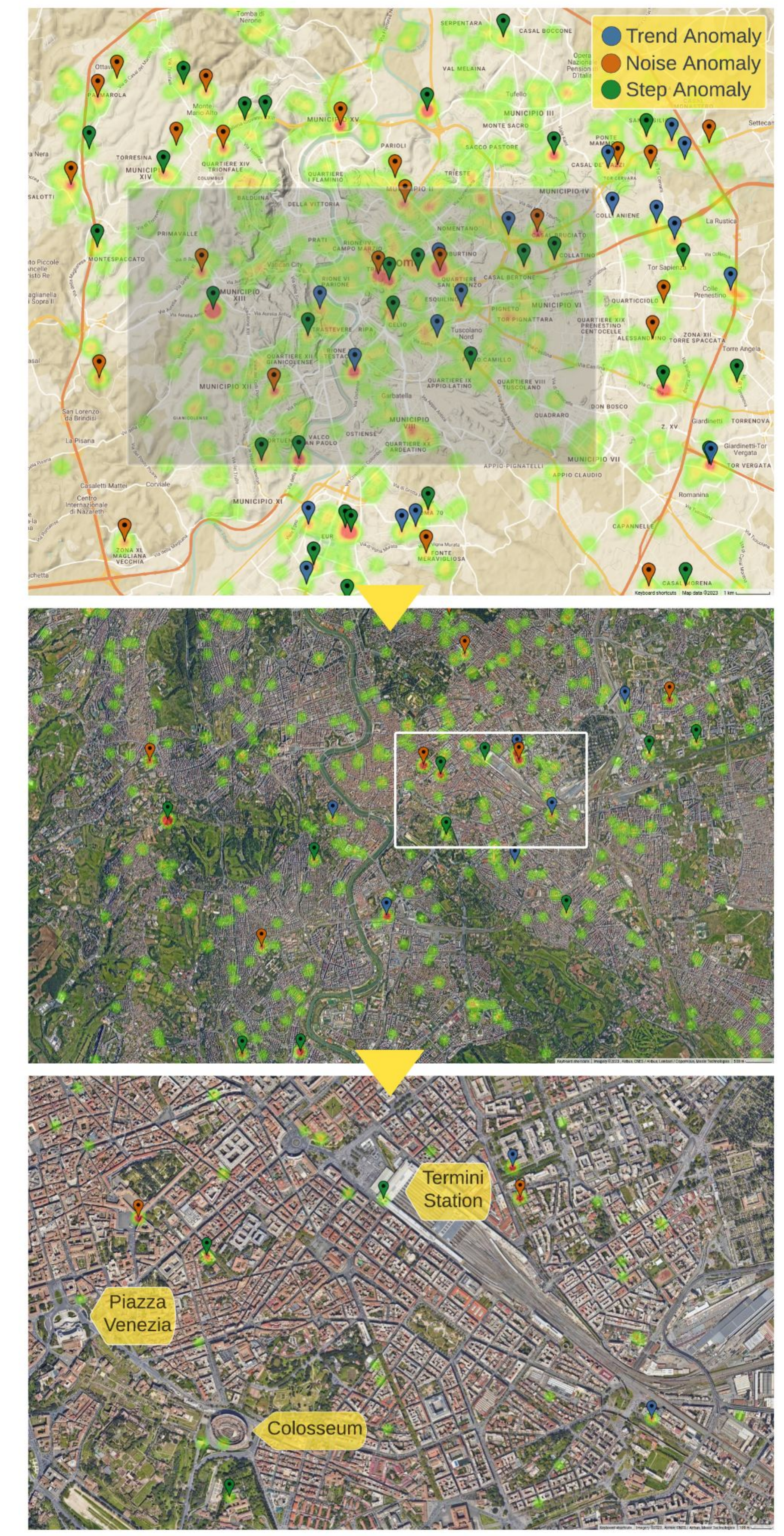
Hann windowing, random permutation, and soft-DTW reconstruction loss improve the overall anomaly detection accuracy, but hinder the detection of specific anomalies.

