Sci-Net: scale-invariant model for buildings segmentation from aerial imagery

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Abstract
Buildings’ segmentation is a fundamental task in the field of earth observation and aerial imagery analysis. Most existing deep learning-based methods in the literature can be applied to a fixed or narrow-range spatial resolution imagery. In practical scenarios, users deal with a broad spectrum of image resolutions. Thus, a given aerial image often needs to be re-sampled to match the spatial resolution of the dataset used to train the deep learning model, which results in a degradation in segmentation performance. To overcome this challenge, we propose, in this manuscript, scale-invariant neural network (Sci-Net) architecture that segments buildings from wide-range spatial resolution aerial images. Specifically, our approach leverages UNet hierarchical representation and dense atrous spatial pyramid pooling to extract fine-grained multi-scale representations. Sci-Net significantly outperforms state-of-the-art models on the open cities AI and the multi-scale building datasets with a steady improvement margin across different spatial resolutions.

Keywords Scale-invariant · Urban remote sensing · Earth observation · Building segmentation

1 Introduction
Semantic segmentation is one of the most investigated computer vision topics, where the aim is to provide a pixel-wise classification over several classes in a particular image. With the current deep learning breakthrough, several fully connected neural network models are proposed for semantic segmentation [3, 24, 30, 34, 39, 45] and employed for various applications such as autonomous driving [19], buildings footprint extraction [8, 18] and medical applications [23].

Buildings’ footprint segmentation from aerial imagery [13, 16, 26, 32, 35] is important for wide range of applications such as urban planning, disaster assessment and change analysis.

Existing buildings’ segmentation models are trained on a fixed spatial resolution. Training a robust and accurate deep learning model capable of segmenting buildings from a wide range of input spatial resolution images remains little investigated in the literature. State-of-the-art buildings’ segmentation models perform well on test images of the exact spatial resolution as the training dataset used to generate the model. However, in practical scenarios, test images might be of various resolutions, resulting in non-optimal performance. This can be attributed to several issues; first, the fragmentation of building segments in high-resolution images, as the model fails to acquire a large enough receptive field to classify pixels closer to the center of large buildings accurately. Second, in low-resolution test images the model seamlessly merges the pixels of small building instances with the background; this is known as under-segmentation of buildings’ instances, where the model suffers from an over-segmentation of the background, leaving false-negative holes in the mask. These problems are commonly addressed by re-sampling the test images to match the resolution of the training dataset. However, as the gap between the spatial resolution of inference and training images increases, in both directions, the quality of the resultant segmentation masks deteriorates.
In this context, we propose Scale-invariant neural network (Sci-Net) architecture that is able to extract a multi-scale representation with wider receptive field of an aerial image to cope with varying spatial resolutions during inference time. The contribution of this paper is three-fold: (i) show that existing SoA buildings’ segmentation models often suffer from fragmentation, under-segmentation, or over-segmentation, (ii) propose Sci-Net, a new model that significantly outperforms existing approaches across different image resolutions and finally (iii) present model evaluation results using Open Cities AI scale invariant testset with spatial resolution varying from 2cm/pixel to 20cm/pixel and Multi-Scale Building dataset with spatial resolution varying from 5cm/pixel to 2.5m/pixel.

The rest of the paper is organized as follows: Sect. 2 reviews current research in the literature related to buildings’ segmentation from aerial images. Practical problems in the process of buildings’ segmentation from aerial images are discussed in Sect. 3. Section 4 introduces the proposed Sci-Net model and related background details. Section 5 describes the Open Cities AI and the Multi-Scale Building datasets along with the training procedure adopted. Experimental results and ablation studies are reported in Sect. 6. Finally, the manuscript is concluded in Sect. 7.

2 Related work

In this section, we details some related work relevant to the problem in hand.

2.1 Multi-scale context for semantic segmentation

Capturing multi-scale context has gained a lot of attention due to its importance for semantic segmentation.

To this end, several methods have been proposed. Image pyramid methods [4,11,28,33] are one of the first approaches, where the feature extractor is applied on the same input with varying resolutions; then, different aggregation mechanisms are applied to gather the features from all resolutions.

Encoder–decoder approaches [1,12,17,27,34] have proven to be successful, where the input is processed by a feature extractor that reduces the spatial size and increases the number of channels progressively; then, the decoder tries to decode the features and produce the output map. These approaches exploit the multi-scale features in the encoder (e.g., using skip connections [34] or transferred pool indices [1]).

