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. We demonstrate a deep learning-based approach which includes green augmentation for measuring and delineating types of greenspace in a city, with satellite imagery. Our method outperforms gold standard methods which use vegetation indices; it segments 80.68% of the greenspace, and correct assigns 83.63% of image pixels as greenspace or not, while the best performing vegetation index only detects 58.11% of the greenspace of which 56.71% of predictions are correct. 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 road surface coverage (Pearson's correlation coefficient (r) shows a significant 0.26 correlation between greenspaces and roads, $p < 0.001$), with a slightly higher correlation between roads and trees versus roads and grass. Quantifying greenspace in Karachi illuminates an important need; the mean per capita greenspace across union councils in Karachi is 2.84 m^2/person 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 [11, 3, 9, 4, 2, 8].

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 [15]. 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 [18, 7].

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. New opportunities for imagery include new satellites offering higher resolution (50 cm or less). Recently, researchers have proposed leveraging deep learning along with other forms of imagery (street view or drones), though none have yet demonstrated effective greenspace cataloging for any comprehensive urban area [7, 12]. 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.

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 [20]. 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 [15]) or study greenspace largely via survey data [16].

We describe a deep-learning based method for quantifying and identifying different types of greenspaces. Given the global importance of greenspaces for improved planetary and human health, this method is relevant to, and can be extended to locations worldwide.

Table 1. Comparison of vegetation indices and deep learning methods for greenspace binary predictions, and by class for deep learning methods which is NA (not applicable) for vegetation indices.

Vegetation index	Vegetation	Recall ↑	Precision ↑	IoU ↑
GRVI	NA	0.4998	0.5247	0.3349
VARI	NA	0.4643	0.5695	0.3363
GLI	NA	0.5811	0.5671	0.4047
Deep learning	**Vegetation**	**Recall ↑**	**Precision ↑**	**IoU ↑**
DeepLabV3+	All	0.7719	0.8373	0.6712
DeepLabV3+ (Aug)	All	0.8068	0.8363	0.6968
DeepLabV3+	Trees	0.7276	0.7894	0.6076
DeepLabV3+ (Aug)	Trees	0.7761	0.7783	0.6343
DeepLabV3+	Grass	0.5569	0.7141	0.4551
DeepLabV3+ (Aug)	Grass	0.6302	0.6839	0.4880

Results

Different vegetation objects (e.g. trees, grass) are combined into a single greenspace class, and each image is first segmented (divided into categories) by pixel-wise binary (greenspace or not) classification using the deep learning and baseline methods (vegetation indices). Table 1 shows the segmentation completeness (Recall), purity (Precision), and accuracy, measured by the intersection of ground-truth masks and the predicted segmentation divided by their union (IoU). The metric Recall=TP/(TP + FN), Precision = TP(/TP + FP), IoU= TP/(TP + FP + FN), where TP, FP, and FN are pixel-wise true positives, false positives, and false negatives for classifying greenspace. Deep learning methods largely outperform the vegetation indices, i.e. DeepLabV3+ (Aug), which is our proposed deep learning method that includes augmentation of green color, segments 80.68% of the greenspace, and has the correct rate of 83.63% of its predictions, while the green leaf index (GLI) only detects 58.11% of the greenspace and 56.71% of its predictions are correct. The green color augmentation method we propose increases training data diversity and further shows improved segmentation accuracy over the deep learning baseline DeepLabV3+ (Table 1).

Given that the 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 (Fig. 1). 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 vegetation types.

