Built-Up Area Mapping at Large-Scale using Sentinel-1 SAR Data and Deep Learning

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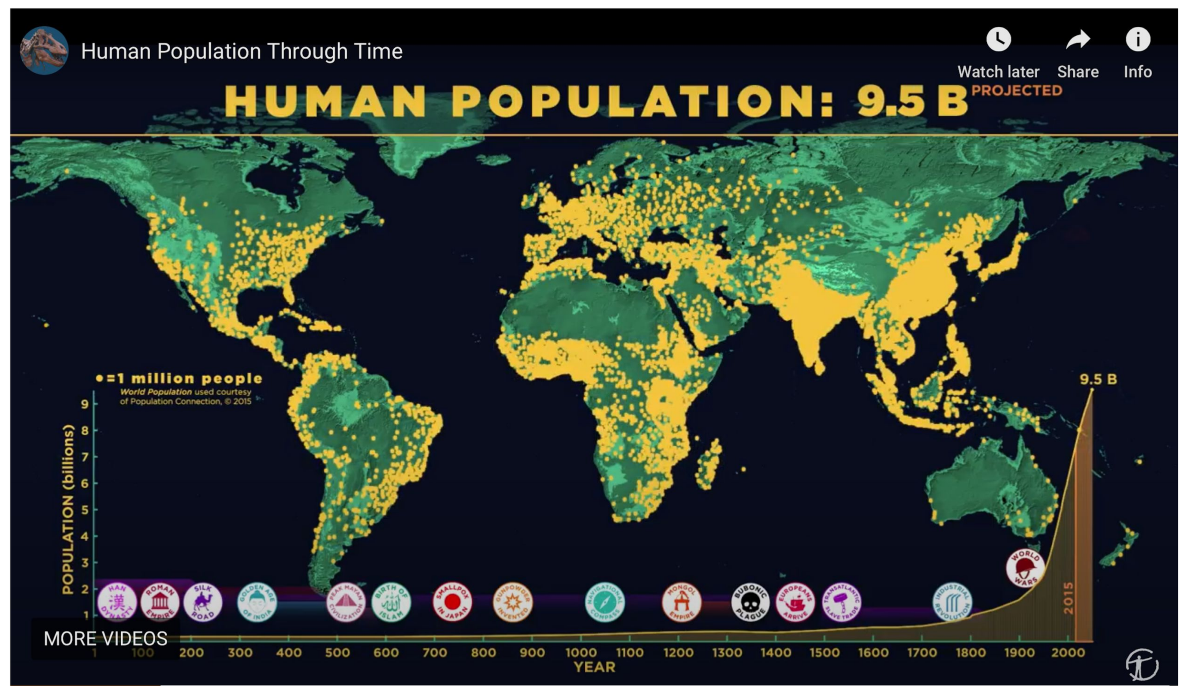
Introduction

Today, more than half of the world population is living in cities, and by the middle of the 21st century, two thirds of the population is projected to reside in urban areas. High resolution, timely and reliable Built-Up Area (BUA) mapping plays an important role in supporting sustainable urban development. Past studies demonstrated that Synthetic Aperture Radar (SAR) is effective in detecting BUA [1, 2]. Deep learning algorithms, specifically Convolutional Neural Networks (CNNs), have recently gained popularity for BUA mapping from Sentinel-2 (S2) MultiSpectral Instrument (MSI) data [3]. The lack of cloud-free data may, however, hamper the updatability of optical-based BUA mapping. In contrast to S2, the Sentinel-1 (S1) Synthetic Aperture Radar (SAR) mission is able to acquire data in cloudy conditions as well as during day and night. Therefore, this research aims to explore the potential of S1 data for mapping BUA using a CNN and open data as labels.



Method

Our proposed workflow to extract BUA from Sentinel-1 SAR imagery is illustrated in Fig. 1. We collected all available S1 SAR scenes acquired in the Summer 2016. S1 SAR scenes were preprocessed to Ground Range Detected (GRD) images using the S1 Toolbox. We then computed the per-pixel temporal mean backscatter to remove speckle noise. Finally, pixel values were normalized. As reference data, we leveraged Microsoft's building footprints dataset which is openly available for the United States. In total, we collect data in 8 American cities, where 6 were used for training and 2 for validation (Fig. 2).

