Empowering Intermediate Cities: Cost-Effective Heritage Preservation through Satellite Remote Sensing and Deep Learning.

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Abstract

In the capitalist rush to attract more visitors, cities are committing significant resources to heritage conservation, driven by the substantial economic benefits generated by the tourism industry. However, less famous or less well-resourced cities, often with smaller populations, also known as intermediary cities, find it difficult to allocate funds to protect their most significant heritage sites. In this conservation context, intermediary cities, often on the periphery or "at the margins", can fill the gaps and needs of urbanism through a better strategic understanding of the challenges of global touristification, thus this research provides urban planning tools for local governments with limited resources to preserve their architectural heritage through remote sensing, for its advantages in terms of lower economic cost, as a valuable monitoring tool to effectively identify high-vulnerability sites that require priority attention in the conservation of architectural heritage. In other words, it allows to reduce in the territory those areas located "at the margins" in terms of urban planning and management, by approaching the territorial, urban, architectural and tourism problems from a transdisciplinary perspective in the preservation of the architectural heritage. This study explores the application of optical (Sentinel-2) using neural networks for classifying the land cover and radar (Sentinel-1 and PAZ) satellite images in order to obtain the ground motion as a geotechnical risk study, together with geospatial data, for the monitoring of architectural heritage in intermediate cities. Focusing on the districts of Bragança and Guarda in Portugal, the approach allows the direct identification of vulnerable architectural heritage, identifying 9 high-vulnerability areas using PAZ data and 7 areas using Sentinel-1 data. Furthermore, this work provides an understanding of the potential and limitations of these technologies in heritage preservation because compares the processing results of freely accessible medium-resolution Sentinel-1 radar images with the high-resolution radar images from the innovative PAZ satellite.

Keywords

Heritage Conservation, PAZ satellite, Multi-temporal Interferometric Synthetic Aperture Radar, Deep Convolutional Neural Network, Sentinel satellite.

1. Introduction

Large cities with tourist attractions have traditionally invested in the preservation, conservation, and promotion of architectural heritage (Vita et al. 2020). However, when looking at smaller cities also known as Intermediate Cities (those between 100,000-500,000 inhabitants) the situation is different, typically due to their limited budgets (Rodríguez-Pose and Griffiths 2021), (Vita et al. 2020). It should be noted that more than 60% of the world's urban population lives in these Intermediate Cities ("Urban Planning | UN-Habitat," n.d.). Consequently, there is a growing awareness of the importance of conserving architectural heritage and efforts are being made to balance the economic, environmental, and tourism aspirations of intermediate cities with those of large global cities (Araoz 2011), (Vita et al. 2020), (Skalski et al. 2018). This highlights the need to recognize the social and political situations of peripheral or "at the margins" cities within the "world of cities" ("Peripheral Cities | UCLG," n.d.), (AUGÈ 2007) (Ali and Rieker 2008), (Kovacs 2016).

As a consequence of this new approach, and considering the global phenomenon of touristification, the focus of heritage protection is being increased on these intermediate cities (Sanchez-Montanes, Romero-Ojeda, and Castilla 2023), (Hiernaux-Nicolas and González Gómez 2015). Policymakers and urban planners require cost-effective tools that help to massively evaluate the architectural heritage of their cities and provide them with objective measures to detect vulnerable elements; and thus, promptly adopt corrective or preservation measures in those elements whose intervention is a priority (Mansuri and Patel 2022), (Bai et al. 2023), (Ortiz and Ortiz 2016), (Klein, Koenig, and Schmitt 2017).

In recent years, remote sensing tools have been proposed to detect geographic areas where architectural heritage may be at risk (Chen et al. 2018). The implementation of automatic monitoring tasks, with the capability to cover large extensions of land, and cost-effective in terms of economy and human resources, has enabled the adoption of remote sensing data for monitoring of architectural heritage (Hadjimitsis et al. 2013). Furthermore, the emergence of cloud-based platforms for geospatial analysis such as Google Earth Engine provides access to high-performance computing resources to process large geospatial datasets efficiently, allowing a variety of problems to be solved by taking advantage of Google's enormous computational capabilities (Gorelick et al. 2017). Additionally, platforms like WEkEO -DIAS, funded by the European Commission, allow users to discover, manipulate, process, and download data and information from the European satellites of Copernicus (Marconcini et al. 2020). Other initiatives also exist as the SARIPA project to mitigate Big Data issues related to current satellite images, particularly Synthetic Aperture Radar (SAR) processing applications due to their significant memory and computational requirements, SARIPA exploiting software architecture and General-purpose Computing On Graphics Processing Units (GPGPU) through the Open Computing Language (OpenCL) framework allowing to significantly reduce storage requirements for wide area monitoring applications (Peternier, Merryman Boncori, and Pasquali 2017). Moreover, the use of various satellite image processing techniques (Asokan et al. 2020) and the advancement of artificial intelligence techniques (Bianchini, Müller, and Pelletier 2022), introduced new methodologies that can be reproduced everywhere in the world. Therefore, this "intelligent, resilient, sustainable and reliable" monitoring of infrastructures means a better use of resources.

The monitoring of ground motion through radar satellite images has been proposed, both for the analysis of geographic accidents and natural disasters, like the detection of deformation precursors in landslides for early warnings (Dai et al. 2020a; 2020b); infrastructure monitoring (Yan et al. 2022), (Montisci et al. 2022). For example, in previous works, the authors captured high displacement patterns before the collapse of the Hintze Ribeiro centennial bridge with ERS-1 and ERS-2 satellite images (Sousa and Bastos 2013); other previous works refer to the detection of problems in buildings, bridges, and dam through ENVISAT and TerraSAR-X satellite images (Bakon et al. 2014).

Also, several studies have demonstrated the effectiveness of using radar satellite images for creating vulnerable maps of architectural heritage, such as the study conducted in Belgium utilizing ERS 1/2, ENVISAT, and Sentinel-1 images (Drougkas et al. 2020). One explored the benefits of TerraSAR-X images for studying and monitoring cultural landscapes and heritage sites (Tapete and Cigna 2019), while the other analyzed the Historical Centre of Hanoi using TerraSAR-X imagery (Le et al. 2016). In 2018 the PAZ satellite was launched by the Hisdesat, with similar technical characteristics as the TerraSAR-X satellite (Imperatore, Pepe, and Sansosti 2021); however, this satellite has been little analyzed so far. One of the first works with the PAZ data is the sinkhole monitoring (Abdikan et al. 2020); suggesting a fantastic opportunity for the evaluation of its application in the architectural heritage of intermediate cities.

In addition, the use of deep learning techniques for the classification of optical satellite images is currently emerging, with numerous examples like the land use and land cover classification using Sentinel-2 satellite images (Helber et al. 2019); the semantic segmentation of building footprints on Inria Aerial Image Labelling Dataset (Bischke et al. 2017); or also the land cover classification of the ISPRS Vaihingen 2D semantic labelling contest dataset (Kampffmeyer, Salberg, and Jenssen 2016). One of the main advantages of using deep learning is its proved ability to process huge areas of study with improved robustness and performance of the classification (Talukdar et al. 2020).

This research aims to bridge the gap between the advantages offered by deep learning-based classification of optical satellite images and the identification of displacement patterns using satellite radar images in cities with relevant architectural heritage sites. By combining these approaches, the study aims to create maps with a focus in the urban planning needs of intermediate cities, fostering equitable relationships between large and small cities within the same territory. Therefore, it reduces in the territory those areas located "at the margins" in terms of urban planning and management, by approaching the territorial, urban, architectural, and tourism problems from a transdisciplinary perspective that considers spatial, technical, economic, and social aspects of urban management in the preservation of the architectural heritage in intermediate cities. This work contributes to the utilization of deep learning techniques and valorization of Earth Observation programs for mapping vulnerable heritage in intermediate cities, leveraging data from Sentinel-1, Sentinel-2, and PAZ satellite images. The primary objective of this analysis is to monitor deformations in the architectural heritage of intermediate cities using open-source tools such as satellite images (Sentinel-1 and Sentinel-2), software (Quantum Geographic Information System - QGIS), and geoinformation layers (EuroSAT dataset (Helber et al. 2019) and the QuickOSM plugin ("QuickOSM," n.d.)). Additionally, the study compares the difference in results with respect to the novel high-resolution images (PAZ images). Ultimately, automatic maps that facilitate the immediate identification of vulnerable locations are developed at a lower cost in terms of resources and human effort, capitalizing on the power of deep learning techniques. For this purpose, the document consists of the following sections: in section 2, the description of the case study (part of the Bragança District and Guarda District) is presented. Section 3 includes the description of the data, and section 4 describes the methodology used. Section 5 presents the results, which are then discussed in section 6. Finally, section 7 summarizes the main conclusions of the work. Finally, section 7 summarizes the main conclusions of the work.

2. Case Study

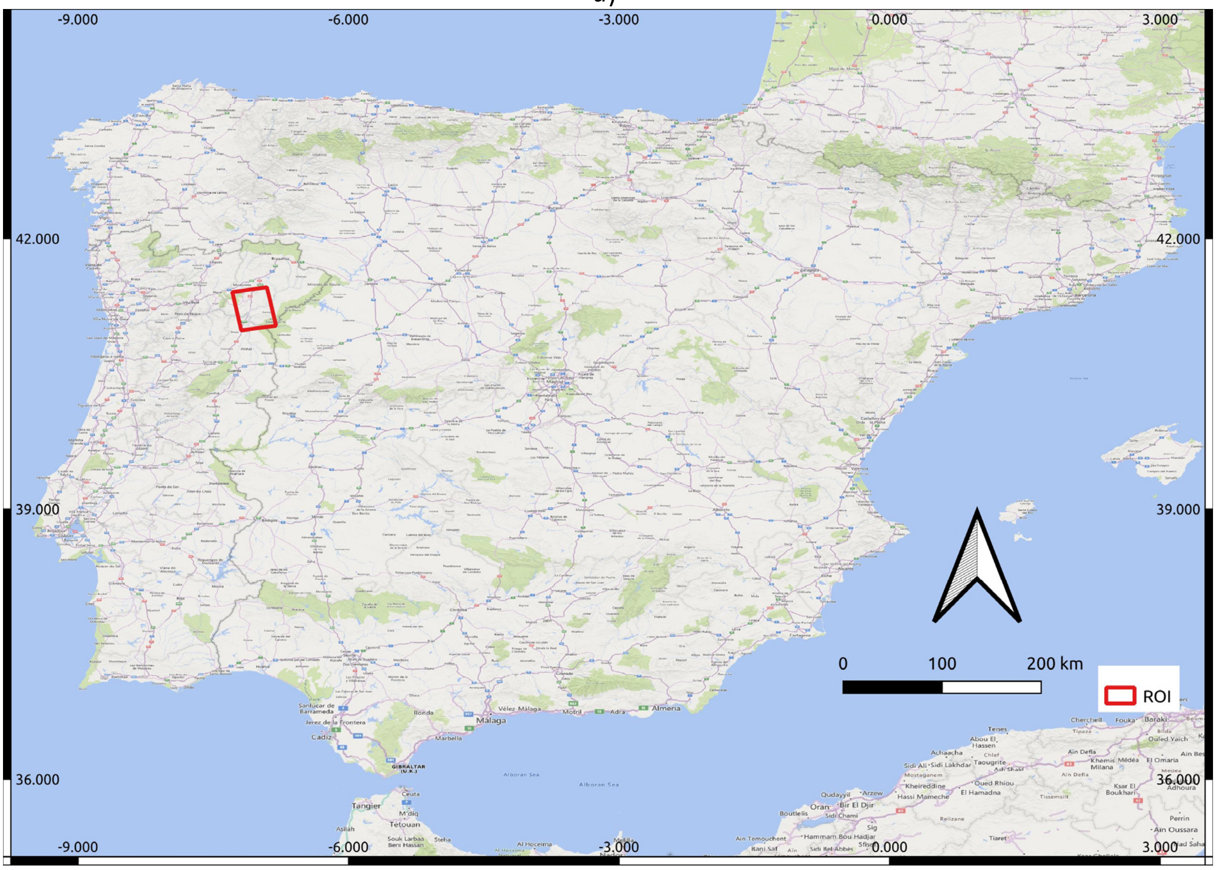
In this study, the Northern Region of Portugal is selected for analysis due to its significance as a prominent tourist destination worldwide ("UNWTO Elibrary," n.d.). Within this region, particular emphasis was placed on the historical province of Trás-os-Montes e Alto Douro, which encompasses parts of the Bragança District and Guarda District. Despite being an area often overshadowed by popular tourist destinations such as Oporto, Trás-os-Montes e Alto Douro boasts unique cultural and historical resources, with four sites classified as World Heritage by the United Nations Educational, Scientific and Cultural Organization (UNESCO). The choice of this specific region is motivated by its neglected status, which paradoxically led to the preservation of cultural traditions and historic heritage. This, in turn, presents an opportunity to promote tourism in the area (Rodrigues, Liberato, and Esteves 2022). Additionally, the Trás-os-Montes e Alto Douro region counts several architectural heritage sites of national importance, where 18 sites are listed as national monuments in Portugal ("Monumentos," n.d.). Notably, the Guarda District within this region features one site listed in the World Heritage List, the Prehistoric Rock Art Sites in the Côa Valley ("Prehistoric Rock Art Sites in the Côa Valley and Siega Verde - UNESCO World Heritage Centre," n.d.). Despite the significant cultural heritage in the study area, it is worth mentioning that it is not adequately represented in the Atlas of Classified Heritage (“DGPC | Pesquisa Georeferenciada,” n.d.).