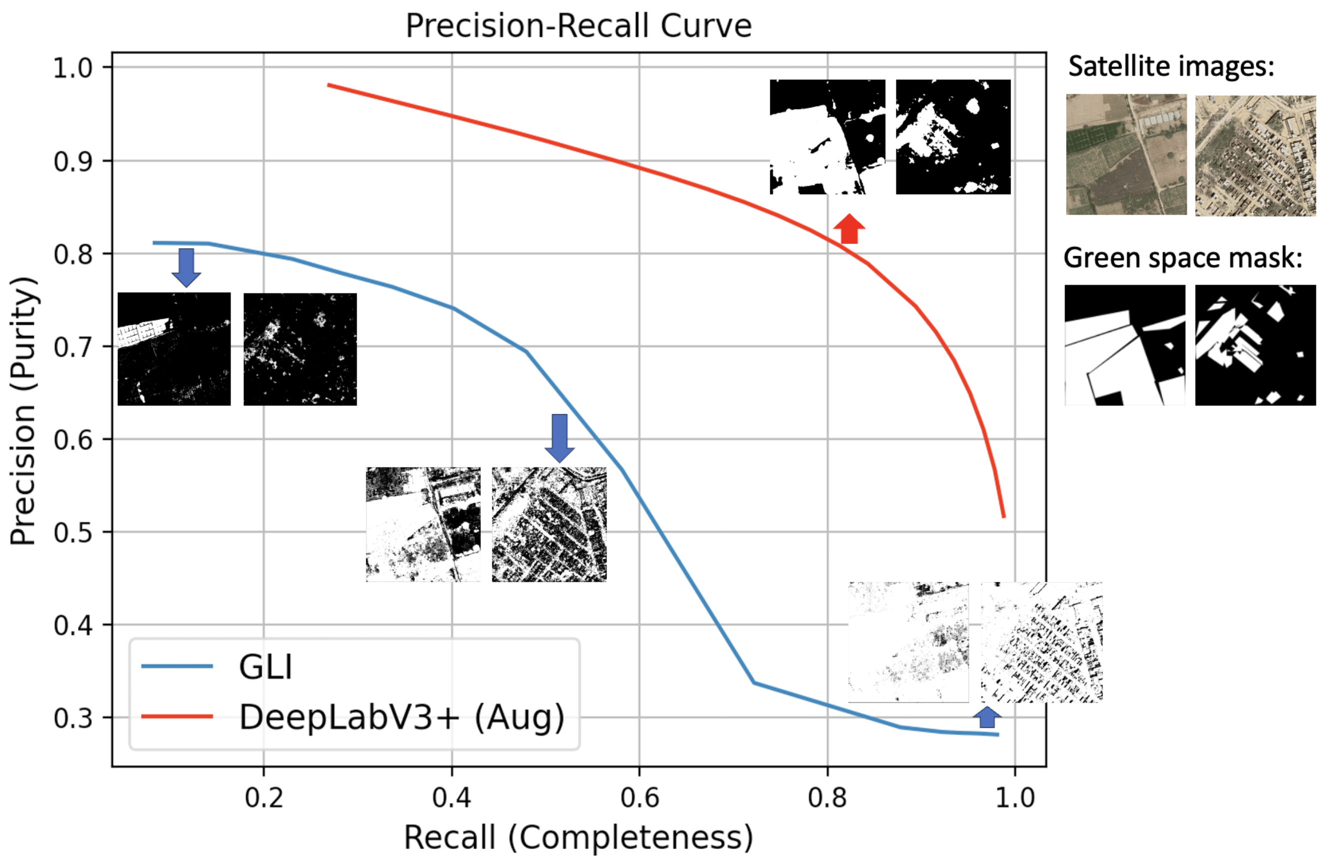

Figure 1. Illustration of the precision and recall trade-off for GLI and the proposed DeepLabV3+ (Aug) method is changed with images illustrating how each method distinguishes between greenspace and background.

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 tree class is annotated for all woody plants including lower shrubs, because tree height is hard to distinguish in the aerial view. We compare the DeepLabV3+ model trained with standard augmentation methods for image data: random horizontal and vertical flips, and besides those, the proposed green color augmentation, noted as DeepLabV3+ (Aug). With the additional augmentation step, the segmentation intersection over union (IoU) is improved by 4.4% for Trees class and 7.2% for Grass class. The improvement is from increased Recall that the model can capture greenspace features more completely with the feature extractor learnt from the synthesized new images, with a slight compromise of Precision.

The method is used to label images of all areas in Karachi, and compute two values. First, as an overall examination of greenspace in the city, we compute per capita greenspace. The World Health Organization recommends a minimum of 9 m^2/capita of greenspace per individual with an ideal value of 50 m^2/capita [17]. The mean per capita greenspace across union councils (smallest administrative level in Karachi) is 2.84 m^2/person. 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. The greenspace availability also varies highly across union councils; the union council with the highest value reaches 37.59 m^2/capita, while 6 union councils with the lowest values have greenspace less than 0.1 m^2/capita. We note that the areas where per capita greenspace is higher than the World Health Organization recommendations are mostly on the periphery of Karachi; they are less populated and occupied by large agricultural lands, thus showing high per capita greenspace.

Next, to understand where greenspaces are located, we examine the greenspace area by union council in comparison to a measure of economic development, roads. Pearson's correlation coefficient (r) reveals that greenspace has a significant positive correlations with road surface coverage (0.2600, $p < 0.001$), and for specific vegetation types, there is a slightly higher correlation for the tree greenspace type (0.2514, p <0.001), versus grass (0.2140, p <0.01).