We trained U-Net [4], a CNN architecture originally designed for medical image segmentation, for 40 epochs with batch size 16 using a Jaccard-like loss function. The learning rate was set to 10^{-4} and Adam was used as optimizer. The network outputs a probability which was split into BUA and non BUA using a cut-off value of 0.5. F1 score was calculated using 10,000 validation points in Beijing. Pixels correctly detected as BUA are considered true positives (tp), while all undetected BUA pixels and incorrectly detected built-up area pixels are considered false negatives (fn) and false positives (fp), respectively.

$$F_1 = \frac{tp}{tp + \frac{1}{2}(fp + fn)}$$

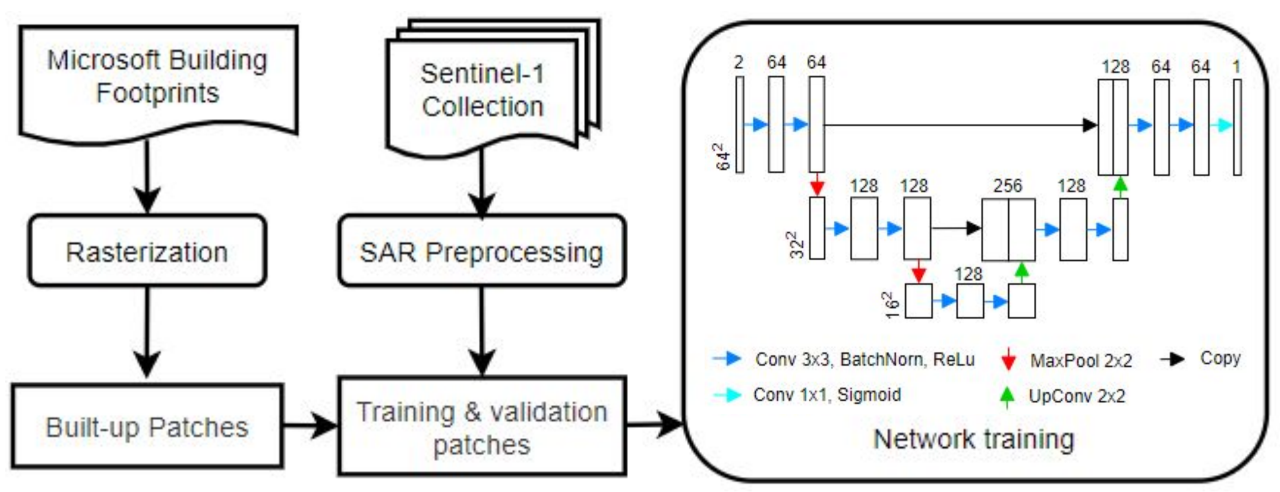


Figure 1: Simplified workflow of our built-up area mapping approach.

