Machine Learning on High Performance Computing for Urban Green space Change Detection: Satellite Image Data Fusion Approach

Green spaces serve important environmental and quality-of-life functions in urban environments. Fast-changing urban regions require continuous and fast green space change detection. This study focuses on assessment of green space change detection using GPU- for time efficient green space identification and monitoring. Using spatio-temporal data from satellite images and a support vector machine (SVM) as a classification algorithm, this research proposes a platform for green space analysis and change detection. The main contributions of this research includes the fusion of the thermal band in addition to Near infra-red, red, green band with the fusion of high spectral information of the moderate resolution imaging spectroradiometer (MODIS) dataset and high spatial information of the LANDSAT 7 dataset. The novel method is employed to calculate the total green space area in the Mumbai metropolitan area and monitor the changes from 2005–2019. This research paper discusses the findings of our strategy and reveals that over the course of fifteen years the overall green space was reduced to 50 percent.

Keywords: satellite image analysis; data fusion; SVM classifier; GPU computing; urban change analysis

Introduction

Recently, green spaces have gained focus in urban planning and governance. The US Environmental Protection Agency defines green space as, “land that is partly or completely covered with grass, trees, shrubs, or other vegetation” (EPA). As such, green spaces include private parks, community gardens, cemeteries, schoolyards, playgrounds, and public seating areas. Urban green space and its functions are under increasing pressures induced by urbanisation including land conversion into impervious surfaces, soil, air pollution, and intense disturbances. Ecological assessment of urban green space can provide valuable information for urban planning and management that can be used to protect and enhance ecosystem services in urban green spaces. Automatic measurements of green spaces come mainly from geographic information system (GIS) data and remotely sensed data (**Parent et al. 2015**). For example, Tian et al. (2014) used high-quality digital maps with a spatial resolution of 0.5 m × 0.5 m to analyse the landscape pattern of urban green space for ecological quality. Gupta et al. (2012) calculated a neighbourhood green index to quantify homogenous greenness from multi-temporal satellite images. Periodically obtained remotely sensed imagery is suitable for updating the spatial distribution patterns of green spaces. However, with rapidly changing landscapes, as well as multiple sources of remote sensing data (available in almost real time), the analysis of green space assessment and change detection face several challenges.

The main motivation of this study is to accurately compute urban green space changes on a high-performance platform as soon as it is detectable from multiple satellite image sources. In considering Mumbai as our zone of interest, distinguishing proof of green space remains a challenge as the metropolitan region is populated with buildings, industrial regions, streets, etc. With the development of urban territory, green space is generally reduced. As indicated in the literature (Nagaraja et al. 2014), green space helps to diminish air and noise pollution, as well as mental pressure. Recently, high performance computing (HPC) frameworks (More et al. 2018) have provided image classification on the planetary scale (Gorelick et al. 2017). It is clear that spatiotemporal fusions of multisource remote sensing data (Zhu et al., 2018) are useful for green space analysis. Although remote sensing technologies have experienced rapid development in recent years, data acquired from a single satellite sensor are often unable to satisfy the information requirements of conventional techniques for green space assessment. A significant amount of research is being conducted in India using geospatial data (Sarda et al. 2018, Stendardi 2018). While data fusion methodologies and HPC technologies have evolved in other applications, the assessment of green space changes remains an open area of research.

This paper presents a HPC approach to green space assessment and change detection based on satellite image classification. The remainder of this paper is structured as follows: the literature review section provides a background of the work done in this area; the methodology section provides the steps in the assessment of green spaces; and in the results and discussion section, this research paper presents the results of our analysis of the Mumbai metropolitan area. In the final sections, the performance of fusion approach for satellite image classification using spectral fusion provides conclusions and topics of future work.

