COMPARATIVE ANALYSIS OF DIFFERENT METHODOLOGIES FOR LOCAL CLIMATE ZONE CLASSIFICATION

Asia Aman[1*], Muhammad Murtaza Khan[2], Khurram Khurshid[1]

[1]Institute of Space Technology Islamabad, Pakistan,

[2]The University of Jedha Jeddah, Kingdom of Saudi Arabia

*For Correspondence; Tel. +923127236589, Email: asia_aman@live.com

ABSTRACT: *Mapping and classification of local climate zones is the most essential area of research in remote sensing for observing the environmental processes and understanding the relationship between natural phenomena and human beings for decision making. LCZ classification maps are beneficial for the climatologists to compare and classify rural and urban areas for temperature and urban heat island studies worldwide and can improve accuracy in reporting climatic changes.*

The basic motive of LCZ classification system is to ease the process of selecting the site and reporting metadata by improving the description of rural and urban surface conditions. Other applications include: defining urban heat island magnitude, climate modeling, weather forecasting, mapping land cover/use and historical temperature analysis. Many cities applied LCZ classification to classify land and selecting site for study.

Local climate zone classification system was introduced in 2012 by Oke and Stewart which is now used as a standard wall over the world. Several techniques are being used to map local climate zones in recent years. They differ on the basis of basis of the study area, data sets used, spatial and spectral data, selecting features, sensors used, post classification filtering, software used, training data, training method, size of the training set, classification method and classifiers used for generating the final LCZ maps.

Every algorithm has its own pros and cons. Numerous factors may affect the accuracy and efficiency of the methodology adopted for classification (such as atmospheric conditions and image resolution) and no one is applicable and perfect in every case. There is a need for knowing and developing a best-generalized classification method that can work efficiently under different conditions to facilitate researchers with limited resources.

In this study, a comparative analysis of different techniques used for local climate zone mapping is done and their results are compared. The results show that each method produces different results for mapping LCZs in case of overall accuracy and kappa coefficient values. Some methods are efficient in saving time consumption, some for producing accurate results of classification, others may be advantageous in requiring efforts. The integration of best properties of different techniques can be done to develop a new technique that is more useful and can enhance the classification performance in any area of interest.

Keywords: Local Climate Zones, Remote Sensing, Urban Heat Island

1. INTRODUCTION

The land is one of the basic needs of human beings. There are several reasons for degrading and decreasing land for their economic development, settlement and food production. The persistent efforts for fulfilling the needs and demands of the growing population is eventually a cause of drastic change in land use.

The information about land use land cover helps in selecting, monitoring, planning land use for human needs and welfare for handling the demands of the increasing population [1]. Keeping in view the significance of the techniques of engineering and science applied to remote sensing of earth, atmosphere and space, society was made in 1962 named as Geoscience Electronics Group. Later on, in 1980 its name was changed to Geoscience and Remote Sensing Society (GRSS) which is still known today Their internationally subscribed journal, Transactions on Geoscience and Remote Sensing (TGRS), monthly publishes the advancements and techniques for processing the geoscientific information.

Every year a Data Fusion Contest is arranged by IEEE GRSS on different topics related to remote sensing with an objective to connect people and resources. This contest is open to everyone and the data is provided by the committee. Multiple sources of information and various methods can be used for estimating and identifying different local climate zones.

Understanding and managing relationships and interactions among natural processes, natural resources and human are done in a better way if done timely and accurately.

Our environment is dynamic and is constantly changing land use land cover. Land use means how the land is being utilized by the human for their development e.g., buildings, roads, industries etc. Land cover refers to the physical appearance of the land such as water (open water or wetlands) or its covering by forests, low plants, deserts, agriculture, snow covering, etc.

Changes in land use and land cover by human activities result in an immense negative impact on surroundings [2-4] and have become a major source of global warming also referred to as climate change. Generally, natural landscapes such as wetland, forestry and grassland are changed into built-up classes and impervious surfaces which affects different environmental processes such as temperature, weather and rainfall etc. Development in urban areas is one of the main causes of urban heat island effect by changing the moist and permeable surfaces to dry and impermeable and raising the temperature than the surroundings.This study aims at:

i. The concept of Local Climate Zones and defining them.
ii. Understanding and reviewing different digital image processing classification techniques for observing the local climate zone classification.
iii. Comparing these methodologies.
iv. Evaluating which technique which provides the best information about the LCZ detection.

On the basis of these objectives, this study answers the following questions:

i. What are the different classes of Local Climate Zones?
ii. Is land-use land cover change detection advantageous?
iii. Can local climate zone change be detected?
iv. What different techniques can be applied in understanding this change?
v. Which classification technique can yield the best possible results?