Spatial pyramid pooling is another way to capture global context; methods like DeepLab [3] rely on dilated convolutions [44] to process the feature map using different rates in parallel. PSPNet [45] proposes to process different pooled feature maps with different resolutions. In [46], authors introduce a modified version of squeeze and excitation blocks denoted as squeeze-and-attention (SA) module. SA module re-weights spatial locations in the features according to the local and global context, thus improving semantic segmentation. Dilated or atrous convolutions are widely used in this context [7,41]

2.2 Multi-scale context for semantic segmentation in remote sensing

Being able to segment objects with multiple resolutions is of high interest for the remote sensing community. While most of the work proposed in the computer vision community can be adapted to satellite images, several works have been also proposed in this context. Hamaguchi and Hikosaka [14] leverage multi-task learning and distillation to produce several output maps depending on the buildings size. Li et al. [25] propose to reuse previous feature maps by the help of the connections from each layer to the same-sized subsequent layers. Lin et al. [29] propose an efficient model based on separable factorized residual block in addition to dilated convolution.

Authors in [32] introduce channel relation module that applies global average pooling over the features and spatial relation module to obtain global spatial relation features.

Furthermore, authors in [13] introduce the local feature extractor (LFE) module, which is composed of a series of dilated convolutions of decreasing rates, after aggressively increasing the rates of dilated convolutions used in the front-end module to attain a high receptive field throughout the feature extraction process.

A semantic segmentation network for building footprint extraction from satellite imagery using a modified DeepLabV3+ model was suggested in [18]. The performance of the proposed model is measured on test datasets with fixed resolution (and not scale-invariant). Authors in [40] present a scale-aware model for multi-resolution aerial imagery semantic segmentation using the LandCover.ai dataset, which contains images of two different resolutions (0.25 and 0.5 m/pixel). They also conduct experiments on resized versions of the MSR Vaihingen dataset at different scales. Authors in [20] introduce MSB, a deep dilated CNN for automatic building footprint extraction. Finally, building extraction from remote sensing images using a Unet+Atrous Spatial Pyramid Pooling (ASPP) model on the WHU dataset is discussed in [38].

3 Problem description

3.1 Challenges

Designing a model that is capable of segmenting buildings footprint from aerial images at different spatial resolutions faces the following challenges:
(i) **Features resolution** Most feature extractors [6,15,36,37,42] are a series of five down-sampling stages, where each stage outputs denser and more meaningful representations than the previous one. However, features spatial resolution is reduced to half at each stage using a 2x2 pooling operation or a convolution with a stride $= 2$. This reduction leads to a loss in spatial information the deeper we go in the network, as the features extracted by the last stage have a resolution $32 \times$ smaller than the input size (output stride $= 32$).

(ii) **Field of view** In feature extraction networks, convolutions are applied with a $3 \times 3$ receptive field (kernel size). Although this works very well in segmenting small- to medium-sized objects, it often fails when dealing with larger objects (i.e., building footprints at very high resolutions such as 2cm/pixel). In the latter case, predicted segments often suffer from fragmentation, under-segmentation, and noise because the field of view is too small for the network to decide whether the pixel belongs to a larger object or the background. On the contrary, increasing receptive field by applying convolutions with an increasing kernel size leads to losing local spatial information and exponential growth in both time and computational complexity.

### 3.2 Motivation

Motivated by the observations above, we propose the following solution:

(i) To avoid losing spatial features details and keep a reasonable computational complexity, we adopt theskip connections from the encoder to the decoder.

(ii) To increase the field of view or the receptive field: (a) we use an encoder/decoder framework where the feature map spatial size decreases/increases with depth for the encoder/decoder, (b) we include dense ASPP with dilated convolutions, at the bottleneck of the encoder.

### 4 Sci-Net

#### 4.1 Dilated convolutions

Dilated convolutions work just like regular convolutions; however, they manage to increase the size of the receptive field by the insertion of holes between the weights of the kernel, according to a selected rate denoted by $r$. For a 2-dimensional input feature map $x$, the output feature map $y$ obtained as a result of a dilated convolution at every spatial location $i$ with a rate $r$ is defined according to Eq. 1:

$$y[i] = \sum (x[i + r \ast k] \ast w[k]).$$  \hspace{1cm} (1)

#### 4.2 Atrous spatial pyramid pooling (ASPP)

ASPP is a module that applies multiple dilated convolutions with different rates on the feature maps to capture multi-scale representations. The concept has been first introduced in [2] and then further developed in [3,5].