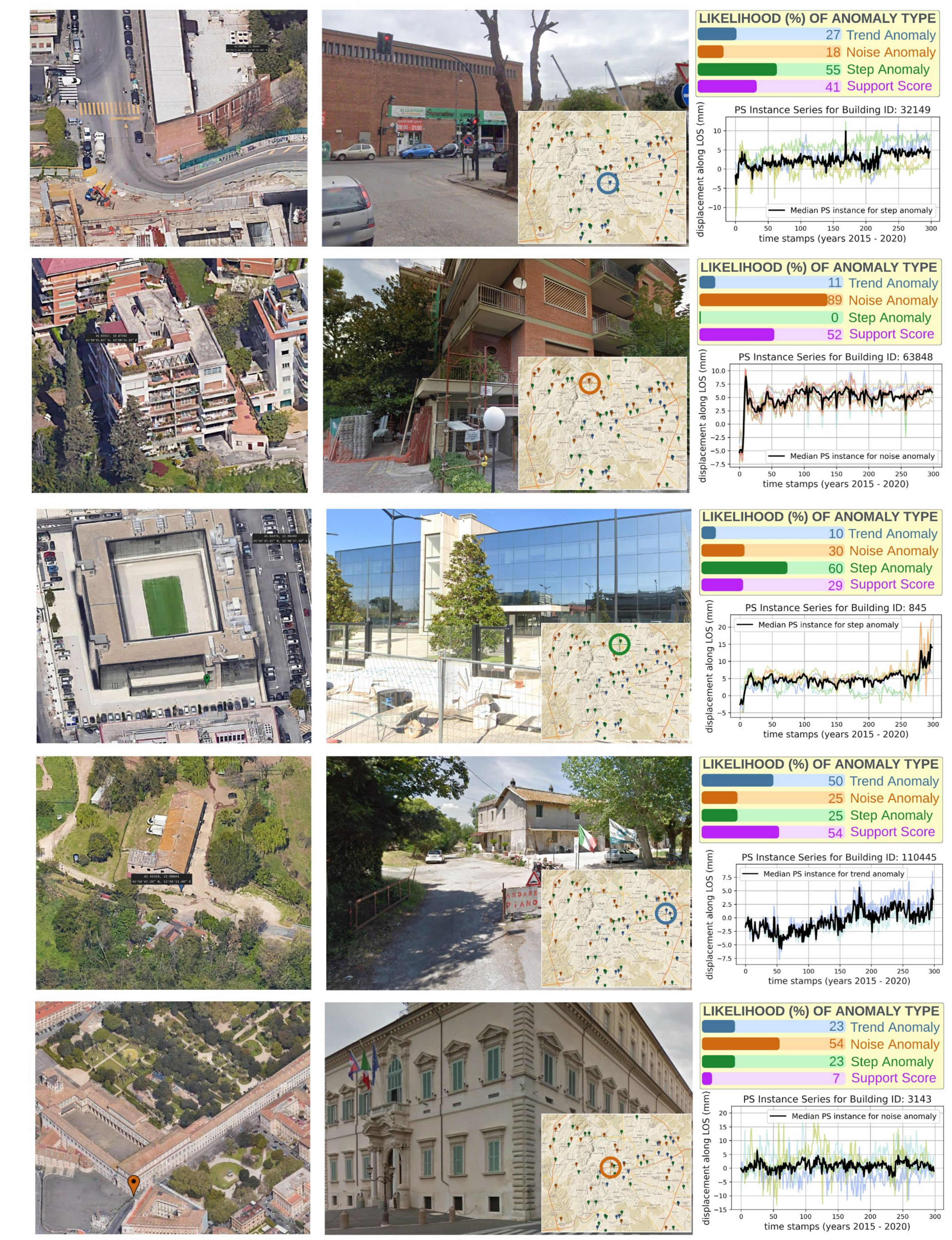
A COMPARATIVE ANALYSIS OF THE IMPACT OF PREPROCESSING AND MODEL TRAINING PARAMETERS ON ANOMALY DETECTION.