Some potential vulnerable architectural heritage areas could be identified with the European Ground Motion Service (EGMS), which provides accurate and consistent information on natural and anthropogenic ground motion, with millimeter precision (“European Ground Motion Service — Copernicus Land Monitoring Service,” n.d.). The use of ascending EGMS data, filtered for temporal coherence above 0.90, reveals several instabilities in the region (Image 1c). The study period available spans from 2015 to only 2020, raising a more recent update of constant monitoring for heritage conservation to discover vulnerable architectural heritage that has not been detected and may be affected by some recent structural problem due to poor maintenance or other factors.

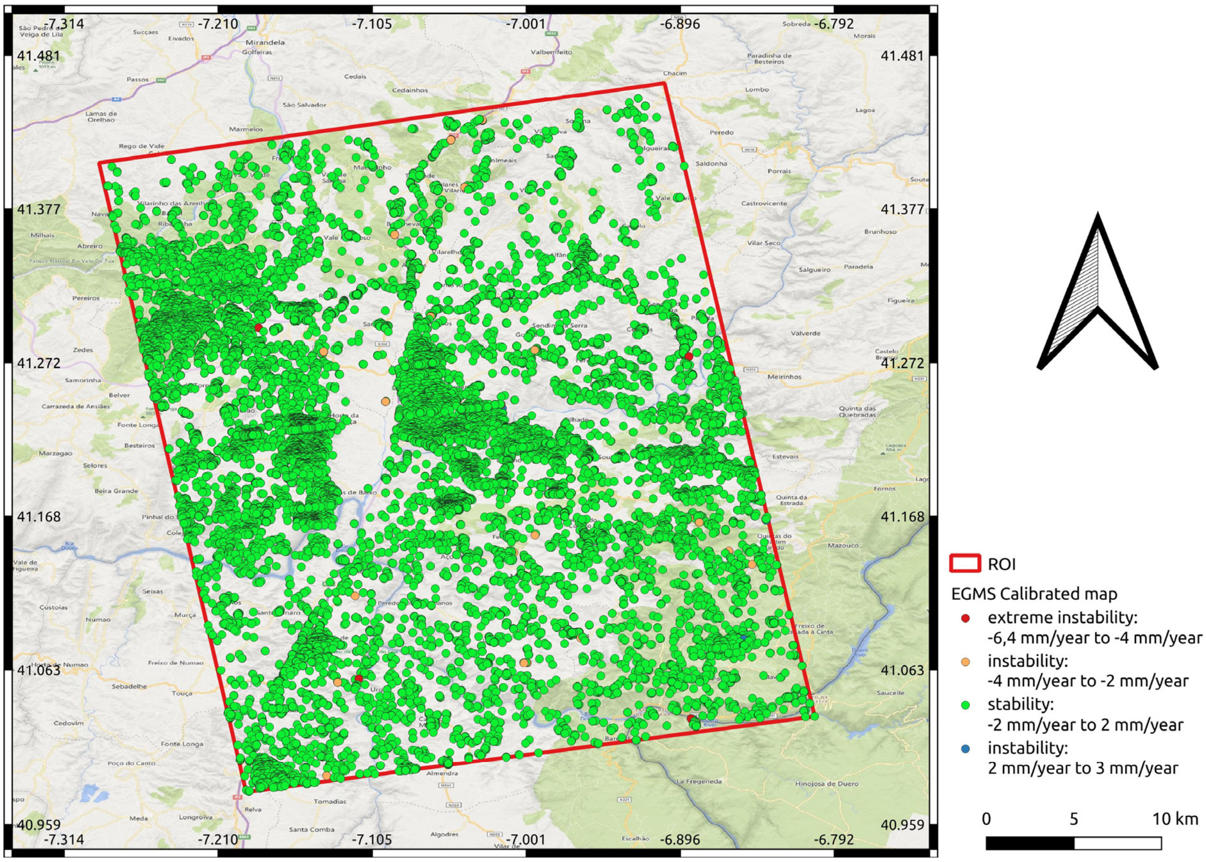
The study takes advantage of the vast coverage of satellite images and their ability to analyze a large area without the need for infrastructure monitoring that may entail high human and economic costs.

The study area is the complete coverage offered by one of the selected PAZ images (Figure 1a), which are smaller in extent than Sentinel-1. The study area is not reduced to a political-geographical limit to check the pros and cons of its processing.

a)



b)



c)

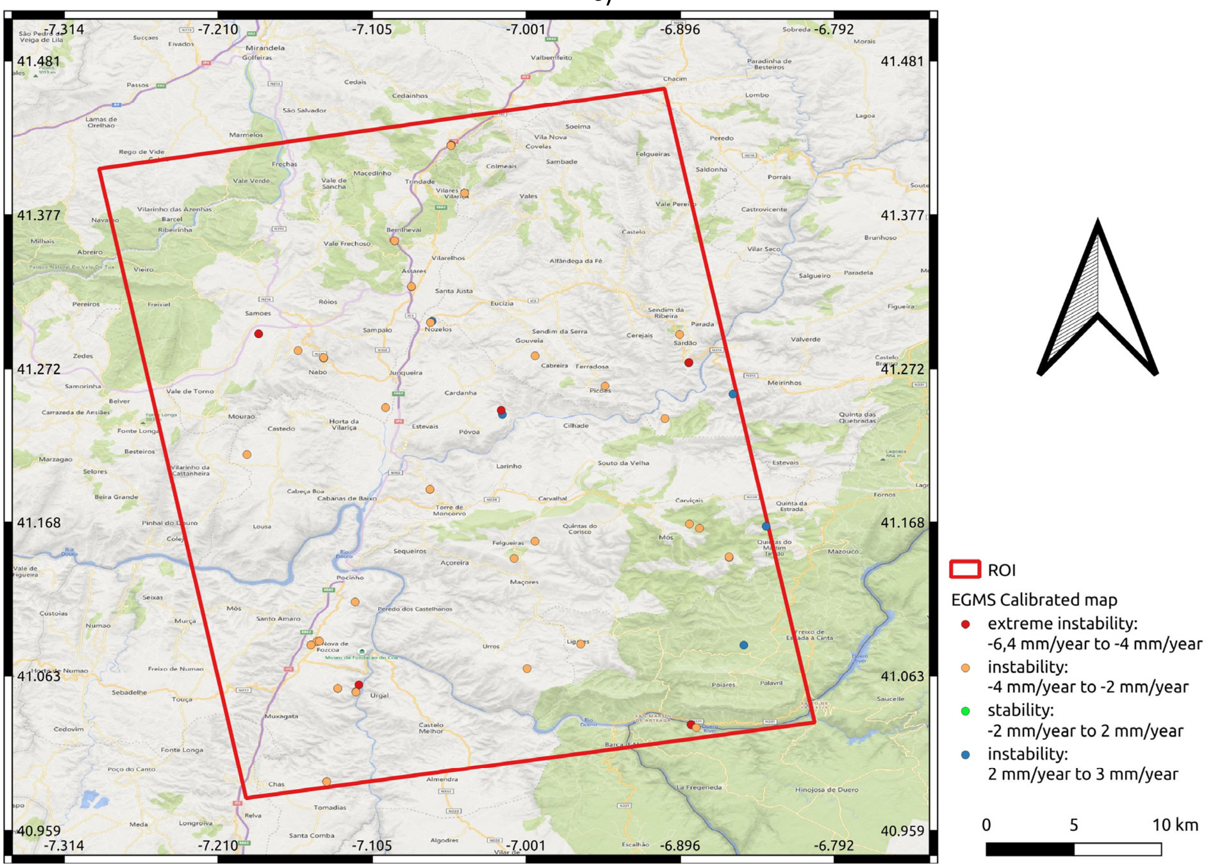


Figure 1. Area of study: *a*) The red box identifies the total study area in the Iberian Peninsula, that coincides with the complete coverage offered by the PAZ images for the analysis of part

of the historical province of Trás-os-Montes e Alto Douro; *b*) EGMS data of the study area; *c*) EGMS data of the study area with just the values that identified the instabilities.

3. Datasets

For the purpose of detecting infrastructure instability in that area, radar satellite images are used to produce interferograms, which are subjected to a Multi-temporal Interferometric Synthetic Aperture Radar (MT-InSAR) processing (Ferretti, Prati, and Rocca 2000) using StaMPS (Andy Hooper et al. 2018). The datasets used are:

- 21 PAZ images (from 2021-09-25 to 2022-05-14), which have an effective resolution for infrastructure monitoring but have been underutilized by the scientific community until now because these images are not freely accessible to everyone (main characteristics of PAZ satellite in Table 1).
- 21 Sentinel-1 images (from 2021-09-27 to 2022-05-13), which are widely available and commonly used but have medium resolution and that difficults its application for infrastructure monitoring (main characteristics of Sentinel-1 satellite in Table 1).

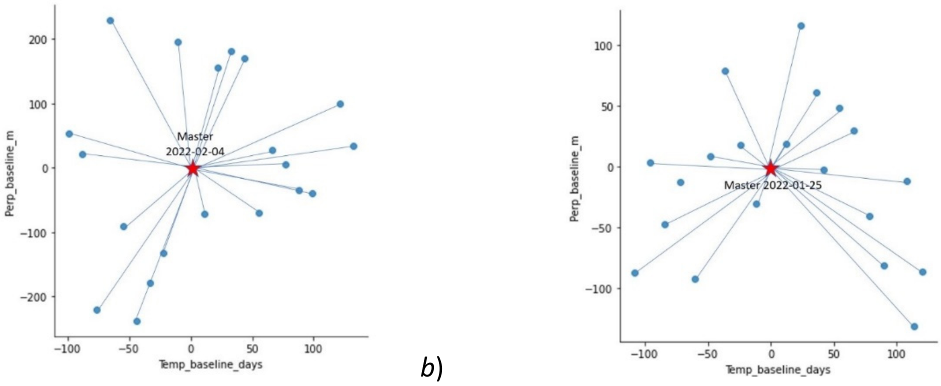
Table 1. Main characteristics of the selected PAZ and Sentinel-1 images datasets.