2. LOCAL CLIMATE ZONES

Our land is divided into different classes on the basis of some properties. By classifying a landscape into these properties many prototype classes are obtained. Some clusters which are considered unsure (like closely spaced trees can be on the impervious are or closely packed buildings can be on some previous area) are removed while the remaining ones are assigned simple names.

As all the classes obtained from dividing the landscape universe are local in scale, climatic in nature and zonal in representation hence they are named as “Local climate zones”. We then define them as regions of the uniform structure, material, surface cover and human activity that covers a hundred meters to kilometers. After defining LCZs, urban areas are created according to their thermal properties which are then used for the analysis of urban heat aspects [5].

A proper classification system can simplify and define the property of the areas and objects under study. On the basis of these properties, the local climate zone is divided into the following classes as shown in figure 1.

3. SUITABLE METHODS FOR LCZ MAPPING

Several methods are being proposed and applied for LCZ mapping using Geo wiki, supervised classification based on pixels [7], object-based image analysis [8-9], and Geographic Information System based approach [10]. No single method can be perfect in all aspects to fulfill the desired criteria.

Supervised classification method can give good results with high accuracy and is based on the previous knowledge about the area under study. Among different classifiers, Random Forest is considered ideal on the basis of its computational performance and accuracy as it is non-parametric and does not require additional data for providing unbiased error estimates. In

the unsupervised method the pixels in the image are grouped on the basis of their reflectance values using Iterative Self Organizing Data Analysis (ISODATA) [11]. Initially, the required input is less and the pixels with similar spectral properties are grouped together [12]. The classes are labeled after the clusters are defined. When extensive fieldwork is difficult, it is advantageous to use.

Hybrid classification technique involves the use of both supervised and unsupervised classifications. It gives accurate results and is also cost effective using satellite imagery [13-14] particularly due to a lack of information about the spectral classes of the inaccessible areas.

Object-Based Image Analysis is based on two processing chains. In the first step, blocks are delimited and then LCZs are assigned to the extracted polygons using spectral and spatial indices. It gives promising results but still, the drawback of this method is that it requires high resolution of data and hence makes it too complex for the user.

Satellite remote sensing is beneficial because of its multi-temporal analysis [15]. Land use land cover change is easy to detect by using high frequency of satellites. Studies are being performed on land use land cover change using various techniques of remote sensing [16-17].

The data in GIS (Geographic Information Systems) combined with the spatial information about land use land cover helps in further spatial analysis and later on developing a model.

Different methodologies used for comparing local climate zone classification study are discussed in the upcoming section:

A. Using World Urban Database And Access Portal Tools (WUDAPT) And Random Forest Classifier [18]

This methodology was proposed by Chao REN, Meng CAI, Ran WANG, Young XU and Edward Ng in 2016 to study local climate zone as a case study of two cities: Wuhan and Hangzhou. Landsat data and WUDAPT were used to apply local climate zone classification.