Typically one $1 \times 1$ convolution, three $3 \times 3$ dilated convolutions of atrous rates equal to (8, 12 and 18), and a global average pooling layer is applied in parallel. The resulting representations are then concatenated together and pooled with a $1 \times 1$ convolution as shown in Fig. 1a. Applying three different and separate dilated convolutions allows the model to extract spatial information at three different scales, with a maximum receptive field size equal to 37 pixels.
4.3 Dense ASPP

Dense ASPP [43] applies dilated convolutions with increasing atrous rates in a cascade manner. The input to each dilated convolution block is the initially extracted feature maps concatenated with all the representation from previous dilated convolutions of lower rates as shown in Fig. 1b. Typically, four atrous convolutions are applied with rates equal to (3, 6, 12 and 18). When two convolutions of different receptive fields are stacked together, the resulting receptive field increases in a linear manner, as shown in Eq. 2:

\[ R_{\text{new}} = R_1 + R_2 - 1. \]  

(2)

where \( R_1 \) and \( R_2 \) denote receptive fields size in pixels of the 1st and 2nd convolutional layers, and \( R_{\text{new}} \) is the size of the new receptive field after stacking the two convolutional layers together.

Usage of dense ASPP would lead to 16 receptive field scales and a maximum value equal to 79 pixels, which means that more pixels are involved in the convolution, resulting in a denser feature pyramid than ASPP.

4.4 Sci-Net architecture

In this subsection, we provide a detailed description of the proposed Sci-Net model architecture and illustrate the role of the modifications that we apply to deliver ultimate performance. The proposed Sci-Net model shown in Fig. 2 adapts conventional UNet encoder–decoder architecture [34] with the following modifications:

(a) Replacing the encoder with a more powerful yet lightweight feature extractor from the RegNet Family (\( \text{RegNet}_Y - 1.6GF \)). RegNets have similar performance to their Efficient-Net counterparts while being 3× to 5× times faster.

(b) Integration of a dense ASPP block to extract multi-scale representation from the features of the last encoder stage. The output features of dense ASPP are the input to the first decoder block. We used the following rates (3, 6, 12, 18) for the dilated blocks, and we set the output channels to 256 for each block. When concatenated, the multi-scale representations alone are a total of 256 \( \times \) 4 = 1024 channels, and the initial feature maps contain 888 channels.

(c) Substitution of the last 3 \( \times \) 3 convolution in the 5-th encoder that has a kernel stride = 2, with a dilated convolution of a low atrous rate = 2 and kernel stride = 1 to avoid down-sampling of stage 5 features. And thus, the output stride becomes equal to 16 instead of 32. This modification preserves a sufficiently good spatial resolution at the dense ASPP input.

(d) No up-sampling is applied at the first decoder block as both stages 4 and 5 feature maps have the exact same spatial resolution.

Each decoder block comprises two 3x3 convolutions with a stride equal to 1 followed by a 2x up-sampling bilinear interpolation.

5 Dataset & training

In this section, we present both datasets used in this work, the training pipeline and implementation details, in addition to the evaluation metrics used.

5.1 Datasets

OCAIC [22]: Open cities AI challenge dataset is also known as segmenting buildings for disaster resilience dataset. The majority of the data are collected across different African cities, where the images and labels quality varies from one region to another. Data is made of 31 GeoTiff images of different spatial resolution and size. Resolution varies from very high (2 cm/pixel) up to medium (20 cm/pixel) resolutions. The resulting dataset contains 40,000 tiles with their corresponding buildings’ masks.

MSB [20]: Multi-scale building dataset is a relatively small dataset made of 2900 images. The images are collected from different public dataset after undergoing horizontally/vertically flip augmentation and saturation transform. The resultant multisensor and multi-scale MSB dataset covers 16 different cities with RGB images of 512 \( \times \) 512 pixels size, with spatial resolution varying from 0.3m/pixel to 2.5m/pixel.

5.2 Training details

For fair comparison, we ensured that all compared methods are using mostly the same hyperparameter choices. Specifically, the encoder is replaced by \( \text{RegNet}_Y - 1.6GF \) for all methods, except for HRNet which uses \( H R N e t V2 - W32 \) backbone. The decoder channels are fixed to (256, 128, 64, 32, 16) except for Deeplabv3+ where the number of channels is fixed to 256, and PSPNet where the number of output channels is 512 (number of filters in Spatial Pyramid). The number of channels for the PAB module in MANet is 64. All encoders are initialized with ImageNet pre-trained weights [9].