Sensor	**Frequency**	**Agency/Country**	**Access**	**Revisit-Time**	**Spatial Resolution of Dataset**	**Polarization of Dataset**	**Frame Size of Dataset**	**Years of Dataset**	**Track of Dataset**	**Orbit of Dataset**	**local incidence angle**
PAZ SAR	X band (9.65 GHz, λ = 3.5 cm)	Hisdesat	Commercial	11 days	Stripmap: 3–6 m	Single: HH	Stripmap: 30–2000 × 30 km	2021 – 2022	33	21409	30.91
Sentinel-1	C band (5.4 GHz, λ = 5.6 cm)	European Space Agency (ESA)	Free and open	Satellite: 12 days Constellation: 6 days	Interferometric Wide Swath (IW): 5 × 20 m	Single: VV	IW: 250 km	2021 – 2022	74	41621	32.44

In this sense, the resolution of satellite images plays a crucial role in infrastructure assessment and monitoring. Indeed, spatial resolution is the ability of a sensor to distinguish between separate objects on the earth's surface. A higher spatial resolution enables the detection of smaller objects, facilitating a more detailed assessment of buildings and urban infrastructure. This, in turn, enhances the accuracy in identifying potential vulnerabilities by capturing subtle changes in the earth's surface. Conversely, lower resolutions lack the precision required to detect individual elements accurately.

However, in order to ensure a fair comparison of the knowledge of the benefits and drawbacks of each data source, an attempt is made to ensure that the images used have common characteristics by cropping the Sentinel-1 images to match the smaller geographic coverage of the PAZ images (Figure 2). Moreover, although both satellites are not synchronized, an effort is made to choose images with a maximum time difference of three days between captures to minimize the differences in the results (Figure 3).

Figure 2. Comparison between the Sentinel-1 image coverage (white box) vs. the PAZ image coverage (red box).



a) *b*)

Figure 3. Baseline plots (temporal vs. perpendicular) of: (*a*) PAZ images and, (*b*) Sentinel-1 images.

Displacement information provided by the PAZ and Sentinel-1 images is filtered using Deep-Learning in order to locate the architectural heritage in the study area. The free Sentinel-2 images are used to identify urban areas, and these are then cross-referenced with the locations of architectural heritage. This data is used as it ensures its reproducibility by anyone interested in the global monitoring as an objective and not just focused on large cities.

The Sentinel-2 image used in this analysis (Table 2) is chosen because it belongs to the same period as the PAZ and Sentinel-1 images of our work. Also, it was captured on a day without cloud cover that is the closest to the day when the Master radar images selected was registered. This absence of clouds is necessary for accurate classification of land cover with the proposed Convolutional Neural Networks (CNNs).

Table 2. The main characteristics of the Sentinel-2 image of the study area used for the inference of its land cover classes.

Filename	**Date**	**Size**	**Orbit numbe r**	**Pass direction**	**Processin g baseline**	**Processin g level**	**Relativ e orbit**	**Sensin g start**	**Sensin g stop**
S2A_MSIL1C_2022 0208T112231_N0400 _R037_T29TPF_202 20208T132948.SAFE	2022-02-08	812.04 MB	34640	DESCEN DING	04.00	Level-1C	37	2022-02-08T11 :22:31. 024Z	2022-02-08T11: 22:31.0 24Z

4. Methodology

As previously announced in section 3, it is necessary to combine the MT-InSAR technique with other filters in order to create the maps for the vulnerable architectural heritage in a large-scale approach. Therefore, in our approach we opt to combine the classification of land uses with Sentinel-2 images that are processed using Deep Learning techniques, and the information on the geographic location of the architectural heritage through the QuickOSM plugin for QGIS using the query 'tourism'='attraction' in Portugal (Figure 4).

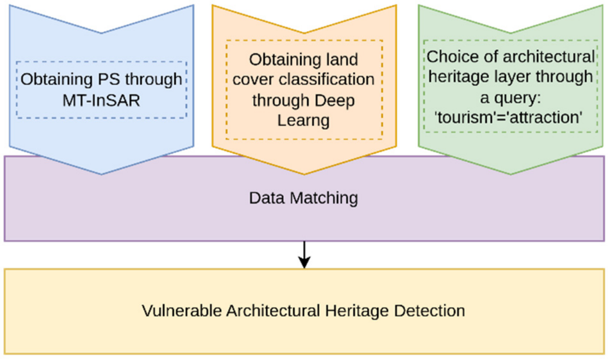


Figure 4. Overall approach on data matching in order to detect the vulnerable architectural heritage.

This methodology is designed aimed at responding to the need of automatically and reliably obtain information about vulnerable architectural heritage. Through a convolutional neural network, the model processes pixelwise information of the satellite images from which we want to obtain information (Sentinel-2). The model is trained in other labelled datasets (EuroSAT) (Helber et al. 2019), and QuickOSM plugin ("QuickOSM," n.d.) to obtain the land classification of interest (architectural heritage of intermediate cities). Afterwards, this classified data is compared with the displacement patterns obtained from the radar images with the purpose of detect the location of vulnerable architectural heritage of aforementioned intermediate cities. The 3 superimposed information layers in QGIS with the following conditions: where unstable values, tourist attraction sites and urbanised land ('Highway', 'Industrial', 'Residential') coincide simultaneously in the same pixel then reveal the vulnerable heritage area.

The MT-InSAR technique (through the Stanford method (by StaMPS)) finds in the interferograms of the radar satellite images those stable points with stable phase characteristics (Andrew Hooper et al. 2004), (Ferretti, Prati, and Rocca 2000). This technique provides the ground displacement pattern through information points, also called Persistent Scatterers (PS), which contain their coordinates, average displacement speed expressed in mm years^{-1} during the entire period of time analyzed. These points also contain each of the displacement values that occur at the moment of capturing every of the slave images compared to the master image (time reference) (Xue et al. 2020), in short, its displacement trend.

The first step of the MT-InSAR technique involves selecting the master image for each analysis (PAZ VS Sentinel-1). The master image will compare the rest of the images of each dataset (PAZ or Sentinel-1). This analysis is performed using the free European Space Agency (ESA) program of Sentinel Application Platform (SNAP) ("SNAP – STEP," n.d.) to obtain the first PS candidates. Then, by using StaMPS, the data obtained from SNAP is exported to a MATLAB environment to calculate temporal coherence by estimating phase noise. A first selection of PS can be made by eliminating those outliers that are considered noise. Next, the data is resampled to remove pixel errors, and it is merged to perform phase unwrapping. Finally, the results are filtered to remove the spatially correlated look angle error and noise coming from atmospheric disturbances. With that, the correct PS and corresponding velocity and time series trend are exported.

The MT-InSAR technique through the StaMPS program requires the definition of various parameters that must be the same for both PAZ and Sentinel-1 data, if the purpose is to know the performance of their respective results in infrastructures monitoring. Table 3 summarizes the parameters set in the case studies presented in this paper; these parameters have been chosen by heuristic methods and are the best adapted to our area of study.

Table 3. Parameters in StaMPS values for PAZ and Sentinel-1.

Parameter	Default	Used
max_topo_err	20	5
plot_scatterer_size	120	30
scla_deramp	'n'	'y'
unwrap_gold_n_win	32	64
unwrapping method	'3D'	'3D_NEW'
weed_max_noise	Inf	2
weed_neighbours	'n'	'y'
ref_centre_lonlat	[0 0]	[-7.0107 41.3126]

For the classification of land cover, we use a pretrained deep learning model (Convolutional Neural Network (CNNs) with sequential architecture ("The Sequential Model," n.d.)) presented in ("Artificial Intelligence for Earth Monitoring MOOC — Copernicus Land Monitoring Service," n.d.) and the geo-referenced dataset EuroSAT (Helber et al. 2019). This processing is developed on the WEkEO platform, which is the European Union (EU) Copernicus Data and Information Access Services (DIAS) reference service for environmental data, virtual processing environments and skilled user support ("Copernicus and Sentinel Data at Your Fingertips | WEkEO," n.d.).

EuroSAT is a reference dataset based on Sentinel-2 images and consists of 27,000 labelled and georeferenced images. The pretrained model (Figure 5) uses 27,000 images with a resolution of 13 by 64 by 64 each, since 13 are the number of bands of the Sentinel-2 image and 64X64 is the pixel resolution of EuroSAT reference data.

The model is pretrained with the following data specification:

- Input: A matrix with 4 dimensions: 27,000 images, where each image has 64X64 pixel information and the information of the 13 bands of Sentinel-2.
- Output: A two-dimensional array that has the number of 27,000 images and then a series of columns indicating the number of the 10 land cover classes ('AnnualCrop', 'Forest', 'HerbaceousVegetation', 'Highway', 'Industrial', 'Pasture', 'PermanentCrop', 'Residential', 'River', 'SeaLake') that have been previously labelled.

The architecture used is the Sequential Convolutional Neural Network (CNN) by Keras ("Keras: The Python Deep Learning API," n.d.). The strength of CNN's is the ability to automatically learn from a large number of filters in parallel and are often able to detect highly specific features on input images. Therefore, CNN's are widely used for image classification. The construction of CNN architecture in our work is built-up with three blocks of layers:

- First layer block: The first layer block consists of two Conv2D layers with 32 neurons and adds non-linear properties by adding an Activation layer between them. Next, a MaxPooling2Dlayer is defined, which reduces the input sample by taking the maximum value of a window size. The layer block ends with a Dropout layer, which randomly omits 25% of the interconnections.

- Second layer block: The second layer block consists again of two Conv2D layers, but this time with 64 neurons and adds non-linear properties by adding an Activation layer between them. A MaxPooling2Dlayer is then defined, which reduces the input sample by taking the maximum value of a given window size. The layer block ends with a Dropout layer, which randomly omits 25% of the interconnections.
- Third layer block: The third block consists of two dense layers, which are fully connected layers. In between, non-linear properties are added again by adding an Activation layer. The number of neurons in the final dense layer must be the same as the number of land use classes.

Once the model architecture is defined, the hyperparameters are assigned by an iterative process to find the best. Using the following as the best values:

- The loss function used is Categorical crossentropy. It measures the difference between the predicted values and the true labels during training. Categorical crossentropy is a loss function suitable for multi-class classification tasks, in our case land cover classification, where there are several classes to predict. It does this operation by calculating the cross-entropy loss between the predicted class probabilities and the true labels encoded.
- Root Mean Square Propagation (RMSprop) is used. It is one of the most widely used optimisation algorithms in deep learning and responsible for updating the neural network weights during training. The RMSprop optimizer is configured with a learning rate (lr) of 0.0001 and a decay rate of 1e-6 because this combination of learning rate and decay has work well for the specific land cover classification problem. The learning rate controls the step size at which the optimiser updates the weights. A lower learning rate allows for more accurate weight updates, but may slow down convergence. The decay parameter introduces a decay of the learning rate over time, which helps the model to converge.
- The metric for evaluating model performance during training and testing is "accuracy". Accuracy measures the percentage of correctly classified samples out of all samples. It is a widely used metric in classification tasks. In the context of land cover classification, accuracy provides a simple and intuitive measure of the model's ability to correctly predict land cover classes.

Finally, the model after a series of transformations and filters (Convolution 2d, Max-Pool, Flatten) can only predict on subsets of 64x64 pixels being the final resolution of our classification.

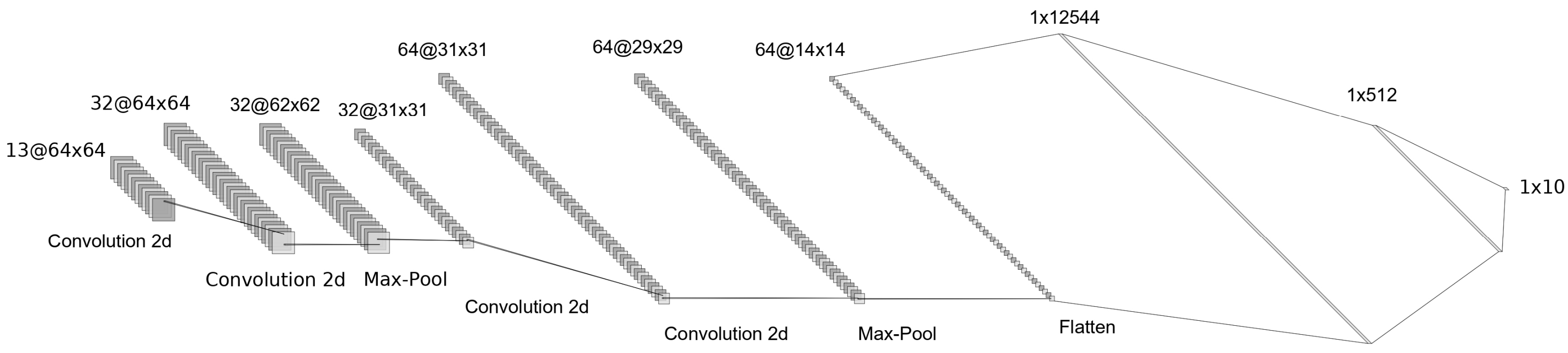


Figure 5. Pretrained model architecture overview.