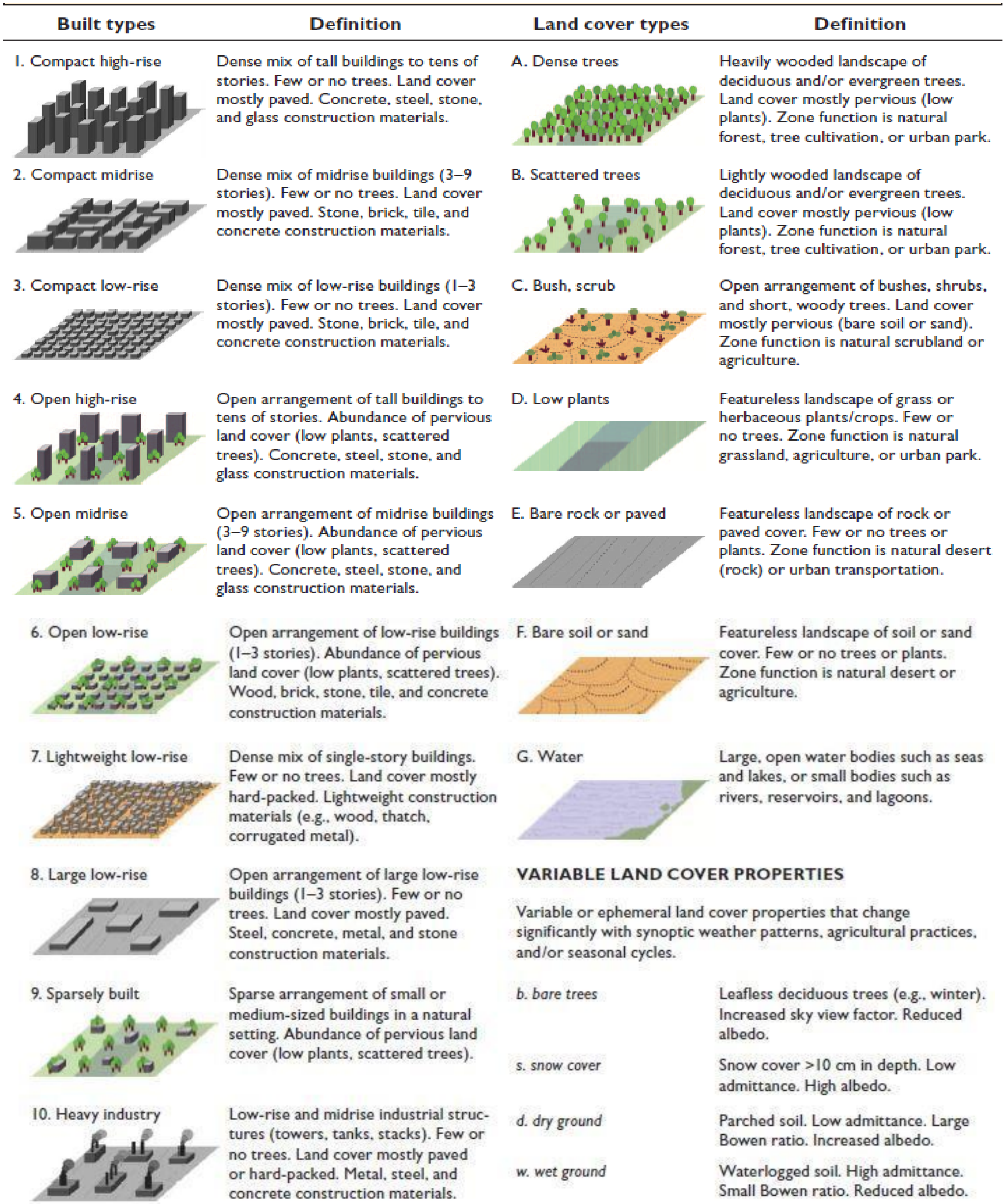
The Landsat 8 (level 1) images of both study areas were acquired from the U.S. Geological Survey (USGS) with 30m resolution.

This study consisted of these steps:

a) Pre-processing of data: The images of the study area obtained from Landsat8 were joined together and then clipped from the boundary to remove the extra area to decrease the computation time. Then this pre-processed image was resampled to 100m to represent a spectral signal of urban structures instead of smaller objects. The image created from remotely sensed data needs validation using resampling and preserving the original values unaltered.

b) Digitization of training data in Google Earth: Digitization is the method of creating vector data from raster data. Google Earth was used to obtain and digitize the training samples (Figure 3.1) of different categories of local climate zones. Polygons were used to select the areas of each class and then saved in kml format.

c) Classification in SAGA GIS: The training data obtained is then fed to SAGA GIS and Random Forest Classifier is used for classifying by comparing the training samples with rest of the area. Training data is based on the LCZ classification scheme presented by Stewart and Oke (2012) and contains 17 classes hence the classification is done accordingly.