In all our experiments, models are trained until convergence using Adam optimizer [21] and polynomial learning rate policy [45].

A weighted combination of dice loss and binary cross-entropy (\( BCE \)) loss is used.
Table 1 Performance metrics of Sci-Net architecture compared to existing SoA models on the OCAIC testset where Sci-Net outperforms all benchmarked models in terms of IoU and F1 scores

| Model       | Micro-IoU | Micro-F1 | Macro-IoU | Macro-F1 | Params. (M) | GFLOPs |
|-------------|-----------|----------|-----------|----------|-------------|--------|
| PSPNet [45] | 78.47     | 87.93    | 85.04     | 89.55    | 12.0        | 8.7    |
| DeepLabV3+ [5] | 79.83     | 88.78    | 86.28     | 90.50    | 12.0        | 13.5   |
| MANet [10]  | 80.08     | 88.93    | 86.20     | 90.38    | 35.5        | 25.0   |
| HRNet [39]  | 80.30     | 89.07    | 82.85     | 90.46    | 29.5        | 45.0   |
| Sci-Net     | 82.25     | 91.04    | 88.42     | 92.62    | 24.2        | 33.1   |

Fig. 3 Performance comparison of Sci-Net (in green) versus SoA models in terms of micro- and macro-IoU and F1 scores using the OCAIC testset

During training on the OCAIC dataset, we use a batch size equal to 12 and randomly crop 512 × 512 chips of the original 1024 × 1024 tiles.

Training framework is done in PyTorch using mixed precision functionality.

6 Experimental results

In this section, we present detailed experimental results and ablation studies of the proposed Sci-Net architecture.

6.1 Evaluation on the OCAIC dataset

Experimental results reveal the performance superiority of the proposed Sci-Net over several SoA models in terms of IoU and F1-score across varying resolutions. At inference time, the images are fed to the neural network at full scale (1024 × 1024). Table 1 shows that the proposed Sci-Net model provides a significant improvement of at least 2% score over benchmarked SoA models on the OCAIC testset. Sci-Net attained a micro-IoU score of 82.25%. Table 1 also shows that Sci-Net scored the highest macro-IoU value of 88.42%, which indicates that it leverages the best per-image performance. Furthermore, at least 2% score improvement margin is also observed for micro- and macro-F1-scores (91.04% and 92.62%, respectively). Thus, the proposed model attains better precision and recall against competitor models. Models like PSPNet and DeepLabV3+ failed to provide near good results at some resolutions leading to a degradation in their scores.

Furthermore, we plot in Fig. 3 the micro- and macro-IoU and F1-scores per resolution (cm/pixel) for every benchmarked model using the OCAIC testset. The green curve corresponding to the Sci-Net model always performs better than all other models across different metrics and resolutions, which shows that it can effectively extract better multi-scale representations than the existing models. Sci-Net curve is consistently above all other curves for the four presented score graphs, which indicates that it is less prone to performance degradation when the scale changes. It is unclear which model holds the “runner up” spot, as these models alternate places on varying resolutions. For instance, UNet+ASPP (in red) achieves competitive scores for resolutions in range (2 cm/pixel up-to 8 cm/pixel); however, its performance deteriorates for larger resolutions. PSPNet (in brown) benchmarks the worst performance for all resolutions.

To better visualize our results, a sample of images from the OCAIC testset and the corresponding predicted masks by each model are shown in Fig. 4. For instance, problems like fragmentation and under-fitting are solved using Sci-Net by acquiring sufficiently large receptive fields capable of relating far pixels that belong to large building instances at high resolutions (Masks in rows 1, 2, 3, and 4). In the first four rows, it is clear that Sci-Net succeeds in segmenting large building instances. For example, models like DeepLabV3+, UNet, and HRNet showed a critical level of mask fragmentation for that large building instance in the first row. Also, at lower resolutions (rows 6 and 7), Sci-Net can avoid over-
Fig. 4 Ground-truth (GT) data and predicted masks for Sci-Net and benchmarked SoA models for various images from the OCAIC testset at different resolutions revealing fragmentation, under- and over-segmentation issues.