To generate the land classification of our study area, we first convert the selected Sentinel-2 image into a matrix with unified spatial resolution across all its bands (10 meters). This is a necessary step because not all bands have the same resolution: bands B2, B3, B4, and B8 have a spatial resolution of 10 meters; while bands B5, B6, B7, B8a, B11, and B12 have a spatial resolution of 20 meters; and bands B1, B9, and B10 have a spatial resolution of 60 meters ("Spatial - Resolutions - Sentinel-2 MSI - User Guides - Sentinel Online - Sentinel Online," n.d.). As a result, the image has dimensions of 10980 x 10980 pixels across 13 bands. However, it must be divided further into multiple subsets with the size 64x64 pixels in order to achieve the match resolution as the EuroSAT data, which enables us to use it in the model, and finally obtain the land classification of our study area.

The resulting classification allows for the identification of possible vulnerable elements by intersecting the urban labels to isolate points indicating an unstable displacement pattern. We retain points with values between -2 and +2 mm year^{-1}, which are considered stable (Cian, Blasco, and Carrera 2019). Additionally, the locations of architectural heritage are obtained directly through the QuickOSM plugin for QGIS using the query 'tourism'='attraction' in Portugal. This query retrieves data from OpenStreetMap, encompassing a diverse range of tourist attractions such as historic buildings, monuments, archaeological sites, and other points of interest pertinent to Portugal's tourism landscape. It is worth noting that while this query captures various tourism elements, some may not be directly related to architecture and architectural heritage. To address this concern, the layer generated by the CNN serves as a filtering criterion, selecting only those pixels situated within urbanized land cover ('Highway', 'Industrial', 'Residential'). Nevertheless, there remains the possibility of refining the filtering process to enhance accuracy and restrictiveness, particularly regarding the identification of architectural heritage locations through the QuickOSM plugin. One potential refinement could involve exclusively selecting heritage sites listed in the Sistema de Informação para o Património Arquitetónico (SIPA) catalog. However, in the interest of ensuring the methodology's applicability on a global scale, broader filters were chosen over more localized criteria. This decision allows for the methodology's potential application beyond Portugal, catering to diverse contexts worldwide.

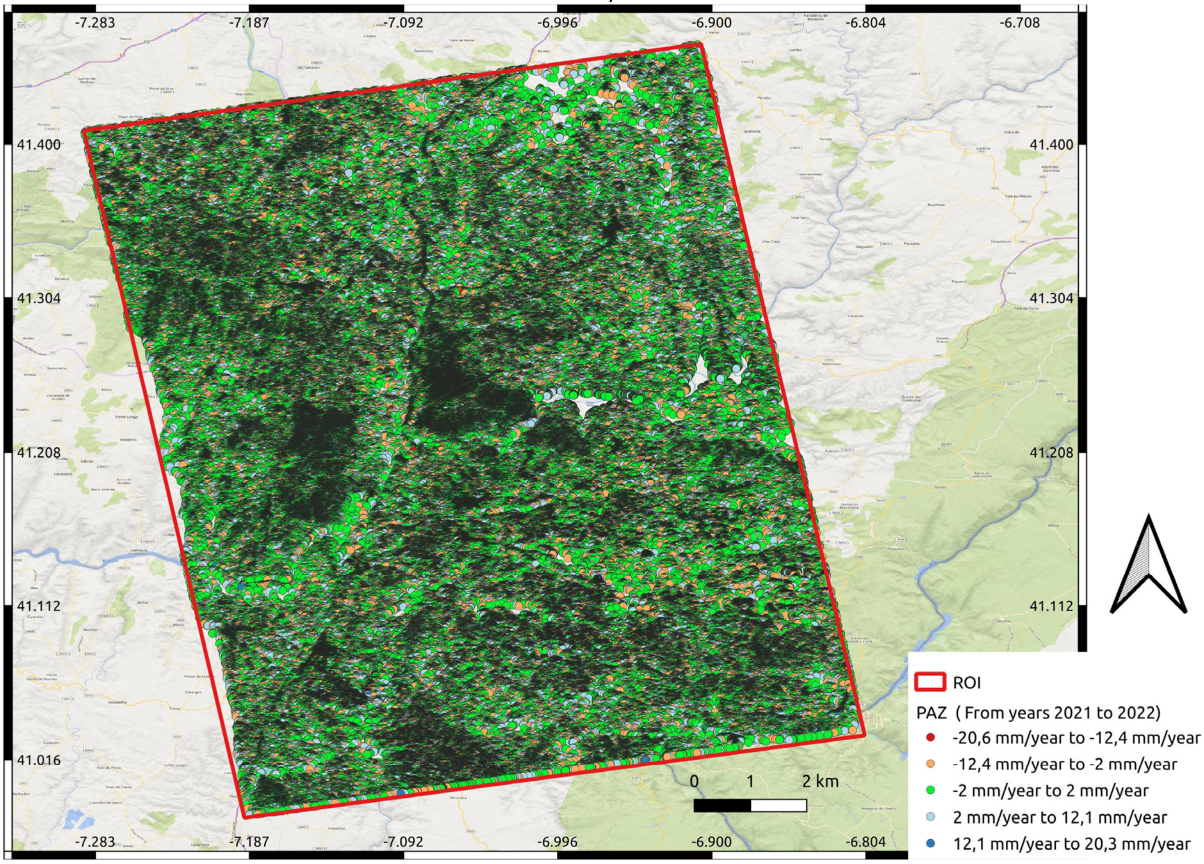
5. Results

For the development of this work, a Dell G5 15 computer is used in order to process the images. It has 15.4 GB memory, with an Intel® Core™ i7-10750H Central Processing Unit (CPU) @ 2.60GHz × 12 processor, an NVIDIA GeForce RTX 2060/PCIe/ SSE2 graphics card and using Ubuntu 18.04.6 LTS as an operating system; In addition, an external memory disk Seagate Expansion Portable drive with 5 TB of memory is used for the storage information.

Regarding the processing performance for the images: the PAZ images require approximately one month of processing to obtain the results, while on the other hand the Sentinel-1 images require approximately 1 week of processing to obtain the results in the same area. The training and inference of the CNNs model for the Sentinel-2 image require a working day. All of this suggests that the use of Sentinel-1 images is more efficient in terms of computational cost.

Concerning the evaluation of the results for the entire coverage of the PAZ images 558,070 PS are obtained (Figure 4), while for Sentinel-1 65,715 PS are found (Figure 6), representing only 12% of the total PS obtained with PAZ. This indicates that PAZ offers a much denser point distribution (this is, more information), which is convenient for a robust infrastructure monitoring. Both types of images showed that the overall study area remains stable (values between –2 and +2 mm year^{-1} are considered stable).

a)


-7.283
-7.187
-7.092
-6.996
-6.900
-6.804
-6.708
41.400
41.304
41.208
41.112
41.016
0 1 2 km
ROI
PAZ (From years 2021 to 2022)
-20,6 mm/year to -12,4 mm/year
-12,4 mm/year to -2 mm/year
-2 mm/year to 2 mm/year
2 mm/year to 12,1 mm/year
12,1 mm/year to 20,3 mm/year

b)

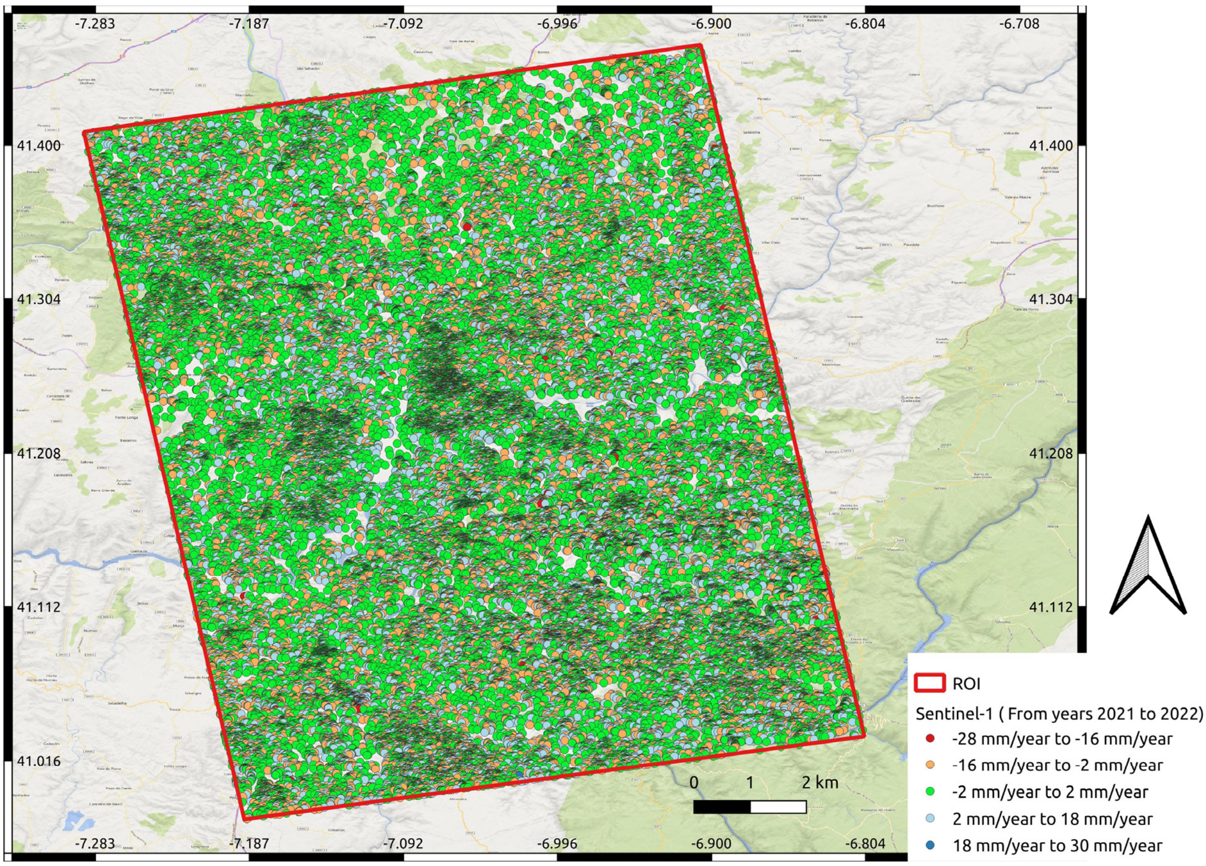
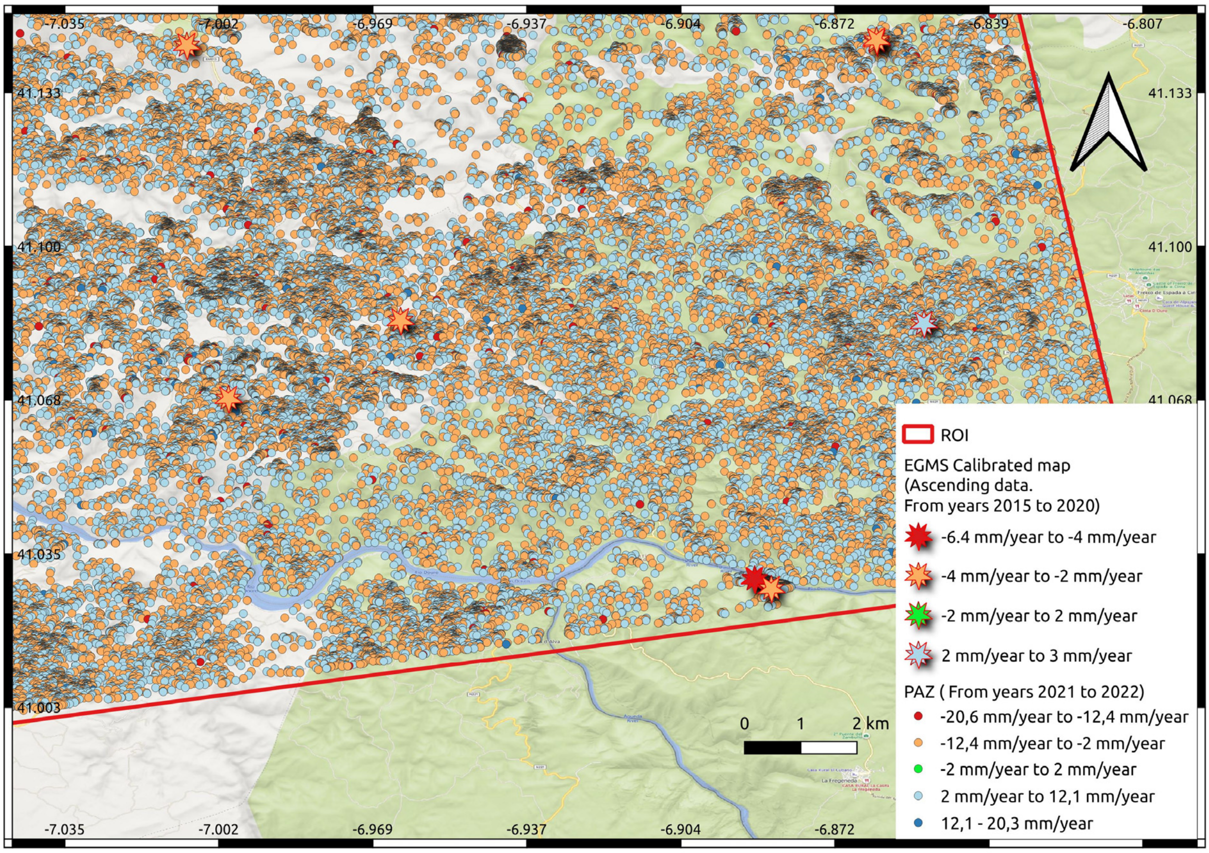