Literature review

Satellite images can be represented in terms of spectral bands, spatial resolution (Gallagher et al. 2018), and temporal information. The various spectral bands available with the dataset can be used to calculate the spectral vegetation indices. Vegetation indices are a ratio of the various bands associated with satellite images. Almost forty such indices have been reported to be available for vegetation analysis (Bannari et al. 1995). Vegetation indices play an important role in vegetation analysis (Chen et al. 2016).

In this study, support vector machines (SVMs) are used as classification algorithms as the literature shows that these algorithms achieve better performance when used with remotely sensed satellite images (Sarda et al. 2018). The Table 1 summarises the different categories and algorithms that are used for satellite image classification (Lu et al. 2007, Nair et al. 2016).

Various algorithms are available for supervised object-based land-cover image classification (Ma et al. 2017) and others available for change detection (Saeid et al. 2018). Urban green spaces are critical components of the urban landscape. The leaves of trees allow dust to settle and thereby reduce particles in the air; they also help to reduce noise pollution, which remains a major problem in cities (Nagraja 2014).

The most commonly utilised classification strategies for multispectral information emphasises the spectral resolution. On this basis, an arrangement of the spectral estimations of every pixel is treated as a set of properties that could be utilised for classification. As indicated by Huang et al. (2013), this permits a decent grouping dependent on the spectral signature of every region. However, this does not take into consideration the spatial resolution of the different structures in the image.

The most commonly utilised grouping techniques for multispectral information emphasise the spectral measurement. On this basis, remote sensed image data is arranged according to surface textures (Huang et al. 2013). A human expert can differentiate synthetic from common highlights in an image based on the 'normality' of the information. Straight lines and ordinary reiterations of highlights suggest man-made objects. This spatial data is helpful in recognizing distinctive fields' of **large sized** remote sensed images.

Study area:

In this work, Mumbai—one of India's **mega cities** and the capital of Maharashtra—together with Navi Mumbai are selected as the area of interest. Figure 1 shows the boundaries of the study area marked in the Google Earth engine.

Insert Figure 1. Area of interest marked on the Google Earth Engine

The approximate area of Mumbai and Navi Mumbai is 964 sq. km. Mumbai lies on the west coast of India at a latitude and longitude of 19.076090 N and 72.877426 E, respectively. It is a densely populated city with a population of approximately 12.5 million. As such, green space management is a critical issue. Additionally, Mumbai suffers from considerable air, noise and water pollution—all of which can be mitigated using green space. On this basis, this research paper chooses Mumbai for our case study.

Proposed methodology

This study involves satellite image classification using SVM and spatio-spectral fusion of satellite image data. The spectral and spatial information from two different datasets can significantly improve the accuracy of classifiers in the process of green space identification. The spatial information can provide information about the shapes of man-made or natural objects in the image, while the spectral resolution can represent features of various colours based on their reflectance in distinct wavelength ranges.

A multispectral satellite image needs to be pre-processed before applying any algorithm as an unprocessed data often leads to misclassification. This spatial and spectral information fusion approach reduces labelling uncertainty and salt-and-pepper noise. In the present study, cloud masking is performed on the satellite images prior to classification.

Pre-processing

Pre-processing includes removal of noise from satellite images of the Landsat 7 dataset, performed as follows:

Function: MaskingClouds(image)

{

(1) Input: Satellite image with multiple bands.

(2) Output: Satellite image with masked clouds.

(3) Bands('B1','B2','B3','B4','B5','B6','B7','pixel_qa')

(4) qa = image.select('pixel_qa');

// If the cloud bit (5) is set and the cloud confidence (7) is high

// or the cloud shadow bit is set (3), then it's a bad pixel.

(5) cloudmask = qa.bitwiseAnd(Bit_1 << Bit_5) AND (qa.AND (Bit_1 << Bit_7))

(6) .OR(AND(Bit_1 << Bit_3));

(7) // Remove edge pixels that don't occur in all bands

(8) // mask the image with mask used here.

