Quantifying greenspace using deep learning in Karachi, Pakistan

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Abstract

Greenspaces in communities are critical for mitigating effects of climate change and have important impacts on our health. Nowadays, the availability of visible spectrum satellite imagery data combined with deep learning methods, allows for automated greenspace analysis at high resolution. We propose a custom deep learning-based approach which includes novel green color augmentation to better detect as well as delineate types of greenspace vegetation (trees, grass) with satellite imagery. Our method outperforms gold standard methods, which use vegetation indices, by 33.1% (accuracy) and 77.7% (intersection-over-union; IoU). With the proposed augmentation technique, we also show improvement over popular deep learning-based segmentation methods for both classification of total greenspace as well as by vegetation type. We apply the method to high-resolution (0.15 meter per pixel) satellite images covering the entirety of Karachi, Pakistan. Detection across the city can inform planning needs based on where greenspaces exist and in what form; we find that greenspaces in Karachi are often linked to areas of development (Pearson's correlation coefficient (r) shows a significant 0.352 correlation between greenspaces and paved roads, $p < 0.001$), with a slightly higher correlation between roads and trees versus roads and grass. Quantifying greenspace in Karachi also illuminates an important need; Karachi has 4.17 square meters of greenspace per capita, which significantly lags World Health Organization recommendations.

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1 Introduction

“Greenspaces” are defined by the U.S. Green Building Council as land that is partly or completely covered with trees, shrubs, grass, or other vegetation. There is a large amount of literature highlighting the environmental, sociocultural, and economic benefits of greenspaces. Briefly, these facilities can be used as therapeutic spaces for rehabilitation exercises, thereby improving the health of its residents, play an important role in biodiversity conservation, contributes to aesthetics, increase economic value, provide nature-based solutions for resiliency (e.g., rainwater management, sewage overflow and flood control), reduce the heat island effect by providing shade and lowering surface temperatures, and also serve as a place to relax and strengthen social organization [35, 16, 29, 19, 6, 26].

Recently, shrinkage of greenspaces due to population growth, industrial expansion, developmental activities, and land encroachment has led to disruption of the ecological balance in many urban centers including in Pakistan [40]. This change is particularly important due to the crucial role of greenspaces for climate change mitigation via several mechanisms; carbon sequestration (greenspaces act as carbon sinks by absorbing and storing carbon dioxide from the atmosphere), reduced energy consumption (greenspaces provide shade and reduce the urban heat island effect which helps decrease energy consumption for cooling buildings), stormwater management (greenspaces absorb and filter rainwater, reducing the load on stormwater infrastructure and preventing water pollution), air quality improvement (greenspaces improve air quality), biodiversity conservation (greenspaces provide habitats for diverse species and diversifying ecosystems enhances resilience and capacity to adapt to climate change impacts). In sum, greenspaces positively affect quality of life across both physical and mental health, and provide various ecological, socio-cultural, and economic benefits to a community. Thus, it is essential to strategically measure and inform urban planning and public health interventions with significant consideration for greenspaces, to develop a sustainable future [49, 23].

New analytic methods and data sources illuminate opportunity for measuring greenspaces in countries which the environmental, sociocultural, and economic benefits have not been quantified. An important exemplar is Karachi, one of the largest cities in the world in terms of urban population. Karachi also has a high urban population density of over 24,000 people/km^2, which far surpasses that of other megacities such as Beijing or New York City [54]. These challenges place greater pressure on limited greenspaces, making their preservation and accessibility crucial for providing recreational opportunities and improving the quality of life for the densely populated areas. Another important reason to focus on Karachi is the current lack of knowledge on greenspaces in Pakistan; studies to-date have been focused on specific geographic areas (e.g. cemeteries in Lahore [40]) or study greenspace largely via survey data [42, 48].

Imagery, such as from satellites, has been utilised to measure greenspace for decades. Specifically, several vegetation indices have been derived using spectral bands and their ratios [51, 32, 20, 33, 5]. New opportunities for imagery include new satellites offering higher resolution (50 cm or less). Beyond measurement of greenspaces, it is also important to distinguish types of greenspaces in order to identify the quantity of each type and inform work improving types that bring the greatest benefits to citizens. Though challenging to obtain via standard greenspace cataloging (manual data gathering or vegetation indices), such detailed knowledge would enable urban planners to augment and repurpose greenspaces strategically.

Researchers have proposed leveraging deep learning along with satellite imagery to detect vegetation land cover [23, 31, 2, 28, 13, 52] and to classify vegetation types [36, 3, 56], via the algorithm of semantic segmentation. Studies have largely focused on examining landscapes in specific local sites with few exceptions (greenspace has been catalogued using deep learning, for four cities in China [31, 12] and the country of Slovenia [3]; but the resolution of the satellite images used is low (1-10 meters per pixel). Moreover, compared to prior work, a unique challenge approached in this work is the limited amount of greenspace in Karachi. The training data includes only 30% of images labelled with any types of greenspace, and further, the grass class label has only in 11% of images. This problem of class scarcity hinders deep neural network training, which relies on large volumes of data to extract representative landscape features [47, 58]. Though studies have adopted image augmentation techniques including random flips, rotations, brightness and contrast change to tackle class scarcity [24, 10, 53], such techniques only increase data variety with respect to basic image properties, and do not provide additional information for the important target feature, greenspace.