-7.283
-7.187
-7.092
-6.996
-6.900
-6.804
-6.708
41.400
41.304
41.208
41.112
41.016
0 1 2 km
ROI
Sentinel-1 (From years 2021 to 2022)
-28 mm/year to -16 mm/year
-16 mm/year to -2 mm/year
-2 mm/year to 2 mm/year
2 mm/year to 18 mm/year
18 mm/year to 30 mm/year

Figure 6. Comparison of the amount of PS obtained using StaMPS processing between: (*a*) the PAZ images; and (*b*) the Sentinel-1 images.

For the unstable points (those with velocities above 2 mm year^{-1} and below -2 mm year^{-1}), an excess of information is observed in the entire study area compared to the EGMS data. This manifests a large amount of noise due to the short time period of the analysis, which prevents adequate and clear monitoring. Nevertheless, the excess of information or noise should not be eliminated from the analysis since the objective is to discover patterns that may indicate possible vulnerabilities in infrastructures.

a)



b)

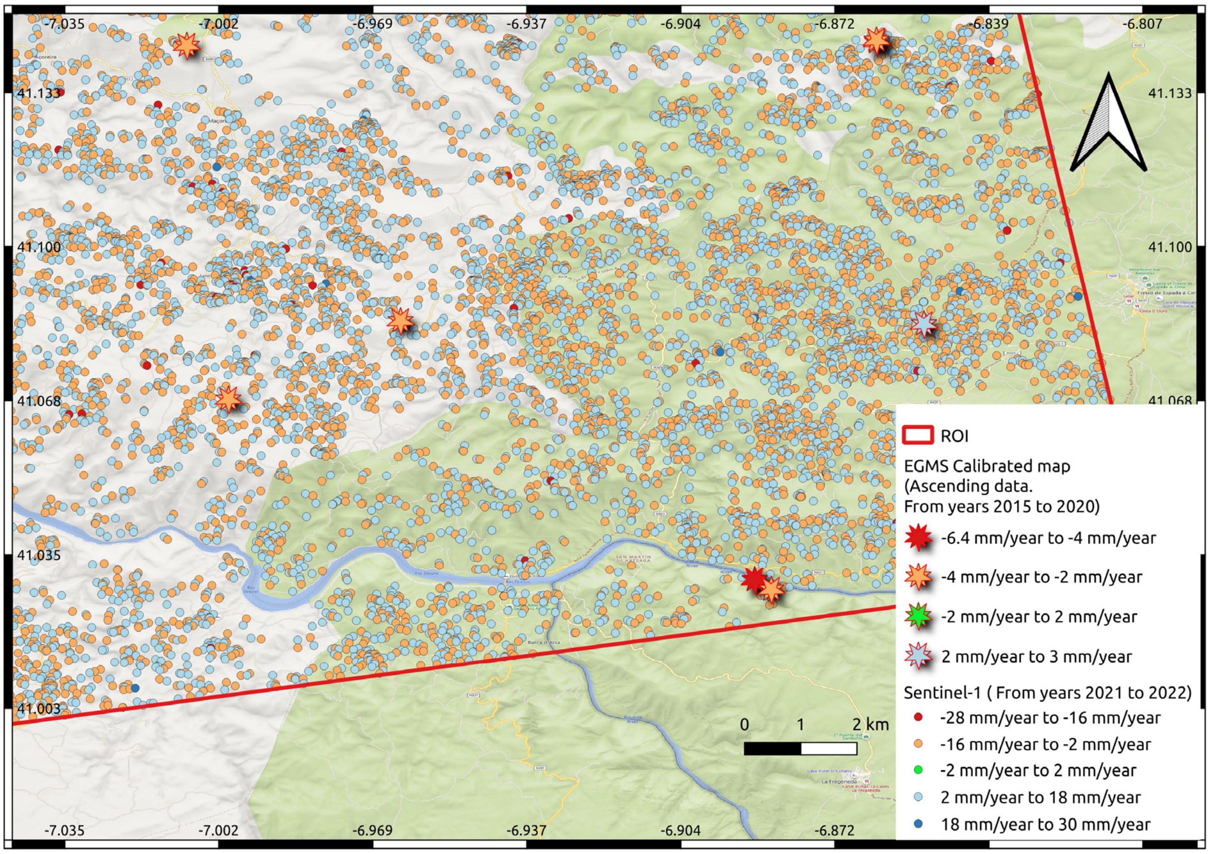


Figure 7. Detail of a part of the study area, with both images (PAZ (*a*) and Sentinel-1 (*b*)). The noisy PS can be easily observed by selecting unstable areas compared to those obtained with EGMS (unstable points are those with velocities greater than ± 2 mm year^{-1}).

Regarding the geographical coincidence with displacement values between the two types of images (27,630 pixels matches when both images are set to the minimum resolution of Sentinel-1, that is, 20 m of pixel size), several points are perceived where the difference between them is notable (Figure 8). Specifically, 24% of the pixels have an error below one millimeter (6,717 pixels). When considering only the selected pixels that match the location of the pixels classified as 'Residential' by the CNNs, there are 11,056 pixels, of which 26% have an error of less than one millimeter (2,918 pixels).

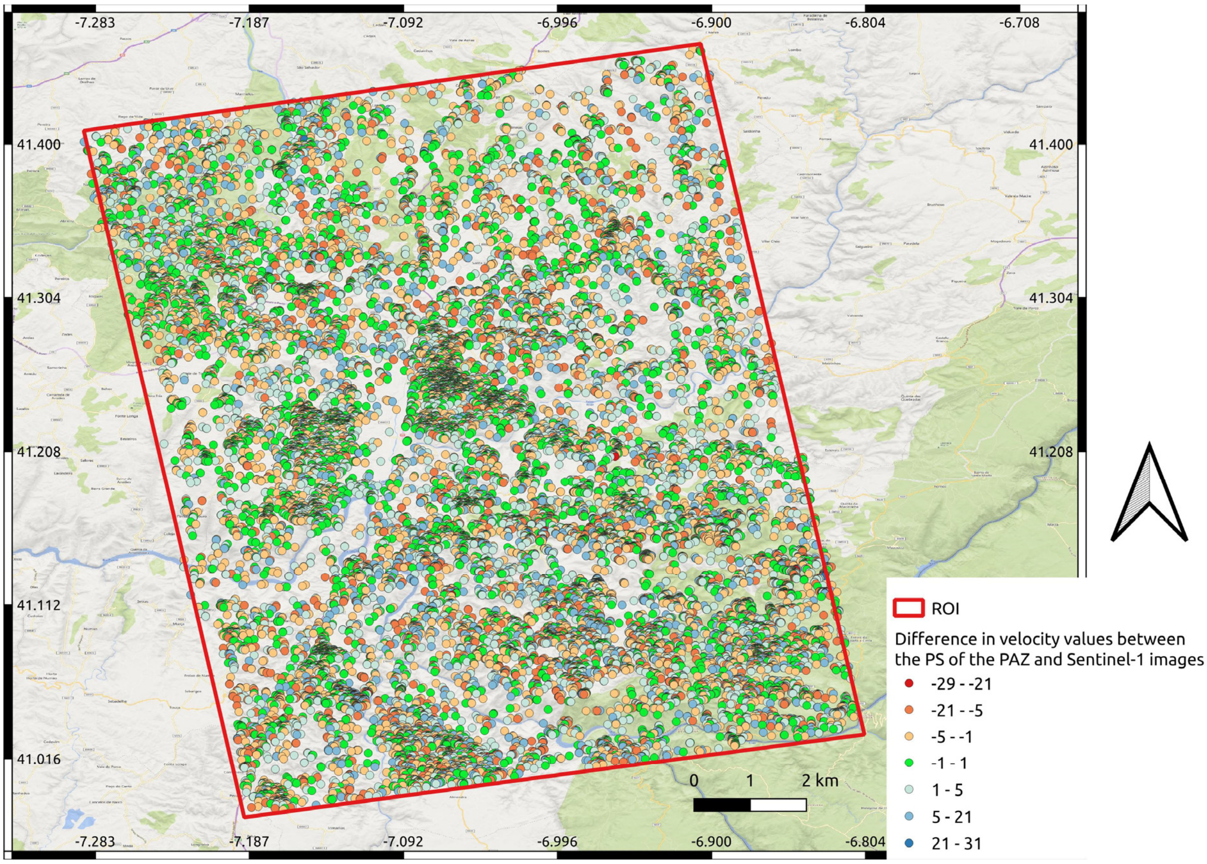


Figure 8. Existing error for the same pixel between the displacement values obtained in the processing of the PAZ images versus the Sentinel-1 images.

Furthermore, our results are supported by the analysis of mean error metrics and the Root Mean Square Error (RMSE) for the entire study area, confirming good accuracy in all comparisons made. Specifically, we observed mean errors of less than one millimeter per year, with values of 0.13 mm year^{-1} between the PAZ and Sentinel images. When validating the results with both images and comparing them with the official and reliable source of EGMS data, we obtain an equally accurate performance in the mean error, achieving 0.14 mm year^{-1} between PAZ and EGMS, and 0.17 mm year^{-1} between Sentinel and EGMS. This is evidence that PAZ data, due to its better resolution, achieves superior accuracy. Furthermore, the RMSE analysis confirms the reliability of our results, revealing consistent values between the different satellite datasets, with an RMSE between PAZ and Sentinel of 4.27 mm year^{-1}, and when validated with the official and reliable source of EGMS data, an RMSE between PAZ and EGMS of 1.95 mm/year, and between Sentinel and EGMS of 2.50 mm year^{-1}. These metrics therefore robustly validate the accuracy and consistency of our deformation data between the various sources used, as well as their comparison and validation with the EGMS data.