Preprocessing and Model Training Parameters				Anomalous Building Detection Accuracy (%) per Displacement Scenario								
Input Data Permutation	Smoothing Window Size	Hidden Embedding Dimension	Reconstruction Loss Function	τ percentile @75			τ percentile @90			τ percentile @98		
				Trend	Noise	Step	Trend	Noise	Step	Trend	Noise	Step
Yes	1	1	*soft-DTW*	96.14	46.45	28.59	89.93	26.33	12.07	65.25	06.06	02.15
No	1	1	*soft-DTW*	43.08	40.89	20.48	38.34	19.87	18.46	34.76	02.07	15.23
Yes	13	1	*soft-DTW*	35.54	26.79	27.45	30.83	11.08	20.00	23.85	02.23	12.01
No	13	1	*soft-DTW*	71.43	26.88	42.55	59.38	11.80	27.55	41.55	03.51	07.35
Yes	1	64	*soft-DTW*	93.22	**51.22**	07.83	81.65	**29.87**	02.49	56.24	**10.37**	00.89
No	1	64	*soft-DTW*	92.70	45.06	17.43	78.18	23.65	06.64	41.55	05.42	01.08
Yes	13	64	*soft-DTW*	**99.53**	16.30	**73.69**	96.85	06.26	**50.50**	90.21	01.60	**23.12**
No	13	64	*soft-DTW*	33.33	39.75	15.96	10.48	17.95	02.86	00.32	03.19	00.36
Yes	1	1	L_1	06.80	24.57	42.69	02.94	10.03	18.87	00.47	02.87	02.15
No	1	1	L_1	05.85	23.77	36.31	02.57	07.63	16.64	00.63	01.75	01.25
Yes	13	1	L_1	07.50	30.42	28.50	03.22	11.88	10.17	00.16	02.55	00.90
No	13	1	L_1	12.05	30.35	28.29	07.18	11.56	13.28	02.69	02.87	03.58
Yes	1	64	L_1	21.57	25.97	55.67	10.73	12.57	33.44	01.74	02.87	07.71
No	1	64	L_1	00.00	48.26	02.20	00.00	19.67	00.17	00.00	04.63	00.00
Yes	13	64	L_1	36.08	26.49	52.19	17.21	12.04	28.76	01.26	03.03	04.30
No	13	64	L_1	08.81	31.55	22.72	01.96	12.36	08.17	00.00	00.80	02.33
Yes	5	32	*soft-DTW*	99.31	30.59	50.38	**97.84**	12.69	30.41	**94.15**	02.07	06.45
No	5	32	*soft-DTW*	57.25	46.43	13.00	34.58	24.73	04.36	15.01	07.34	00.90
Yes	5	32	L_1	23.70	27.94	52.96	11.09	12.73	29.05	01.74	02.87	05.02
No	5	32	L_1	04.05	31.33	22.27	00.77	10.20	08.71	00.00	01.75	01.25
Yes	7	32	*soft-DTW*	99.05	24.18	59.17	96.90	08.31	40.29	93.20	01.11	15.95
No	7	32	*soft-DTW*	82.07	40.33	22.49	66.64	18.06	07.93	39.65	03.99	01.61
Yes	7	32	L_1	33.45	28.94	52.95	16.39	11.84	28.42	01.58	02.71	04.84
No	7	32	L_1	17.74	34.78	15.66	11.95	11.60	05.81	07.74	01.91	01.61

QUALITATIVE EVALUATION

The figures on the left display the positions of unusual buildings in Rome with a support score (S) above 10% and a minimum of 5 anomalous PS instances, using colored pins. The heatmap illustrates the density of detected anomalous PS points, independent of their support scores. Additionally, The figures on the right show aerial and street view assessments of some identified anomalies.





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