Our contributions in this study are: (1) We propose a novel deep learning method for greenspace semantic segmentation with satellite images. The method incorporates green color augmentation by shifting the image hue channel, and outperforms state-of-the-art methods by a substantial margin; (2) We apply our method to quantify greenspace over all 173 union councils in Karachi, Pakistan and demonstrate their association to economic development reflected by paved road construction. Given the global importance of greenspaces for improved planetary and human health, our method is relevant to, and can be extended to locations worldwide.

2 Method

2.1 Study area

The study location is Karachi, the largest city in Pakistan (has an area of 3,530 km^2)[1], and population of over 17 million[2]. The analysis unit is union council (n=173), the fifth (lowest) level of government in Pakistan. The extant shows a need to quantify greenspaces at a high resolution covering Karachi for effective urban planning and sustainability [7, 43]. Being a metropolitan city, Karachi faces a huge influx of urbanization and industrialization and ranks as the third largest city in the world with respect to population, as of 2018[3]. These challenges combined pose a threat to resources and environment in the city, most susceptible being the green and open spaces [42]. Indeed, Karachi's green areas have decreased by 4%, whereas the urban extent in the core city has expanded by 8% between 2005 and 2017 [1]. The tropical climate with hot arid summers and short dry winters also creates difficulty in maintenance of urban green spaces. Surveys conducted in Karachi show that more than half of the respondents rarely or never visit city natural spaces and they express concerns about lack of maintenance and public conveniences in and around greenspaces [42]. In sum, there is an urgent need of comprehensive greenspace measurement for city planning to maintain the quality of life and socio-environmental sustainability in Karachi.

[1] City K-OWPoKM. Karachi the Gateway to Pakistan. http://www.kmc.gos.pk/contents.aspx?id=14

[2] World Population Review. https://worldpopulationreview.com/world-cities/karachi-population

[3] Largest cities in the world CITYMAYORS STATISTICS2018. http://www.citymayors.com/statistics/largest-cities-population-125.html.

Class	Pixel count	Frequency
Background	4.53×10^8	0.697
Tree/Shrub	1.24×10^8	0.190
Grass	7.34×10^7	0.113

Table 1. Distribution of labels for each class in the dataset.

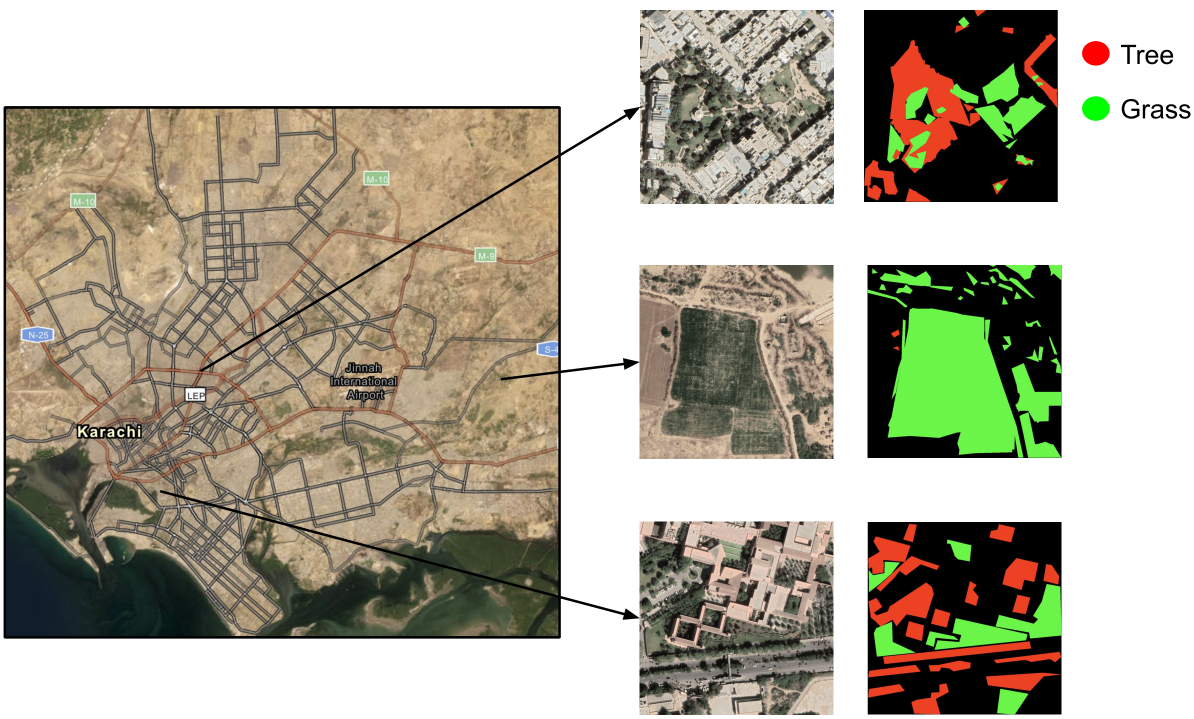

Figure 1. The Karachi city map (background: ©OpenStreetMap contributors, TomTom, Garmin, Foursquare, METI/NASA, USGS). We download satellite images covering the whole city and select 620 image tiles for labeling. Examples of satellite image tile and labeled greenspace masks are shown.