The differences between the predicted displacements by the two sources of images may be due to the differences in atmospheric conditions at the moment of acquisition, which greatly influence the results in the treatment of radar images. Additionally, the Line Of Sigh (LOS) direction and resolution have different values in PAZ and Sentinel-1 images. Finally, the vegetation areas may not be entirely accurate, which causes large differences when comparing the values obtained from Sentinel-1 and PAZ images, respectively. However, the graph (Figure 9) shows that the vast majority of the pixels that coincides between Sentinel-1 and PAZ, have comparable displacement values, with minor differences of $\pm$4mm.

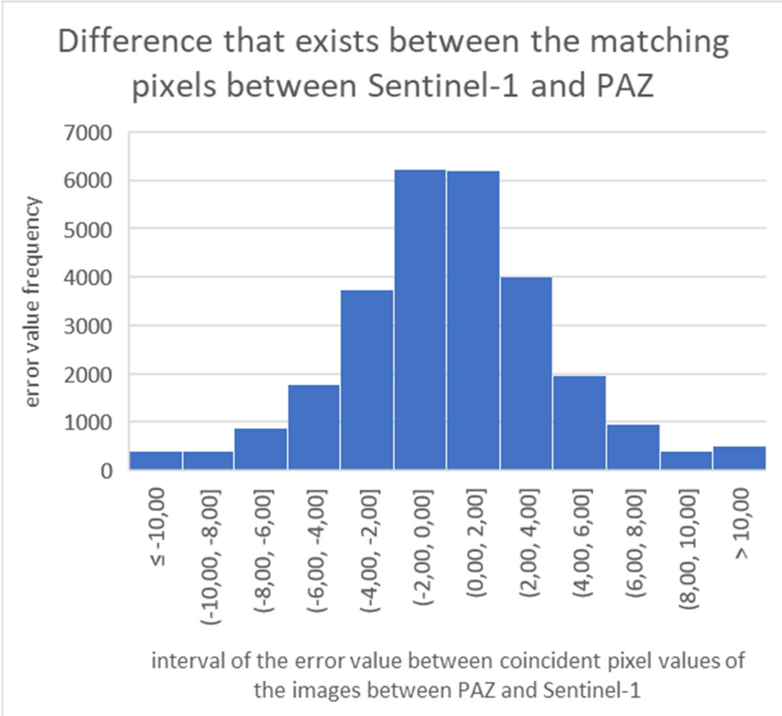


Figure 9. Difference that exists between the matching pixels between Sentinel-1 and PAZ.

This excess of information of unstable values is solved by overlaying the map generated through the CNN model and also adding the architectural heritage layer obtained directly through the QuickOSM plugin for QGIS (Figure 10). In this sense the overall classification accuracy of the deep learning method used in the identification of the Earth's large-scale land surfaces (or in other words the detection of changes in land use and land cover) is 98.57% (Helber et al. 2019).

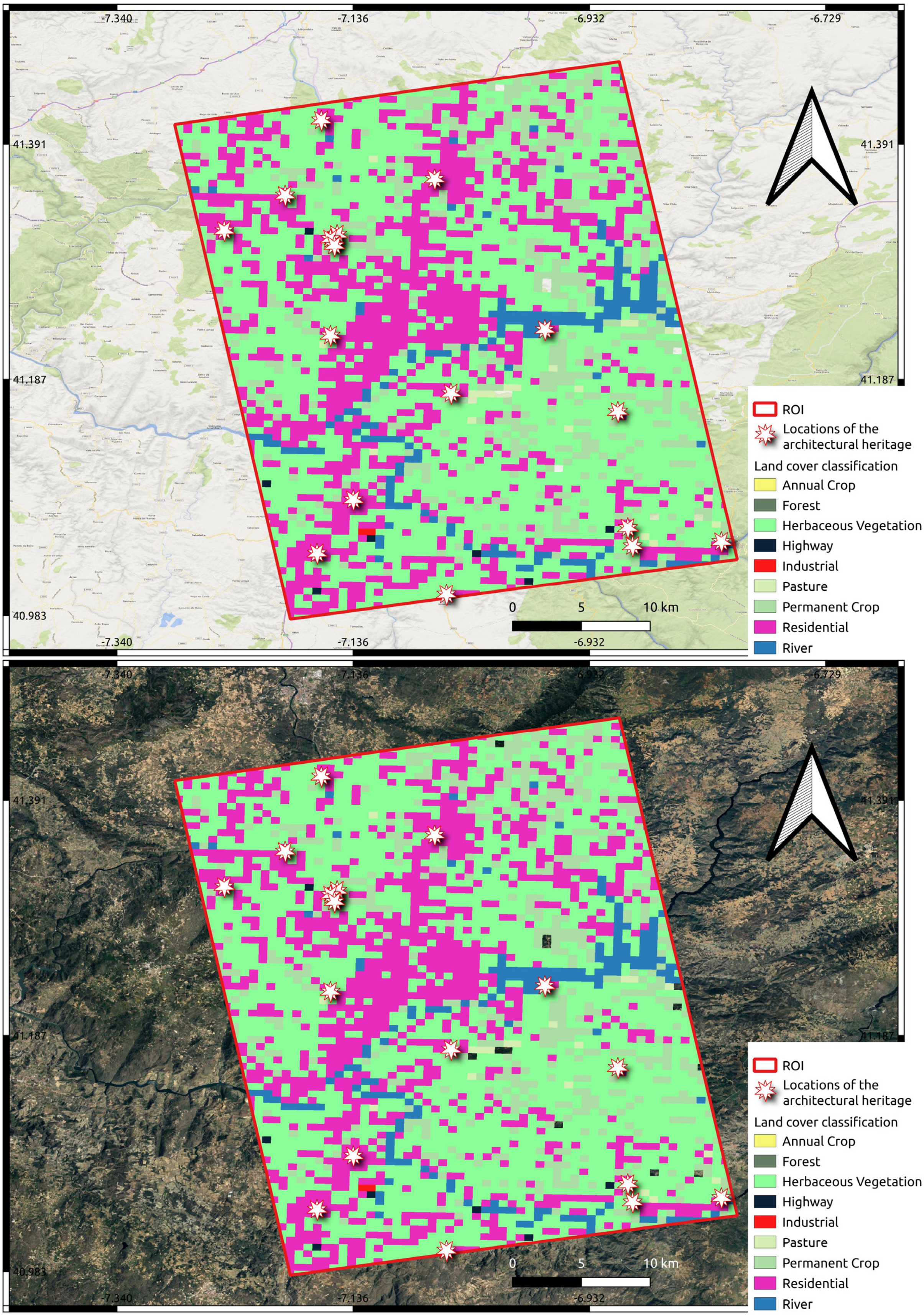
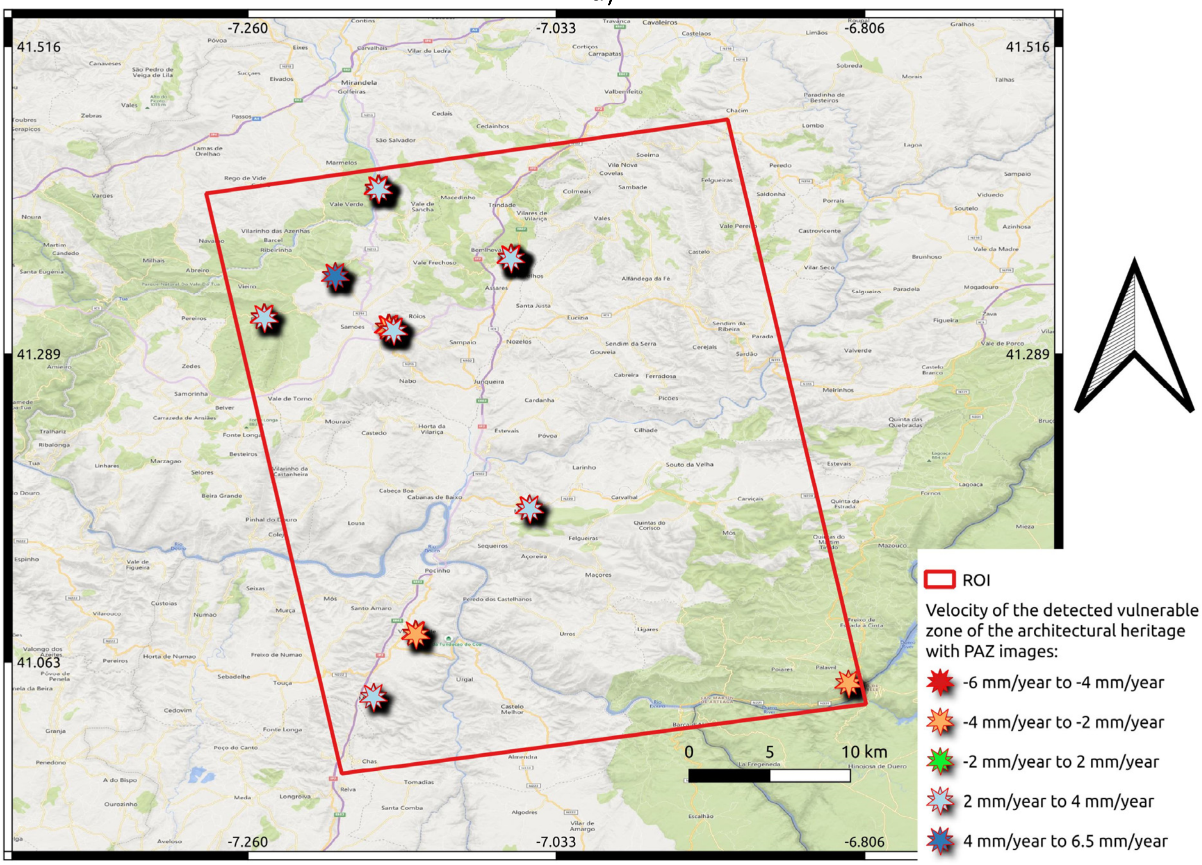


Figure 10. Land cover classification obtained through a Sentinel-2 image and Deep Learning, adding the location of the architectural heritage.