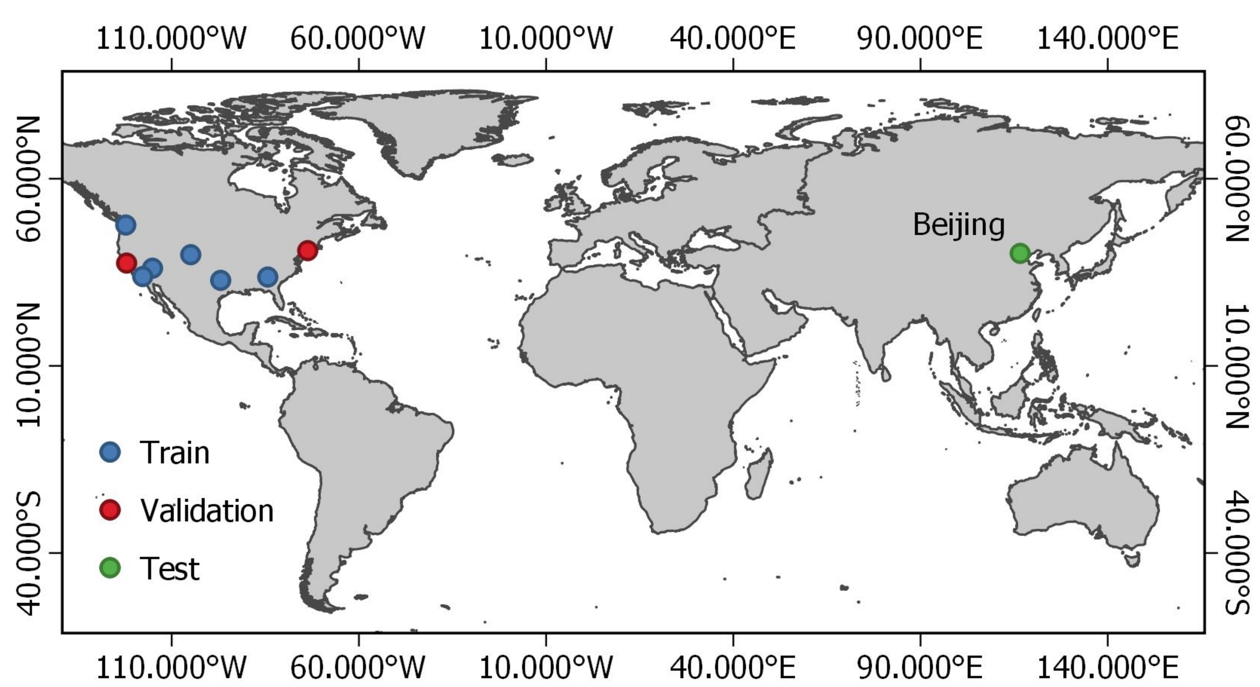


Figure 2: Overview of study area showing training, validation and test sites.

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Results

The left subplot of Fig. 3 shows the training loss. Initially, the loss decreased rapidly and then converged after approximately 10 epochs. The right subplot of Fig. 3 shows a precision-recall curve comparing our results for Beijing to those of the GHS-S2Net [3]. Since similar curves were obtained for both products, we demonstrate that our approach using S1 SAR data is capable of producing BUA maps of comparable quality to a network trained on S2 MSI data. For the quantitative assessment with the 10,000 validation points, we obtained an F1 score of 0.863 and precision and recall values of 0.995 and 0.763, respectively. These results emphasize the good quality of our results.

Qualitative results are shown in Fig. 4 a) for Beijing. Additionally, zoomed in regions of Beijing with varying built-up density are shown for two Region Of Interests (ROIs) in Fig. 4 (b-e). The network performs well in neighborhoods with high built-up density but also in regions with sparse density as shown by Fig. 4 c) and e), respectively. Moreover, the network is capable of distinguishing roads from buildings. Therefore, our mapping approach shows strong potential to produce a global product of BUA with frequent updates.

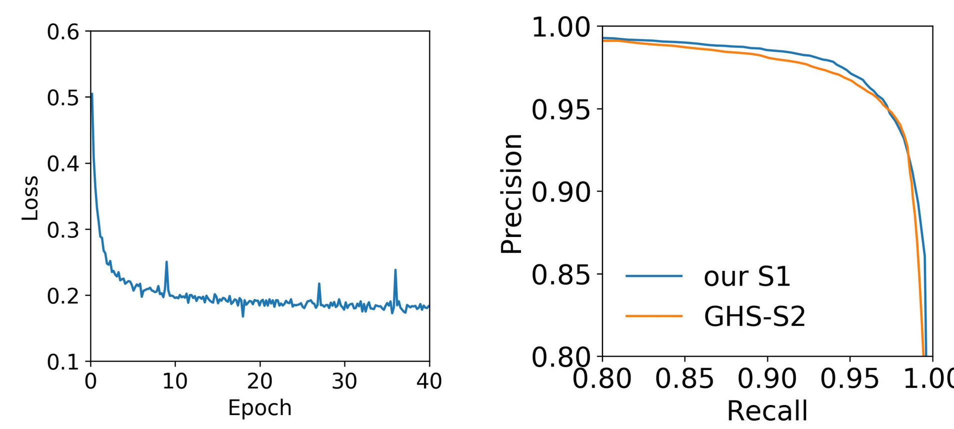

Figure 3: (left) Training loss curve and (right) precision-recall curve comparing our results to GHS-S2 [3].