(9) Maskedimage=image.apply(cloudmask)

(10) return (Masked image)

}

General information and mathematical modelling

Green space analysis is a classification problem in which green space needs to be identified in a satellite image. Currently, there are three approaches to identifying green spaces (Adesuyi et al. 2016): supervised, unsupervised, and semi-supervised (Banerjee et. al. 2015). The texture of a satellite image can be used to identify green space (Joshi et al. 2014)

Occasionally, vegetation indices alone are sufficient for identifying changes in vegetation space. However, to achieve higher accuracy in identifying and analysing changes, supervised machine **learning** algorithms—such as SVM, random forest, and naive Bayesian classifiers—can be used (Wang et al. 2018, Xiao et al. 2009).

Assuming urban green space (Tc) is a set and various regions (x) are the members of an area under consideration, this research paper attempt to determine whether the area is green space or not.

$$x \in Tc \tag{1}$$

In **Formula** (1), x can be a pixel or a pixel with many dimensions—such as vector($x_1, x_2, \ldots, x_n$)—in a satellite image. If x is a pixel, then pixel-based classification can be employed; if it is a pixel vector, then an object-based classification algorithm (Belgiu et al. 2018, Cheng 2016) can be used. In the present study, object-based classification approach is used as follows:

The following function, $f(x)$, can be used to classify x:

$$f(x): x \rightarrow \Delta; x \in R^n, \Delta = \{C_1, C_2, \ldots, C_L\} \tag{2}$$

where

x = Pixel or pixel vector

n = Number of bands

L = Number of classes and

$C_1 \ldots C_L$ = Set of classes to which pixel vector can belong

$f(.)$ is a function assigning a pixel vector to a class in a set of

$C_1 \ldots C_L$ classes.

In this study, this research paper attempts to determine whether the pixel vector represents green space or not—a typical binary classification. Satellite image classification is the science of turning remote sensing data into meaningful categories representing surface conditions or classes. Spectral pattern recognition procedures classify a pixel or its many dimensions based on its pattern of **radiance measurements in each band**. Spatial patterns are used to classify a pixel based on its relationship to surrounding pixels. A temporal pattern recognition classifier observes changes in pixel vectors over time to assist in feature recognition.

One of the focuses of this study is the fusion of the thermal band with the near infra-red, red, and green bands commonly used in tree canopy and green space assessment. The thermal band is used because green spaces reduce the temperature of the environment, thus providing an additional parameter for differentiation between vegetated and non-vegetated space. Approximately forty-five different vegetation indices are available for vegetation analysis (Mousaei 2014). However, some of them are highly correlated and therefore are not included in the classification process (Baycan-Leven et al. 2009).

This study focuses on the fusion of high spectral information from the moderate resolution imaging spectroradiometer (MODIS) dataset with high spatial information of the Landsat 7 dataset; our model learns from the former and is tested using the latter. As high spectral and spatial resolution is not available from a single source, this research paper combines the information from these two datasets to increase classification accuracy.

$$accuracy \propto Spectral_{High} \cup Spatial_{High} \tag{3}$$

In the present study, the green space analysis problem is mathematically modelled using an SVM algorithm based on the supervised machine learning technique. D. Luet et al. (2007) and Nairet et al. (2016) determined that SVM is one of the most accurate algorithms for satellite image classification (Lazar et al. 2009). The advantage of SVM over other algorithms is that it can process high-dimensional data efficiently with the help of different kernel types (Bekkari et al. 2014).

Support vector machine

If the points are not linearly separable and the boundary separating the two classes i.e., green or non green is nonlinear, then an SVM classification algorithm can be used. The idea is to consider a larger satellite image with pixels in this larger satellite image area associated with the original pixels from image and apply the SVM classifier to this new set of data points in the larger satellite image area. This will produce a linear decision boundary in the enlarged satellite image area and a nonlinear decision boundary in the original satellite image area. With this approach, the nonlinear boundaries are reduced by separating the satellite image into a linear one and using the classification algorithm to classify the pixels in the image.