2.2 Data and annotation

We collected satellite images using the Application Programming Interfaces (APIs) from Google Maps Platform, consisting of aerial view of Karachi with a resolution of 0.15 meter per pixel. The resulting number of images was 42,735, comprehensively covering 173 Union Councils across the city. Each image was 1024 $\times$ 1024 pixels, equivalent to 152 m^2 on the ground. We labelled 620 acquired images manually, pixel-wise, to identify areas covered by trees, shrubs, and grass using the Labelbox tool[4]. Among them 400 images were selected randomly and another 220 images with large greenspace areas were selected to increase the observation of deep learning models on the vegetation classes.

To ensure labeling quality, two members of the research team each labelled every image and the union obtained. Labels were validated by a third reviewer to ensure no obvious greenspace areas are missed or labelled incorrectly. The label consensus for shrub areas was relatively low because of its similarity to trees, given that plant height is hard to estimate from the aerial view. Since woody vegetation is usually studied as one biodiversity component [46, 50], following the literature of building deep learning models to recognize mixed tree and shrub landcover [21, 55, 17], we merged the shrub labels into tree labels for the following analysis. The final class distributions are presented in Table 1. Satellite view of the study area and example greenspace annotations are shown in Figure 1.

Population data of Karachi for computing per capita greenspace was obtained from Meta High Resolution Population Density Map[5]. The map provides 2020 population statistics with geo-coordinates for grid units around the world at a 30 meter resolution. We compute the population sum of units located in each Karachi union council as the population distribution of the city.

2.3 Analysis

2.3.1 Visible band vegetation indices

Vegetation index methods can directly infer greenspace based on the image RGB channel value, computed via their equations and a threshold parameter. The output of each index is a binary prediction: vegetation or non-vegetation, for each image pixel. Three visible band vegetation indices are used: (1) green-red vegetation index [GRVI = $(\rho_{green} - \rho_{red})/(\rho_{green} + \rho_{red})$], where ρ_c is the reflectance value of the visible band in color c. The index is based on the contrast between reflectance in green and red bands of green vegetation ground cover [37]; (2) visible atmospheric resistant index [VARI = $(\rho_{green} - \rho_{red})/(\rho_{green} + \rho_{red} - \rho_{blue})$], which reduces atmospheric effects by including the blue band [20]; and (3) green leaf index [GLI = $(2\rho_{green} - \rho_{red} - \rho_{blue})/(2\rho_{green} + \rho_{red} + \rho_{blue})$], proposed for wheat cover estimation [32]. These indices have shown to be useful vegetation indicators [37, 2, 22].

2.3.2 Deep learning model and setup

Encoder-decoder structural models are commonly used for deep learning based semantic segmentation [4, 11, 15, 34, 27]. The encoder produces low resolution and highly abstract representation from images, and the decoder maps the representa-

[4]Labelbox. https://labelbox.com/

[5]https://dataforgood.facebook.com/dfg/tools/high-resolution-population-density-maps