Table 2 Performance metrics of Sci-Net architecture compared to existing SoA models on the MSB testset. Sci-Net outperforms all benchmarked models in terms of micro-IoU, micro-F1, macro-IoU and macro-F1 scores, respectively.

| Model            | Micro-IoU | Micro-F1 | Macro-IoU | Macro-F1 |
|------------------|-----------|----------|-----------|----------|
| PSPNet [45]      | 57.42     | 72.95    | 54.90     | 69.72    |
| DeepLabV3+ [5]   | 74.16     | 85.17    | 71.58     | 82.84    |
| MANet [10]       | 73.38     | 84.65    | 72.37     | 83.69    |
| MSB [20]         | 72.30     | 83.92    | 70.34     | 82.18    |
| Sci-Net          | 75.18     | 85.84    | 73.71     | 84.53    |

segmentation, unlike other architectures such as HRNet that misclassified a significant amount of background pixels, as shown in row 6.

While models that use pyramid pooling like PSPNet performed well in segmenting large building instances (row 1 and 2), they often fail in capturing small- to medium-sized buildings at lower resolutions. Unet+ASPP could not capture enough multi-scale information to segment large structures properly (rows 1, 2, and 3). Hence, Sci-Net proved to be the most efficient approach across various spatial resolutions.

In terms of model complexity, Table 1 shows that our model is smaller than MANet and HRNet, which indicates that the improvements are not due only to adding more modules/parameters.
6.2 Evaluation on the MSB dataset

We conducted more experiments using the MSB dataset [20] to verify and validate claimed advantages of our proposed Sci-Net architecture. As shown in Table 2, Sci-Net attained a micro-F1 score of 85.84% and a macro-F1 score of 84.53% which is 2% higher than the MSB model results reported in [20]. DeepLabV3+ falls short behind by 1% in terms of micro-F1 but is 2% lower than Sci-Net in terms of macro-F1 scores. This shows that Sci-Net is ensured to perform well on a per-image and per-dataset basis. Indeed, Sci-Net outperforms other benchmarked models in Table 2 in terms of all measured metrics. Similar to [20], we explored the robustness of our proposed model for difficult scenarios with complex roofs and evaluated how sensitive is Sci-Net toward outliers. Sci-Net performs outstanding building segmentation task with low false positives and low false negatives for those complex roofs. Sci-Net resulted in an F1-score between 85% and 94%, which outperforms results reported in [20] for all complex roof image scenarios.

6.3 Effective receptive field (ERF) analysis

The effective receptive field (ERF) or field of view is of crucial importance for dense prediction tasks, such as semantic segmentation. The larger the receptive field the better the capture for a larger context about a given pixel, which is desirable, especially for large objects. The receptive field (RF) can be computed manually, however, in [31]; authors show that the ERF is much lower than the theoretical RF. Similarly to [31], we use the back-propagation of gradients to visualize ERF. Specifically, we back-propagate the gradient of the central pixel backward to the input image and visualize the gradients. Results are shown in Fig. 5, where we show that the ERF of Sci-Net is wider than that of UNet, validating the importance of the proposed architecture.

|  | Micro-IoU | Micro-F1 | Macro-IoU | Macro-F1 |
|---|---|---|---|---|
| UNet [34] | 80.18 | 89.00 | 86.01 | 90.16 |
| UNet + ASPP | 80.47 | 89.18 | 86.65 | 90.79 |
| Sci-Net | 82.25 | 91.04 | 88.42 | 92.62 |

6.4 Ablation studies

In this subsection, we investigate the importance of our design choices in terms of Dense ASPP and loss function adapted.

**Dense ASPP:** From Table 3, we can notice that the dilated convolutions at the bottleneck (UNet+ASPP), bring only slight improvements to the UNet model. On the other hand, the dense ASPP module leads to significant improvements compared to ASPP for the UNet model. This observation also holds for the evaluation on several resolutions as shown in Fig. 3 and the quantitative comparison in Fig. 4.

**Loss function:** To justify the choice of loss function used for model training, we conducted three experiments where Sci-Net was trained on the multi-scale building dataset [20] to test the model performance with/without each component of the loss function. As stated in Sect. 5.2, we are using a weighted combination of dice loss and binary cross-entropy (BCE) loss. The model achieves 3% higher micro-IoU score when using BCE+Dice loss compared to using each one of them alone, where BCE+Dice loss scored 75.18% micro-IoU compared to 71.57% and 72.03% for BCE only and Dice only, respectively.

7 Conclusion

This paper proposes Sci-Net, a new model capable of accurately segmenting buildings’ footprint at multi-scale spatial resolutions. We compare the performance of Sci-Net with other well-known SoA models using both OCAIC and MSB datasets. We show that the proposed Sci-Net architecture is useful to mitigate fragmentation, over-segmentation, and under-segmentation problems that SoA models suffer from.

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**Declarations**

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