Discussion

The deep learning model performs consistently better than all vegetation indices, the existing best practice for vegetation detection. This new approach also has the benefit of high granularity and the ability to distinguish types of greenspaces. 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 method adds to this improved performance via a 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 8.16% greenspace pixels from the collected satellite images) data augmentation provides a critical step in order to avoid over-fitting on the limited greenspace patterns and losing accuracy on new unseen images.

The deep learning method shown here can be used to understand greenspaces and inform urban planning. For example, in places such as Karachi, where greenspace currently correlates with economically developed areas, there is a need for improve their prevalence city-wide. Overall, the scalable 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.

Methods

Satellite imagery data. The study location is Karachi, the largest city in Pakistan with an area of 3,530 km^2 [1], and population of 16,839,950 [2]. We collect images using the Application Programming Interfaces (APIs) from Google Maps Platform, consisting of aerial view of Karachi with a resolution of 256 x 256 pixels and length of 38 x 38 meters. The total number of images is 42,735, comprehensively covering 167 Union Councils in Karachi City. We label 463 acquired images manually, pixel-wise, to identify greenspaces using the Labelbox tool[3]. Among them, 423 images are selected randomly,

[1] City K-OWPoKM. Karachi the Gatway to Pakistan. http://www.kmc.gos.pk/contents.aspx?id=14
[2] World Population Review. https://worldpopulationreview.com/world-cities/karachi-population
[3] Labelbox. https://labelbox.com/

and another 40 images which have large greenspace area are selected to increase the observation of deep learning models on the vegetation classes. Two members of the research team each labelled every image, and labels were validated by a third reviewer to ensure no obvious areas are labelled incorrectly. The union of the greenspace classes from the two annotators is used as the final label.

Visible band vegetation indices. Three visible band vegetation indices are used: (1) green-red vegetation index, based on the contrast between reflectance in green and red bands of green vegetation ground cover, defined via the following, where ρ_c is the reflectance value of the visible band in color c: [GRVI = $(\rho_{green} - \rho_{red})$/$(\rho_{green} + \rho_{red})$] [13]; (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 [5]; 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 [10]. These indices have shown to be useful vegetation indicators [13, 1, 6].

For the three indices, a pixel which produces a positive index value represents green vegetation (such as grass, conifers and deciduous trees); otherwise, it represents background such as soil, water/snow, buildings, roads or other non-living ground cover.

Green color augmentation for deep learning. A challenge for in-the-wild greenspace detection 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 special 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 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.

Implementation steps of the green color augmentation are: 1) convert the RGB image into HSV (hue, saturation, value) representation. 2) produce a random hue shift Z following a normal distribution. We use $Z \sim \mathcal{N}(0, 0.06^2)$ which obtains the best results for the data used in this work. 3) Apply Z to the hue channel of pixels labeled as greenspace. Assuming that the range of green color hue for the whole dataset is $[h_l, h_r]$, 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 as part of the training data.

Road detection. We use a pre-trained land-cover deep learning model [19] to quantify road surface for satellite images used in this work. The model is trained on and can detect major road with two or more lanes like highways. During the inference, the model outputs a probability of each pixel belonging to the class of road, and a threshold of 0.3 is selected based on performance on validation images to produce the final road detection results.

Additional implementation details. The vegetation index method 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 binary prediction: vegetation or non-vegetation, for each image pixel. The deep learning method requires firstly training the CNN based semantic segmentation network with labelled images, termed as the training set. The network will next analyze and label unseen new images, termed as the test set, to validate its performance. The output of the model is one of three classes for each image pixel: grass, trees, or non-vegetation. A 5-fold cross validation is used: images are split into 5 different training (80% / 392 images from 228 union councils) and test (20% / 98 images from 86 union councils) sets, and the final evaluation result is based on the mean performance over the 5 test sets. We implement the training and testing using PyTorch [14]. During training, our proposed green color augmentation, and other augmentations including random rotation and flip are used with a probability of 0.5. Input images are randomly cropped into the dimension of 512×512×3 where 3 indicates the RGB bands. The output dimension of the network is 512×512×3, where 3 represents the probability of each pixel belonging to each vegetation class or background. We use cross-entropy (CE) loss, and stochastic gradient descent (SGD) as the optimizer with a momentum of 0.9 and a weight decay of 10^{-4}. The batch size is set to 8 and the total training epochs are 70, during which the original learning rate is 0.01 and is decayed using a polynomial learning rate scheduler.

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