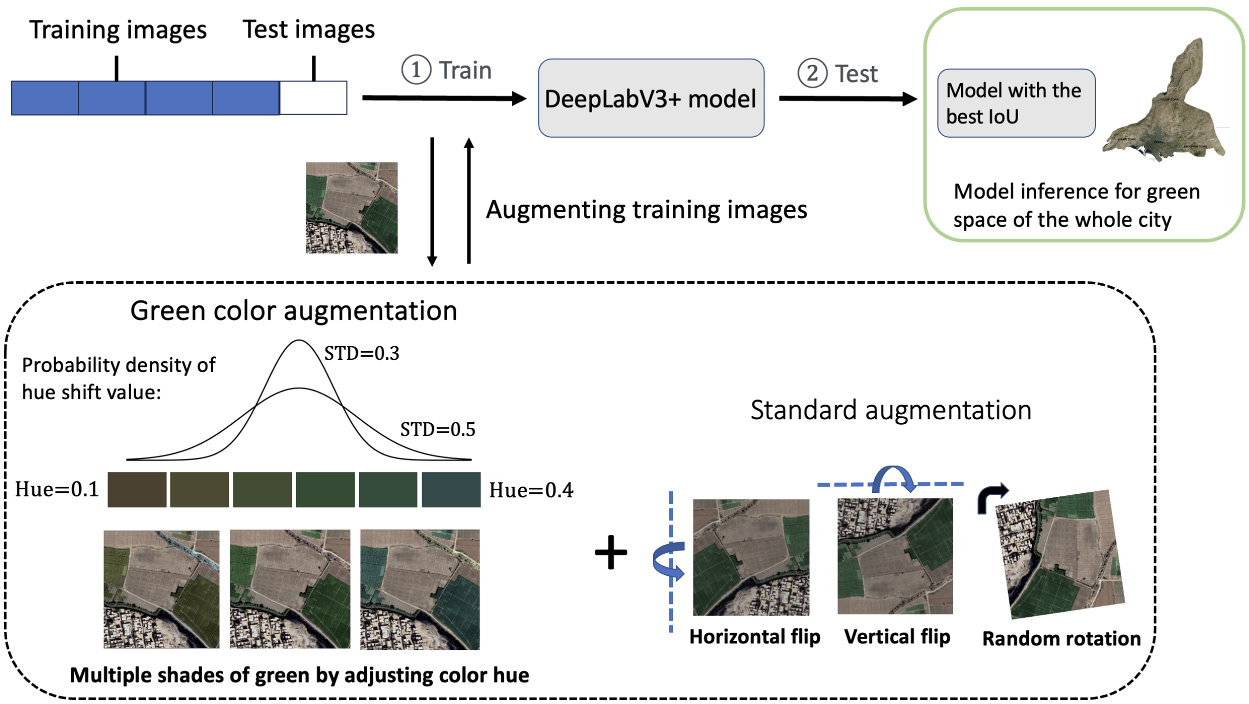

Figure 2. The overview of developing green color augmentation for deep learning based greenspace segmentation: The model DeepLabV3+ is trained on 80% of the labeled images, the training set, with schedules and hyper-parameters fine-tuned. Trained models are tested on 20% of the labeled images and the model which obtains the best Intersection over Union (IoU) is selected to analyze the distribution of overall greenspace and different vegetation types across the city. Illustration of green color augmentation method during training: The green hue of images is shifted with a value randomly selected from a normal distribution, to simulate new greenspace patterns. This custom augmentation is used in addition to traditional image augmentations including flip and rotation.

tion to pixel-level class predictions. We apply DeepLabV3+, a deep convolutional neural network based on parallel atrous convolution structures [11]. This model has been shown to achieve state-of-the-art semantic segmentation performance for vegetation detection and classification [3, 2, 10, 13]. In contrast to vegetation indices, the deep learning approach can distinguish greenspace classes, thus here is also trained to identify the greenspace types, tree and grass.

We follow the standard protocol for training deep segmentation model as used in [60]. Input images are randomly cropped into the size of 512 $\times$ 512 with a batch size of 16. Image augmentations including random horizontal flip, vertical flip, and rotation for 90 degrees are applied. The loss function is pixel-level cross entropy which measures model prediction error and a stochastic gradient descent (SGD) optimizer minimizes the error by updating model weights. The initial learning rate is 10^{-3} with a momentum of 0.9 and a weight decay of 10^{-4}. The learning rate is decayed during training using a polynomial learning rate scheduler implemented in PyTorch [39]. The model is trained and validated for 100 epochs and final performance is evaluated on the test images. An overview of the training pipeline is shown in Figure 2.

2.3.3 Green color augmentation for vegetation detection

A challenge for greenspace detection in real-world situations is the non-uniformity of colors. For example, some shrubs or grass may have a straw yellow or pale brown appearance, which are less distinguishable from non-vegetation objects. Accordingly, to train the deep learning model to recognize the multitude of vegetation patterns, we design a simple but effective data augmentation method; by shifting the hue value of the original images, new images are generated which depict the same vegetation objects but with a new color. The augmented images reduce the deep learning model's over-fitting to the training data and increase generalizability to different shades of green. Importantly, the augmentation does not impact the semantic (content) information of the original images; it only operates on the greenspace regions and the hue value change is restricted to a reasonable range. For example, when changing the hue from 0.1 to 0.4, the color of the grass region changes from olive green to dark green.

Algorithmic steps of the green color augmentation are to: 1) Convert the RGB image into HSV (hue, saturation, value) format. 2) Produce a random hue shift Z following a normal distribution, which has the mean of 0 and standard deviation of σ. A bigger σ indicates a higher probability to apply large hue shifts, also referred to as "augmentation strength". We choose randomized hue shifts during training instead of fixed value to maximize the variety of simulated colors. The setting of $Z \sim \mathcal{N}(0, 1.0^2)$ obtains the best results for the Karachi data used in this work, and the method's sensitivity to different σ parameters are analyzed in Figure 4. 3) Define the range of green hue $[h_l, h_r]$ of greenspace pixels in the whole dataset. 4) Apply Z to the hue value of pixels labeled as greenspace, within the range $[h_l, h_r]$. As a result, the adjustment for a pixel with hue value h_i will be:

$$h_i = \begin{cases} h_i + max\{Z, h_r - h_i\}, & \text{if } Z > 0 \\ h_i + max\{-Z, h_i - h_l\}, & \text{if } Z < 0. \end{cases} \tag{1}$$

Finally, the augmented images with the new hue values are converted back into RGB format. The images are further processed with standard augmentation functions to be input to the model. How the augmentation method simulates greenspace with different shades of green color is visualized in Figure 2 (bottom left).

2.4 Road detection

We use a pre-trained road extraction model, D-LinkNet [59], to quantify road distribution in Karachi. The model can detect paved road from high resolution satellite images and achieves the first place performance in the DeepGlobe 2018 Road Extraction Challenge [14]. During the inference, we use the parameters as in the original model to assign binary predictions for whether each pixel belongs to the road class.