With the proposed methodology, the vulnerable architectural heritage can be immediately identified, reducing excess information or alert in areas that do not belong to the architectural heritage (Figure 11). Due to the fact that PAZ images provide a much greater density of points of information, it is more suitable for applications needing more detailed monitoring as is the case of infrastructure assets (due to its higher spatial resolution. In the case of PAZ, this spatial resolution (as noted above in section 3 in Table 1) was 3 to 6 m, as opposed to 20 m for Sentinel-1, which allowed it to capture finer details on the surface of buildings). Thus, in our case study 9 vulnerable areas were found from PAZ data, compared to the 7 areas found from the Sentinel-1 data. It should be noted that, if we were to use the SIPA catalogue data as a filtering mechanism to identify architectural heritage locations, only the church area of the city of Vila Nova de Foz Côa would rate as vulnerable architectural heritage when crossing all datasets (including ground movement and land cover classifications) for the whole of our Case Study. This is due to the more stringent criteria imposed by the SIPA catalogue for delimiting architectural heritage, in contrast to our methodology, which takes a broader approach to the inclusion of architectural heritage.

a)



b)

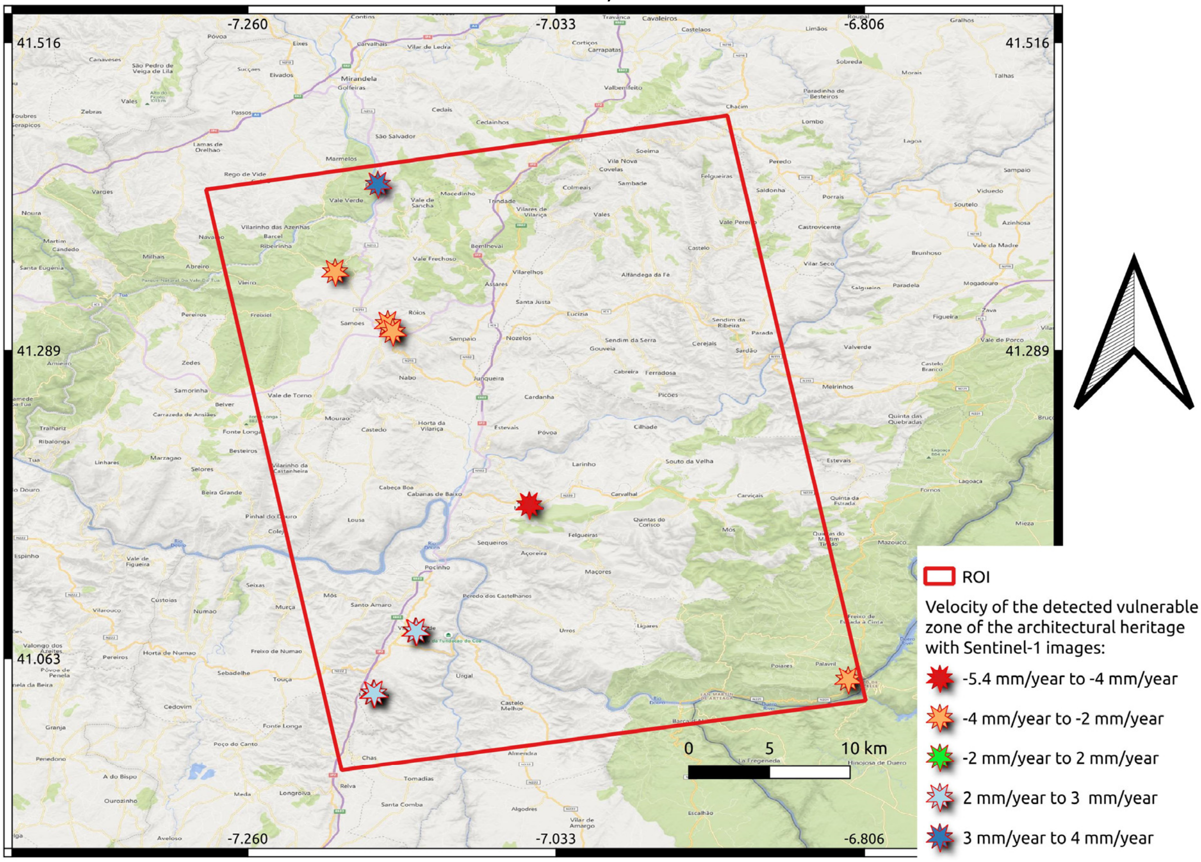


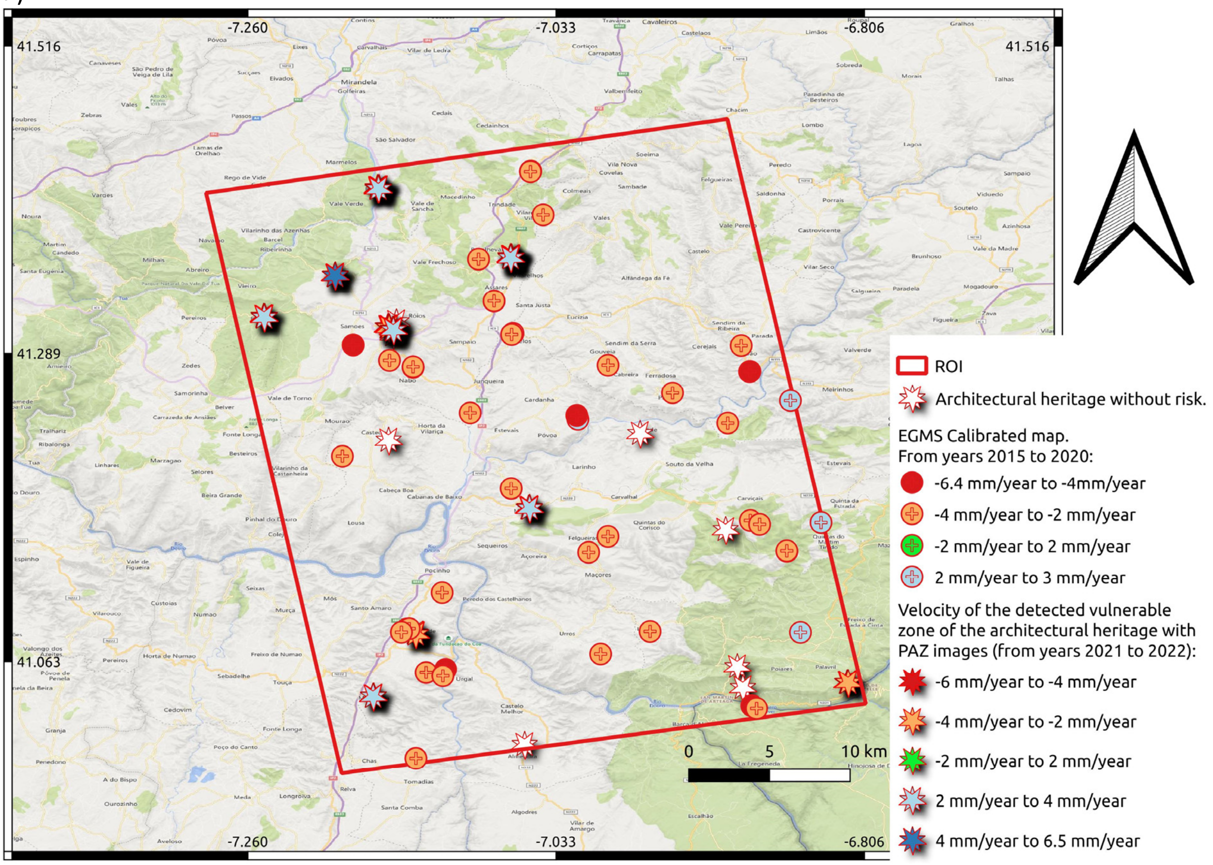
Figure 11. Final result of the vulnerable architectural heritage map combining all the information layers (PAZ (*a*) vs Sentinel-1(*b*)).

Figure 12, in the figure a) shows six areas (in white star symbol) where architectural heritage with stable values (within a range of ±2 mm year^{-1}) were identified but excluded from vulnerability considerations. Conversely, nine areas neighboring architectural heritage displayed unstable values (with a star symbol, both blue or red tones), prompting vulnerability considerations. However, an analysis of ground motion data spanning from 2015 to 2020, sourced from the EGMS, identified 30 regions marked by unstable velocity values (marked with a circle and a cross). Intriguingly, only one of these regions overlapped with the vicinity of the identified architectural heritage. In the figure b) of the Sentinel-1 data similarly identifies seven vulnerable zones derived from unstable values (with a star symbol, both blue or red tones), while eight regions are observed that present stable values and are therefore considered as non-vulnerable heritage (in white star symbol). Again, when analysed with the EGMS data (marked with a circle and a cross), only the case of unstable EGMS values is located in the vicinity of architectural heritage.

In the Figure 12 it is evident that, with the EGMS data, the only unstable value that is close to the architectural heritage (marked with a circle and a cross) is located in the Vila Nova de Foz Coa, however, upon closer examination of this city (in Figure 13), the unstable areas indicated by EGMS data (marked with a circle and a cross) do not precisely align with the explicitly identified architectural heritage (Igreja Matriz). However, vulnerable areas are specifically detected in the surroundings of the church both with the images Sentinel-1 (locating 2 vulnerable areas with unstable values from + 2 mm year^{-1} to + 3 mm year^{-1} identified with a cross symbol) and with the images PAZ (locating 4 vulnerable areas with unstable values from

- 2 mm year-1 to -4 mm year^{-1} identified with a star symbol). Haga clic o pulse aquí para escribir texto.

a)



b)

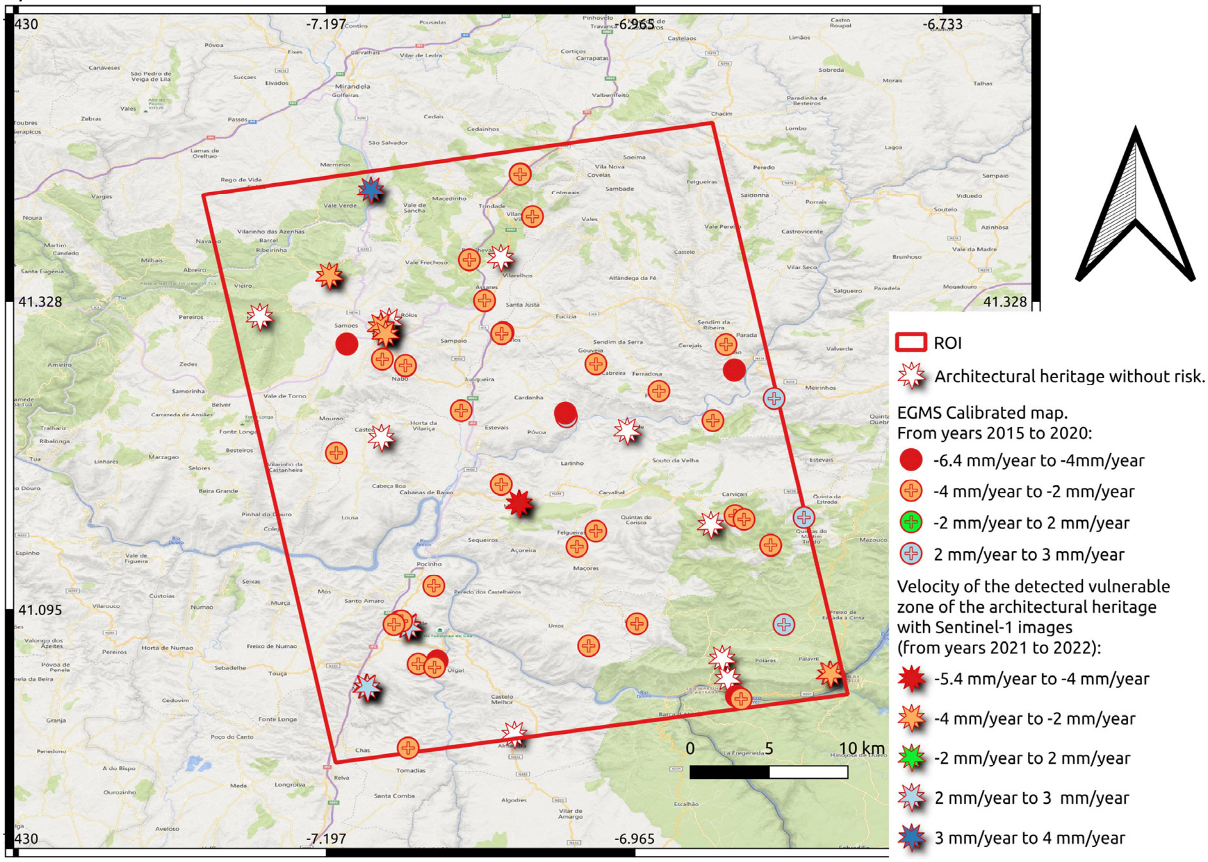


Figure 12. Comparison of the results obtained with both PAZ (*a*) and Sentinel-1 (*b*) with the EGMS data.