Suppose $(x_1, y_1) \ldots (x_N, y_N)$ are our training data points x_i is a p-dimensional vector Each x_i is a p-dimensional vector

$$p = f(\beta n)$$

where n is the number of bands in the image, and β gives the image dimensions. The feature space is denoted S^p, while S_i is the satellite image. We have to enlarge S^p by mapping each pixel, x, to a vector in S^M, which is a larger space.

Let f: S^p **to** S^M be given by

$$f(x) = (f1(x), f2(x) \ldots\ldots fM(x),$$

where f_i from $S^p \rightarrow S^M$ are some functions and f_i are called the *basis* functions.

If $f(x_1), f(x_2) \ldots f(x_N)$ is our original set of points,

$(f(x_1), y_1)\ldots(f(x_N), y_N) \in S^M$

$(f(x_1), y_1)\ldots(f(x_N), y_N)$ is our new training dataset.

Using the new training set in the new feature space, SVM classifier is applied and obtained a hyperplane in S^M that softly separates points $f(x_1)$ through $f(x_N)$. For training the SVM, high spectral resolution image data from the MODIS dataset is used and then downscaled to the Landsat 7 dataset which has high spatial resolution.

$$f(x_i)=C(\beta_l(x)) \cup C(\beta_M(x))$$

On this basis, the training dataset will have selected bands from both the Landsat and MODIS datasets.

With this new value of x_i, the dual Lagrangian becomes

$$L_D(x) = \sum_{i=1}^{N} \alpha_i \frac{1}{2} - \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j \, y_i y_j f(x_i) f(x_j)$$

Solving the optimisation problem gives

$$\partial = \sum_{i=1}^{N} \alpha_i y_i f(x_i)$$

Any point which lies in the test feature dataset can be classified according to the above equation.

Spectral fusion approach for classification

This research paper adopts a spectral fusion approach to green space assessment, as shown in Figure 2. The approach is based on the spectral fusion of the MODIS and

Landsat 7 datasets—similar to the methodology explained by Gallagher et al. (2018). Classification is performed on the fused data using the SVM to monitor green space changes over a period of fifteen years.

Function: Spectral_fusion(image)

{

(1) B_n = select bands from satellite images

(2) High_Spectral_images from MODIS dataset

(3) High_Spatial_images from LANDSAT dataset

(4) Training_dataset_features= (B_n from MODIS)

(5) out=Classify(image,training_dataset_features,training_data,SVM)

//calculate area of green space of output image

(6) Calculate_area(out); //calculated area for year from 2005 to 2019.

(7) Testing_dataset_features(B_m from LANDSAT)

(8) Calculate_chnage_from_area(year1,year2);

}

Insert Figure 2. Steps in green space assessment based on spectral fusion of the high spectral resolution of the MODIS dataset with the high spatial resolution of the Landsat 7 dataset

Results analysis and discussion

This section presents an experimental analysis of classification performed by the spectral fusion approach. The analysis is visualised in the form of charts and figures.

Computing platform and experimental setup

For the experiments, the Google Colaboratory (Carneiro et al. 2018) and Google Earth Engine (GEE) platforms. Google Colaboratory is based on Jupyter notebook standards, which is open-source software that enables the development and sharing of **Python** code on notebooks. Using Google Colaboratory, code can be saved in Google Drive. The platform enables the use of graphic processing unit (GPU) and tensor processing unit (TPU) hardware accelerators for 12 hours continuous duration. Using GPU and TPU, parallel application is developed. The GPU available in Google Colaboratory is the NVIDIA Tesla T4 with 12 GB of usable space.

Google Earth Engine data is used in Google Colaboratory and Python 3. Google Earth Engine is a geospatial big data tool and provides access to massive amounts of geospatial data, which in our case consist of 15 years' worth of Landsat and MODIS imagery. The intermediate data can be downloaded and used locally while experimenting with different classifiers. Google Earth Engine increases data availability and provides good visualisation.