3 Results

Vegetation index	Vegetation	Recall ↑	Precision ↑	IoU ↑	Accuracy ↑
GRVI	NA	0.573	0.588	0.393	0.643
VARI	NA	0.442	0.721	0.371	0.696
GLI	NA	0.633	0.640	0.466	0.669
Deep learning	**Vegetation**	**Recall ↑**	**Precision ↑**	**IoU ↑**	**Accuracy ↑**
DeepLabV3+	All	0.821	0.855	0.721	0.872
DeepLabV3+ (Aug)	All	0.894	0.906	**0.828**	**0.927**
DeepLabV3+	Trees	0.714	0.828	0.621	0.905
DeepLabV3+ (Aug)	Trees	0.774	0.857	**0.685**	**0.926**
DeepLabV3+	Grass	0.772	0.698	0.579	0.9360
DeepLabV3+ (Aug)	Grass	0.777	0.759	**0.623**	**0.941**

Table 2. Comparison of vegetation indices, baseline deep learning method DeepLabV3+, and our proposed method DeepLabV3+ (Aug). Segmentation tasks include binary prediction (Vegetation is “All"), and multi-class prediction by vegetation types for deep learning methods, which is NA (not applicable) for vegetation indices. Evaluation metrics and results are all class-wise.

3.1 Model performance

Segmentation performance of vegetation index methods and deep learning methods are evaluated on the testing split of labeled images. For the first task of greenspace detection, different vegetation objects (e.g. trees, grass) are combined into a single greenspace class and each image is segmented by pixel-wise binary (greenspace or not) classification using vegetation indices, baseline DeepLabV3+, and DeepLabV3+ applied with the proposed green color augmentation (“DeepLabV3+ (Aug)”. Table 1 shows the segmentation completeness (recall), purity (precision), overall segmentation quality, measured by intersection of ground-truth masks and the predicted segmentation divided by their union (IoU), and pixel-level accuracy (accuracy). The metrics are defined based on TP, FP, TN, and FN, which are pixel-wise true positives, false positives, true negatives and false negatives for classifying greenspace:

$$\text{recall} = \frac{TP}{TP + FN} \tag{2}$$

$$\text{precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{IoU} = \frac{TP}{TP + FP + FN} \tag{4}$$

$$\text{accuracy} = \frac{TP + TN}{TP + FP + FP + FN} \tag{5}$$

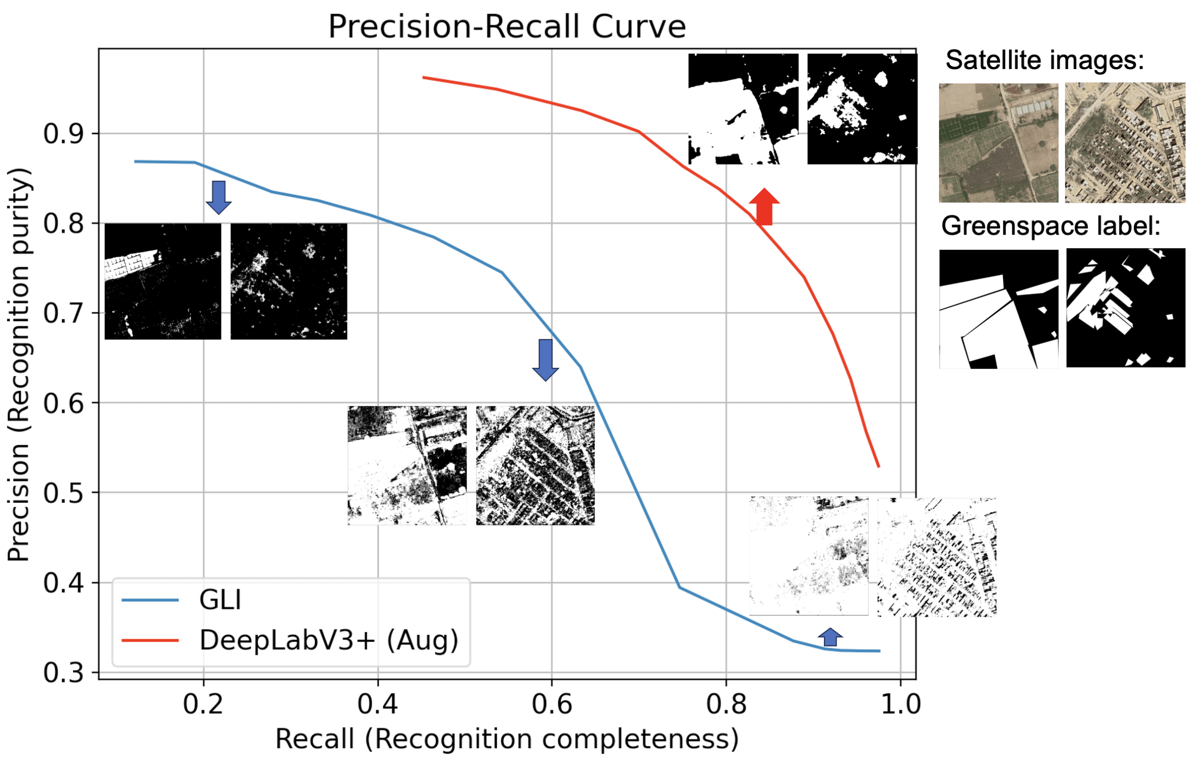

Figure 3. The precision and recall metric trade-off for greenspace segmentation, using GLI and the proposed DeepLabV3+ (Aug) method. White pixels represent greenspace and black pixels represent background.