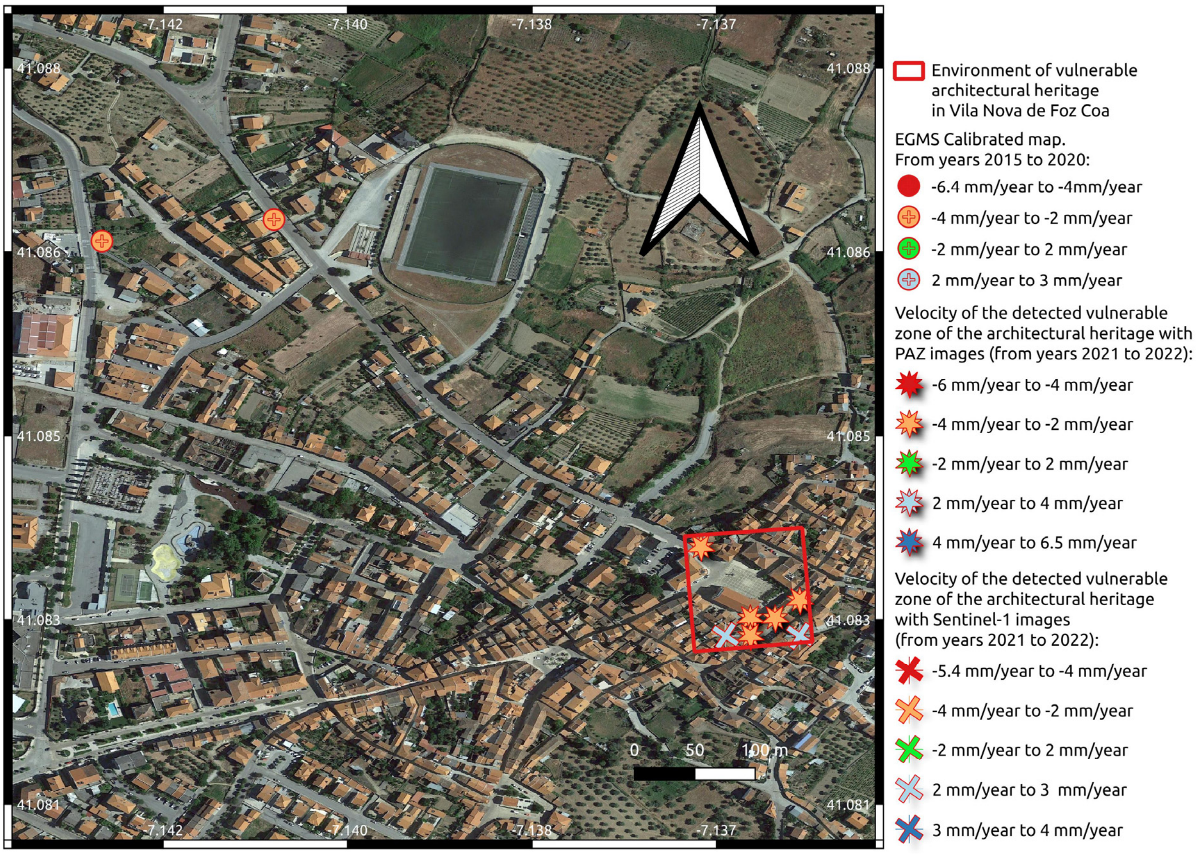


Image 13. Detail of 1 of the areas detected as vulnerable architectural heritage environment in Vila Nova de Foz Coa.

Therefore, comparing the results obtained with both PAZ and Sentinel-1 with the EGMS data, there is no coincidence in the identification of vulnerable areas except for Vila Nova de Foz Coa (Figure 12) where several buildings in the town show pathological patterns typically associated to settlements of the terrain, suggesting exposure to geotechnical risk. Even so, the most vulnerable EGMS data is not located in the architectural heritage environment of Vila Nova de Foz Coa either (Figure 13). It must be noted that the EGMS service is based on medium resolution Sentinel data and is not constantly updated with the latest data, so it aims to provide a large-scale information service, i.e. it is not intended to analyse infrastructures in detail. Therefore, since X-band satellite images (PAZ) offers higher sensitivity to target displacement, higher resolution and higher robustness compared to C-band (Sentinel-1) (Ferretti et al. 2011), using this data in our methodology allows to detect vulnerable areas with higher accuracy.

6. Discussion

The utilization of MT-InSAR technology has significantly advanced the field of risk anticipation, as evidenced by numerous studies focusing on infrastructure such as bridges (Sousa and Bastos, 2013), as well as dams and buildings (Bakon et al., 2014). Additionally, there exists particular research dedicated to the analysis of architectural heritage (Drougkas et al., 2020; Le et al., 2016; Cigna et al., 2014), and archaeological and cultural heritage (Tapete and Cigna, 2019). These studies have predominantly relied on established satellite image sources such as ENVISAT, TerraSAR-X, ERS 1, Sentinel-1, and COSMO-SkyMed StripMap. However, our study represents a novel approach by exploring the potential of Spanish PAZ satellite images, which have only recently come into use, yielding promising results in detecting vulnerable architectural heritage sites.

Furthermore, traditional soil classification methods have heavily depended on optical images. Yet, recent advances in deep learning have catalyzed a paradigm shift in this domain, enhancing classification accuracy and automating processes. Notably, deep learning techniques have facilitated the extraction of building footprints (Bischke et al., 2017) or for tasks such as land cover mapping focused on small objects such as buildings (Kampffmeyer, Salberg, and Jenssen 2016). In our study, we leverage these advancements by utilizing the Eurosat dataset and deep learning methodologies (Helber et al., 2019) to identify architectural heritage locations, through cross-referencing them with QuickOSM data. This approach enables the identification of urban areas in regions where such information is otherwise unavailable, facilitating the creation of maps for specific vulnerable environments. Also enables a reproducible methodology applicable across various geographic contexts at minimal costs.

The results presented in the precedent sections suggest that radar images, despite their current wide use, are an interesting source of information to be considered in urban planning. This is one more element providing relevant information to support the vulnerability analysis of architectural heritage from a large-scale perspective. Starting from different satellite data, Sentinel-1images as well as PAZ images it is possible to submit both datasets to a methodology that allows identifying vulnerable infrastructures. As expected, the higher quality in terms of spatial resolution of PAZ overperform the of Sentinel-1 results; considering that the cost of accessing to PAZ images (operated by a private company), further investigations are needed to improve the outputs of Sentinel-1 images and thus valorise the EU investments in the freely accessible Earth observation.

In view of the results obtained when implementing our proposed methodology, we suggest to adopt a multi-scale approach where Sentinel-1 images are used for a coarse analysis (larger scale) to identify vulnerable areas and subsequently acquiring PAZ images for a detailed analysis of the infrastructure assets in those areas that have been previously detected at a potential vulnerabilities. This approach allows for the confirmation or elimination of suspicions and can be accompanied by an on-site expedition to confirm potential vulnerabilities. Compared to other on-site monitoring techniques such as Global Positioning System (GPS), levelling, and accelerometers, this methodology is less costly and requires fewer human resources to cover large areas of land. Thus, it helps to prioritize those constructions that need to be further monitored with more sophisticated systems.

The combination of multiple techniques, including MT-InSAR (Sousa and Bastos 2013; Bakon et al. 2014; Drougkas et al. 2020; Le et al. 2016; Abdikan et al. 2020; Cigna et al. 2014; Tapete and Cigna 2019), Deep Learning (Helber et al. 2019; Bischke et al. 2017; Kampffmeyer, Salberg, and Jenssen 2016), and satellite images, which are typically applied in isolation, represents significant contribution in applications to cultural heritage preservation. Our research advances in the knowledge by showcasing the potential of this integrated approach in generating accurate maps.

Higher-resolution optical satellite images (like QuickBird or WorldView-4) could offer finer details, but their cost limits accessibility. Our approach aims for broad replicability, crucial for heritage preservation in resource-limited urban areas. We primarily used Sentinel-2 adequate spatial resolution for the analysis of threats to cultural and archaeological heritage, complemented by PAZ and Sentinel-1 high and medium radar imagery to identify vulnerable heritage sites and adjacent unstable areas, ensuring the effectiveness of conservation efforts.

In this study, we explore the use of PAZ images, which demonstrate promising resolution results for urban analysis. Although their utilization has been limited thus far, our findings suggest that PAZ images can offer significant benefits in the conservation of architectural heritage. However, it is important to note that our study can be further enhanced by incorporating a larger sample of images over an extended period. This would definitely increase the robustness of results, contributing to a more comprehensive understanding of the capabilities and limitations of PAZ images in urban planning. For that reason, it is important to consider the potential offered using cloud-based mass-analysis applications such as Google Earth Engine or WEkEO or SARIPA. These platforms provide powerful tools for efficient image processing and analysis on a large scale. Integrating ground motion data into such platforms could significantly expand our capabilities for urban assessment and architectural heritage conservation. This approach would not only allow us to work with a larger volume of data, but also to take full advantage of the processing power and advanced analysis tools available in the cloud.

It is essential to continue investigating planning strategies for the conservation of architectural heritage using maps. Urban planning in intermediate cities can serve as strategic planning to guide sustainable development of future cities, making them more inclusive and diverse. This implies the reduction of "the margins" in terms of planning and urban management of the territory, for the conservation of the architectural heritage (especially present in these intermediate cities), using a transdisciplinary perspective that considers spatial, technical, economic and social aspects, comprehensively addressing territorial, urban, architectural and tourism challenges of urban planning and management.

7. Conclusion

This paper presents a novel methodology for the assessment of urban infrastructure stability in intermediate cities that may not have sufficient resources for effective monitoring of their architectural heritage, comparing high-resolution PAZ images and medium-resolution Sentinel-1 data. The combination of these diverse data sources, along with the application of advanced processing techniques, forms the basis of our approach. By harnessing the power of convolutional neural networks (CNNs) and leveraging the EuroSAT dataset and the information on the geographic location of the architectural heritage through the QuickOSM plugin, we are able to detect architectural heritage vulnerable to ground subsidence.

In this study, we analyze 21 high-resolution PAZ images to compare and determine whether the same period and number of medium-resolution Sentinel-1 images can achieve similar results. The use of free images with satisfactory outcomes can enhance accessibility to information for prevention. The automatic generation of maps through deep learning represents a significant advantage, particularly for areas with limited economic resources, such as intermediate cities, in the monitoring of their architectural heritage.

Our results demonstrate that both PAZ and Sentinel-1 successfully detect vulnerable infrastructures. However, due to its higher resolution, PAZ outperforms Sentinel-1 in detecting a greater number of vulnerable assets. Therefore, high-resolution images are ideal for infrastructure monitoring as they provide a higher density of information points. Nonetheless, access to PAZ images comes at a cost, making the use of Sentinel-1 more favourable for the automatic creation of maps due to its high-quality results.

To validate our methodology and identify unstable areas, we utilized the official and reliable EGMS data (from 2015 to 2020) with an ascending acquisition geometry similar to that of PAZ and Sentinel-1 images. Allowing validation using mean error and RMSE metrics, resulting in high accuracy and consistency in the deformation data between the different images used, as well as with the EGMS data, ensuring the accuracy and reliability of the data analysed. However, we found that the locations of vulnerable architectural heritage identified in our analysis do not coincide geographically with the EGMS data as EGMS is a large-scale information service, i.e. it is not intended to analyse infrastructure vulnerabilities in detail. Moreover, the differences in results can be strongly conditioned by the characteristics of the images. We found that X-band satellite images (PAZ) offers higher sensitivity to target displacement, due to its higher resolution and higher robustness compared to C-band (Sentinel-1).

In this study, we demonstrate the value of integrating multiple techniques to extract valuable information from optical and radar satellite images. Specifically, we employ convolutional neural networks (CNNs) and the EuroSAT dataset to extract land cover information from Sentinel-2 optical images. This synergy enables us to rapidly identify patterns of instability and vulnerable areas in architectural heritage.

Despite the mismatch between instability patterns and the EGMS data, our work represents a significant advancement in leveraging the advantages of earth observation using satellite images and deep learning in intermediate cities.

Furthermore, our study allows for a comparison of the advantages and disadvantages of PAZ images, which have been underutilized until now, with the widely adopted Sentinel-1 images. We discover that PAZ images provide a higher density of displacement information points, which is crucial for effective infrastructure monitoring.

Overall, our work emphasizes the importance of employing a diverse range of techniques and data sources to attain a comprehensive understanding of complex phenomena like urban infrastructure stability. We hope that this study will inspire further research in this field, as we firmly believe that the combination of deep learning and satellite imagery holds immense potential to enhance our comprehension of urban environments and foster sustainable development by reducing "the margins" in terms of urban spatial planning and management.

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