Datasets

The research paper uses the **MODIS MOD13Q1 Terra Vegetation Indices 16-Day of 250m resolution** Global dataset as it provides high spectral resolution **(Xiao 2009, Gallagher 2018).** The MOD13Q1 dataset contains 250 m reflectance information of the MODIS with bands 1–7 balanced utilizing a bidirectional reflectance appropriation capacity to show the qualities as though they are gathered from a nadir. The data are created daily; however, each image contains 16 days' worth of information and is dated on the ninth day of the 16-day time span. This item consolidates information from both the Terra and Aqua satellites, selecting the best delegate pixel from the 16-day time span. The MODIS dataset contains information from 2000 to the current date. The MODIS dataset is selected for green space change detection in the Mumbai area as it provides high spectral resolution The Landsat 7 dataset of 30 m resolution is also used for experimentation purposes. This dataset contains information from 1999 to the current date..The Landsat 7 dataset provides atmospherically corrected data from 1999 to the current date. This research focuses on use of above datasets because it aims to analyse 15 years of data—from 2005 to 2019—for the Mumbai Metro area

Table 2 shows the different bands of the Landsat and MODIS datasets and the bandwidth values. The classification techniques which are typically used for green space analysis include pixel-based or object-based. In the case of pixel-based approaches, the training sample contains a set of pixels and is compared with the pixels in the satellite image. In object-based classification, the training samples are polygons with a set of values.

Results analysis

This research paper applies analyses Mumbai Metro area (approximately 963.78 sq. Km), consisting of Mumbai and Navi Mumbai. The amount of green space in Mumbai has steadily declined by 47% of the maximum from 2005 to 2019, with the exception of a modest 5% increase from 2012–2014. Figure 3 shows the changes observed over the 15-year period using the spectral fusion method. In this research the area is calculated in (sq. Km) of green space from the classified images.

Insert Figure 3: Change in green space (area in sq. km) from 2005–2019 using the fusion approach

The results of the spectral fusion approach confirm a decrease in green space—approximately 50% of the maximum from 2005–2019. However, the accuracy of the approach (96.73%) is higher than that obtained by Xiao et al. (2009). Table 3 shows the overall accuracies obtained using the different datasets with the SVM.

Insert Figure 4: Accuracies obtained by the SVM classifier for different datasets

The accuracies obtained after applying the SVM algorithm in three different datasets are shown in Figure 4.

Insert Figure 5: Kappa coefficient per year

Figure 5 shows the Kappa coefficient calculated per year, which is also used as a measure of accuracy. **The numbers of images used for classification** are also important in the classification process. So Figure 6 shows different number of images used for year for classification of the data.

Insert Figure 6: Number of images considered for classification from 2005–2019

Figure 6 shows the number of images per year used for classification of the data. Figure 7 shows the classifier output: green spaces are marked in the map by the spectral fusion approach.

Insert Figure 7: Classification output with green space marked in green

Map as shown in the figure 8 is the output generated for each year from 2005 to 2019. This is used for generating change map. The change map is a binary image generated from the difference between classified images of two successive years.

Insert Figure 8: Map of green space change visualisation from 2005–2019

The time required for classification is shown in Table 4. From the table 4, this research paper can conclude that good performance is achieved using machine learning for green space analysis with a spatio-spectral fusion approach. **The green colour in the image shows positive changes and red part shows the negative changes in the green space of Mumbai.**

Conclusion and future scope

This research demonstrates green space change detection in the Mumbai and Navi Mumbai area based on fusion of high spectral resolution and high spatial resolution images. The result shows that the spectral fusion approach outperformed those using only the Landsat or MODIS dataset.

A drastic reduction in the green space of Mumbai is observed from 2005 to 2019. This study can be further extended to improve green space coverage in the city. Additionally, parallel- or deep-learning-based approaches can be used in future work to further improve the performance of the system. Finally, government bodies can use the methods in this research to determine the densely vegetated areas of Mumbai.

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