As reported in Table 2, deep learning methods largely outperform the vegetation indices on all metrics. DeepLabV3+ (Aug) segments 89.4% of the true greenspace, and has the correct rate of 90.6% of its predictions, while the green leaf index (GLI) segments 63.3% of the greenspace and 63.98% of its predictions are correct. A comparison between our method and other deep learning based greenspace segmentation baselines, including UNet [24, 13] and LinkNet [30], is provided in A. These analyses reinforce the improved performance with custom augmentation, even on different deep learning architectures. Given that classification accuracy can vary by the threshold used for classifying greenspace versus other, we examine the segmentation performance at different pixel-wise classification decision thresholds (Figure 3). Increasing the threshold for the GLI method improves recognition of outlier greenspace pixels such as vegetation with moss green appearance (which can have abnormal index value of red reflectance higher than green reflectance), thus improving recall. However, this increase simultaneously increases irrelevant background predictions and causes worse Precision. The DeepLabV3+ (Aug) model shows a similar trend but has consistent higher performance. This consistent improved performance shows advantage of the deep learning method in real-world applications where different choices of thresholds are often set for detecting different types of greenspace.

We next train the deep learning models to segment two vegetation species, trees and grass, with its multi-class classification mechanism which the vegetation indices are not capable of distinguishing. The Trees class is grouped for all woody plants including lower shrubs, as motivated above. We compare the DeepLabV3+ model trained with standard augmentation methods, and besides those, the proposed green color augmentation, noted as DeepLabV3+ (Aug). With the additional augmentation step, the segmentation IoU is improved by 10.3% for Trees class, 7.60% for Grass class, and 14.8% for the greenspace class in binary prediction task. The improvement is from both increased recall, in that the model can capture greenspace features more completely with the feature extractor learnt from the synthesized new images, and improved precision, to distinguish greenspace from other land covers instructed by the features.

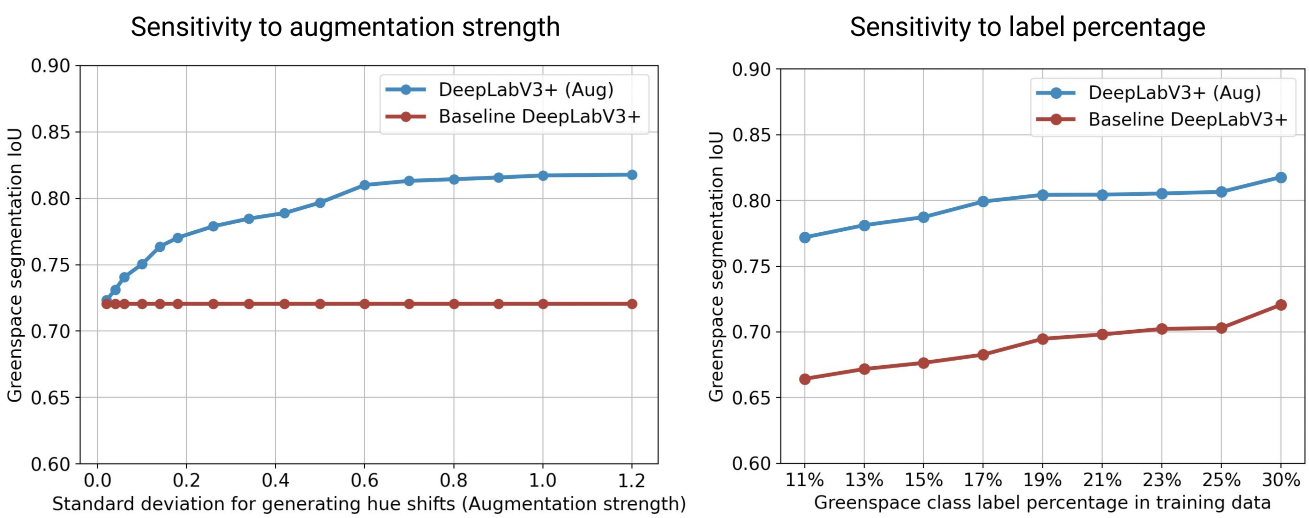

Figure 4. The greenspace class segmentation IoU of the proposed method: DeepLabV3+(Aug), trained with different standard deviation parameter used in the green color augmentation (left), and with different training label percentages (right). The method presents consistent advantage over Baseline DeepLabV3+ under various experimental settings.

3.2 Sensitivity analysis

We investigate how the main parameter, the standard deviation σ used to generate random hue shift, affects model performance. As shown in Figure 4 (left), when $\sigma = 0$, hue shift is 0 and the result is same as the baseline training with only standard augmentations are applied. When increasing σ to use higher augmentation strength, model performance keeps improving until reaching a plateau at approximately $\sigma = 1.0$. This value and the overall sensitivity of green color augmentation to σ should be affected by specific greenspace color patterns in different datasets. Thus, we further analyze the robustness of the augmentation method to dataset composition, i.e., if the method is effective on training images with scarce greenspace labels. Figure 4 (right) illustrates segmentation performance for 11% to 30% target labels, by selecting subsets of the training images and evaluating on the same set of testing images. The proposed method maintains its advantage over the baseline method throughout different training label volumes.