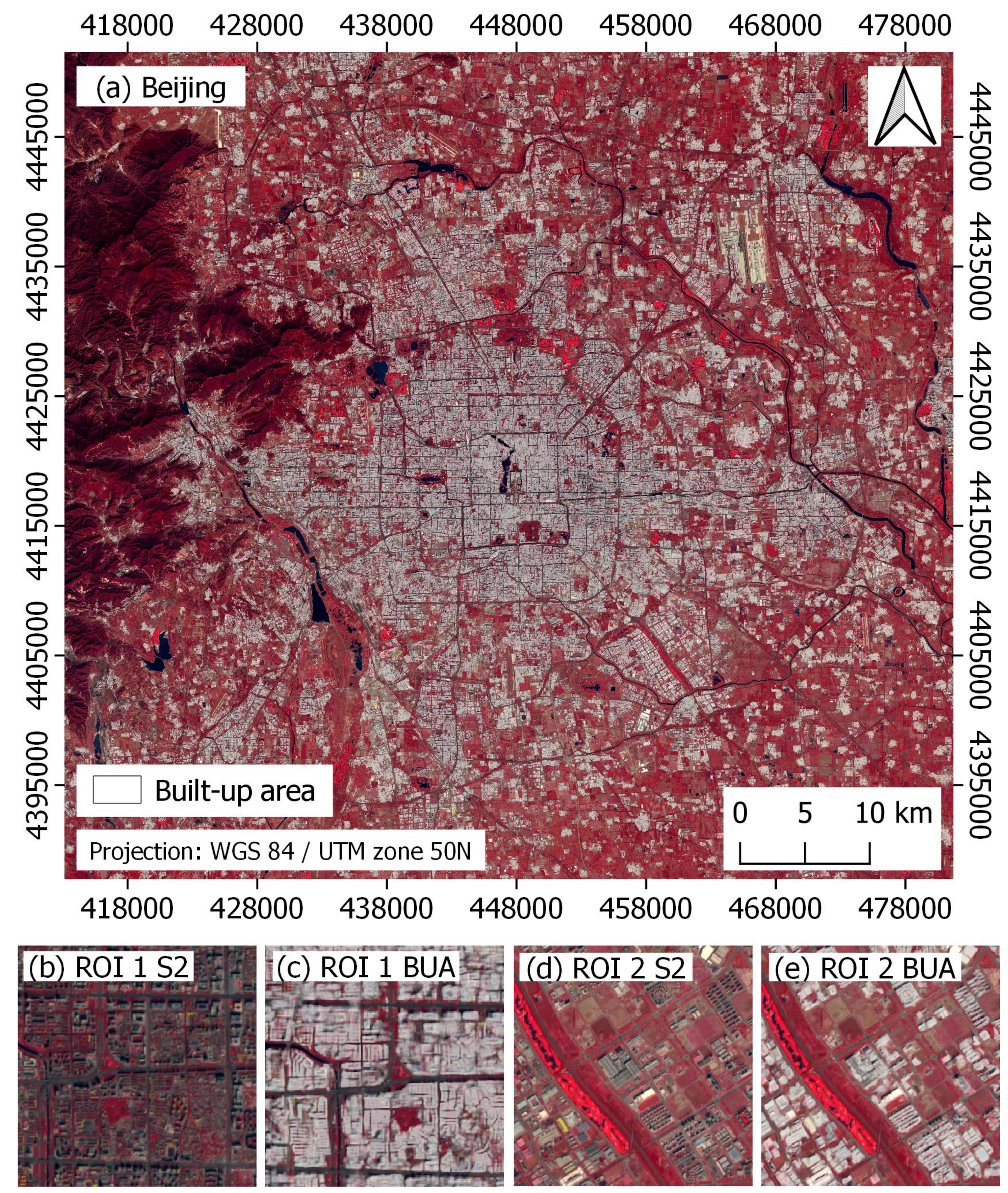

Figure 4: Built-Up Area (BUA) maps at 10 m resolution for (a) Beijing and (c & e) zoomed in regions with varying built-up density. (b & d) show the corresponding Sentinel-2 (S2) images (red: B8, green: B4, blue: B3) which are also used as background for the BUA maps.

Conclusion

Detailed and up-to-date BUA maps provide essential information about the ongoing urbanization. In this poster, we developed a BUA mapping approach using S1 SAR data and deep learning. The proposed S1 SAR-based approach produced accurate results that are of comparable quality in Beijing to the state-of-the-art using S2 MSI data. Furthermore, we demonstrated that a network trained in North American cities is transferable to a Chinese city, specifically Beijing. However, more research is required to further test the generalization capability of the proposed approach in a diverse set of cities.

Future Steps

- Test the proposed BUA mapping approach globally and improve its generalization capability.
- Investigate SAR-optical data fusion for BUA mapping by incorporating S2 MSI data into our current methodology.
- Develop methods to effectively detect newly constructed BUA in dense S1 SAR time series using the proposed mapping approach

References

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