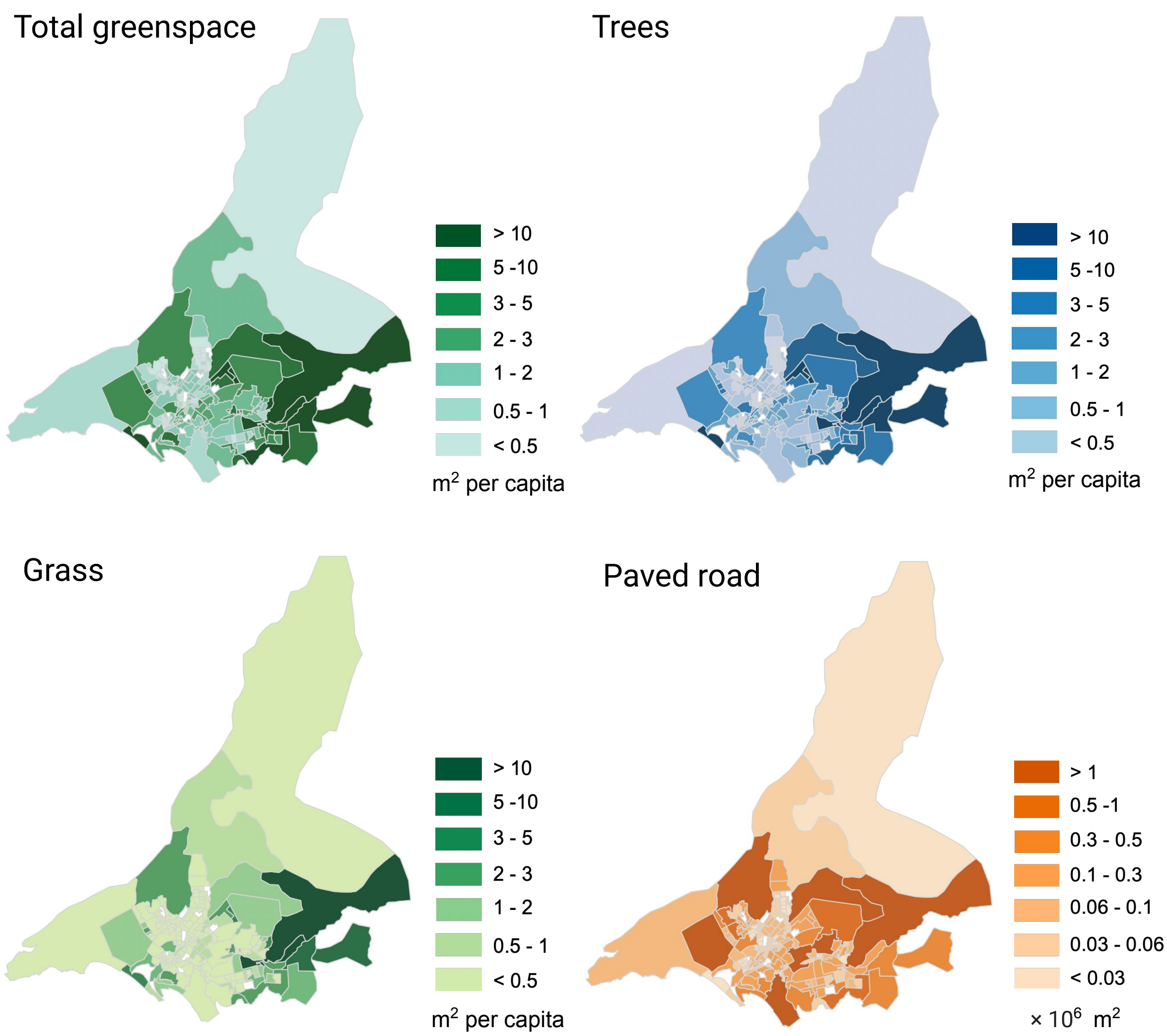

Figure 5. Spatial distribution of total greenspace, trees, and grass per capita, and areas of paved road in Karachi, union councils.

3.3 Greenspace distribution in Karachi

The proposed deep learning method is used to label images across all of Karachi, and compute two values. First, as an overall examination of greenspace amount and availability in the city, we compute per capita greenspace. The World Health Organization (WHO) recommends a minimum of 9 m^2/capita of greenspace per individual with an ideal value of 50 m^2/capita [45]. Using our method, we find that the mean per capita greenspace across union councils (smallest administrative level in Karachi) is 4.17 m^2/person. The greenspace availability also varies highly across union councils; 3 union councils have the highest greenspace values of over 80 m^2/capita (Darsanno Channo, Murad Memon, and Gulshan-e-hadeed), while 5 union councils have the lowest values of less than 0.1 m^2/capita (Darya Abad, Behar Colony, Chushti Nagar, Banaras Colony, and Gulshan Said). We note that the areas where per capita greenspace is higher than the World Health Organization recommendations are mostly on the periphery of Karachi (Figure 1), especially the eastern region. The region has rich surface water resources and collects most cultivated areas [25]. Therefore, the union councils located there are less populated and occupied by large agricultural lands or wild forests, showing high per capita greenspace. Moreover, we compute specific greenspace types per capita predicted by the trained multi-class semantic segmentation model. As shown in Figure 1, the spatial distribution of trees and grass have a similar pattern to the total greenspace.

Next, to understand where greenspaces are located, we examine the greenspace area by union council in comparison to a measure of economic development, paved roads [38, 41]. Pearson's correlation coefficient (r) reveals that greenspace has a significant positive correlations with paved road coverage (0.352, $p < 0.001$), and by vegetation type, there is a higher correlation for the tree greenspace type (0.367, p <0.001), versus grass (0.233, p <0.01). The map in Figure 1 shows that roads have a similar spatial pattern with per capita greenspace.

4 Discussion

In this work we first confirm that using visible-band satellite images, deep learning consistently outperforms vegetation indices for greenspace extraction [57, 18, 9]. This new approach has the benefit of resolving green spaces with high spatial granularity (e.g. single trees), as well as the ability to distinguish types of greenspace. The deep learning models consist of multiple convolutional neural network layers, providing a more complex functional form than the vegetation index, to capture features of greenspace such as vegetation object shapes, textures, colors, and other semantic visual cues through a high dimensional representation. Our new method further improves performance via a custom data augmentation step; data augmentation is commonly used in deep learning model training to increase image diversity. As the greenspace coverage is overall low in Karachi (there are only 1.65% greenspace pixels from the collected satellite images covering the city), data augmentation provides a specifically relevant step in order to avoid over-fitting on the limited greenspace patterns and losing accuracy on new unseen images. The augmentation paradigm we propose shows consistent improvement using it with different deep learning architectures, by increasing training data diversity with respect to the important feature for the application, the green hue of vegetation. Notably, the method requires no additional learning structure or GPU computing, thus it can be easily integrated into different pipelines. Robustness of our proposed method is also demonstrated based on using different proportions of images with greenspace pixels for training the model, showing its consistent advantage on datasets with limited greenspace representations or annotations. Our other contributions include using the method to audit the greenspace per capita in Karachi, and demonstrating current distribution of greenspace in the city.

Practically, the deep learning based method shown in this work can be used to understand greenspace and inform urban planning. First, we showo the per capita greenspace in Karachi is below WHO recommendations. In comparison, Singapore, which is densely populated (8358 people/km^2), has planned and incorporated greenspaces within the urban environment, reaching the minimum recommended, with 9.9 m^2/capita illustrating the feasibility of this target with appropriate planning efforts. Further, in places such as Karachi, where as we show, greenspace currently correlates with economically developed areas, there is a need for improve their prevalence in other parts of the city, or other criteria for their development. Overall, the scale-able nature, high granularity and delineation of using deep learning and satellite images can be used to monitor and plan for such resources to be available for all communities. The benefit of greenspace quantification is to understand its relationship to other land features.

This work is not without limitations. Importantly, for the analysis of greenspace distribution, we only focus on the feature of road infrastructure to investigate the relationships, limited by the availability of other socioeconomic data at comparable granular levels (i.e. union council). Further, we focus primarily on trees and grass, though methods that adequately resolve other greenspace types should be studied in more detail as well. There are several aspects of future work to extend this new approach proposed here.

A Evaluation on different model structures

Deep learning	Vegetation	Recall ↑	Precision ↑	IoU ↑	Accuracy ↑
UNet	All	0.835	0.847	0.725	0.897
UNet (Aug)	All	0.894	0.898	**0.811**	**0.920**
UNet	Trees	0.785	0.791	0.650	0.910
UNet (Aug)	Trees	0.824	0.828	**0.703**	**0.918**
UNet	Grass	0.691	0.810	0.595	0.937
UNet (Aug)	Grass	0.735	0.780	**0.609**	**0.945**

Table 3. Comparison of baseline deep learning method UNet, and with our proposed augmentation method UNet (Aug). Segmentation tasks include binary prediction (Vegetation is "All"), and multi-class prediction by vegetation types.

Deep learning	Vegetation	Recall ↑	Precision ↑	IoU ↑	Accuracy ↑
LinkNet	All	0.845	0.841	0.728	0.863
LinkNet (Aug)	All	0.888	0.895	**0.805**	**0.930**
LinkNet	Trees	0.751	0.809	0.638	0.884
LinkNet (Aug)	Trees	0.807	0.827	**0.691**	**0.921**
LinkNet	Grass	0.691	0.807	0.593	0.917
LinkNet (Aug)	Grass	0.771	0.810	**0.653**	**0.941**

Table 4. Comparison of baseline deep learning method LinkNet, and with our proposed augmentation method LinkNet (Aug). Segmentation tasks include binary prediction (Vegetation is "All"), and multi-class prediction by vegetation types.

In this section, we apply the proposed green color augmentation method on two additional deep learning model architectures, UNet [44] and LinkNet [8], used in previous work for segmenting greenspace. They use the same encoder and decoder structure as DeepLabV3+ but with variations in feature extraction procedure. Comparison results in Table 3, Table 4 show that our augmentation method is generalizable to different segmentation models and achieves improved performance on all metrics.

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