Built types	Definition	Land cover types	Definition
1. Compact high-rise	Dense mix of tall buildings to tens of stories. Few or no trees. Land cover mostly paved. Concrete, steel, stone, and glass construction materials.	A. Dense trees	Heavily wooded landscape of deciduous and/or evergreen trees. Land cover mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
2. Compact midrise	Dense mix of midrise buildings (3–9 stories). Few or no trees. Land cover mostly paved. Stone, brick, tile, and concrete construction materials.	B. Scattered trees	Lightly wooded landscape of deciduous and/or evergreen trees. Land cover mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
3. Compact low-rise	Dense mix of low-rise buildings (1–3 stories). Few or no trees. Land cover mostly paved. Stone, brick, tile, and concrete construction materials.	C. Bush, scrub	Open arrangement of bushes, shrubs, and short, woody trees. Land cover mostly pervious (bare soil or sand). Zone function is natural scrubland or agriculture.
4. Open high-rise	Open arrangement of tall buildings to tens of stories. Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.	D. Low plants	Featureless landscape of grass or herbaceous plants/crops. Few or no trees. Zone function is natural grassland, agriculture, or urban park.
5. Open midrise	Open arrangement of midrise buildings (3–9 stories). Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.	E. Bare rock or paved	Featureless landscape of rock or paved cover. Few or no trees or plants. Zone function is natural desert (rock) or urban transportation.
6. Open low-rise	Open arrangement of low-rise buildings (1–3 stories). Abundance of pervious land cover (low plants, scattered trees). Wood, brick, stone, tile, and concrete construction materials.	F. Bare soil or sand	Featureless landscape of soil or sand cover. Few or no trees or plants. Zone function is natural desert or agriculture.
7. Lightweight low-rise	Dense mix of single-story buildings. Few or no trees. Land cover mostly hard-packed. Lightweight construction materials (e.g., wood, thatch, corrugated metal).	G. Water	Large, open water bodies such as seas and lakes, or small bodies such as rivers, reservoirs, and lagoons.
8. Large low-rise	Open arrangement of large low-rise buildings (1–3 stories). Few or no trees. Land cover mostly paved. Steel, concrete, metal, and stone construction materials.	**VARIABLE LAND COVER PROPERTIES**	Variable or ephemeral land cover properties that change significantly with synoptic weather patterns, agricultural practices, and/or seasonal cycles.
9. Sparsely built	Sparse arrangement of small or medium-sized buildings in a natural setting. Abundance of pervious land cover (low plants, scattered trees).	*b. bare trees*	Leafless deciduous trees (e.g., winter). Increased sky view factor. Reduced albedo.
		s. snow cover	Snow cover >10 cm in depth. Low admittance. High albedo.
10. Heavy industry	Low-rise and midrise industrial structures (towers, tanks, stacks). Few or no trees. Land cover mostly paved or hard-packed. Metal, steel, and concrete construction materials.	*d. dry ground*	Parched soil. Low admittance. Large Bowen ratio. Increased albedo.
		w. wet ground	Waterlogged soil. High admittance. Small Bowen ratio. Reduced albedo.

Fig. 1. Local Climate Zone Classification System. (LCZs correspond to Stewart and Oke, 2012 urban climate zones) [6]

B. Classification With Multi-Source Data Using Co-Training Approach [19]

This approach was adopted by Yong X., M. Fan., D. Meng., C. Ren. and L. Yee. in 2017 to develop an improved method for Local Climate Zone classification without requiring any prior knowledge or training data of target cities which is sometimes laborious to perform.

As this work was done for the Data Fusion Contest held in 2017, therefore, the data used was provided by the Image Analysis and Data Fusion Technical Committee of IEEE Geoscience and Remote Sensing Society (GRSS) [20].

Dataset included Sentinel 2, Landsat 8 and OpenStreetMap (OSM) for nine cities. Among the five cities (Rome, Paris, Hong Kong, Berlin and Sau Paulo) were used as training data and four (Madrid, Amsterdam, Chicago and Xi'an) as testing data. The images from the satellites contain 9 multispectral bands at 100×100 m^2 resolution.

The proposed method is shown in figure 2.

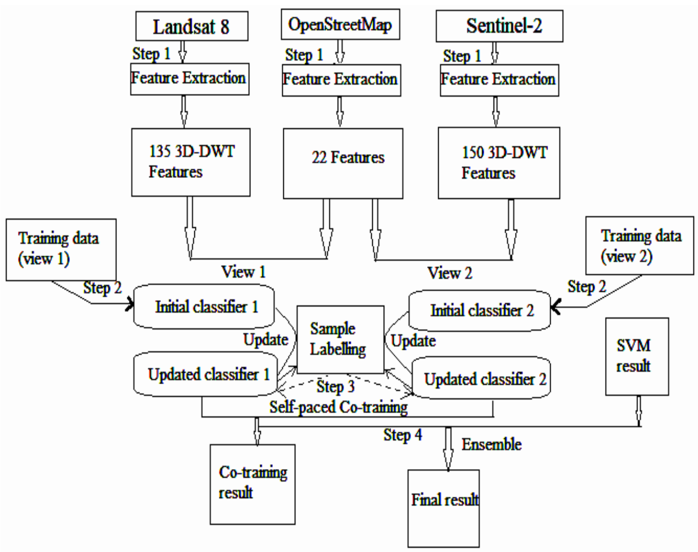


Fig. 2. Co-training approach for LCZ classification [19]

It involves the following steps:

a) Feature Extraction: To generate the spatial and spectral features from Sentinel 2 (150 features) and Landsat 8 (135 features) three-dimensional discrete wavelet transform [21] was used. OpenStreetMap generated 22 features as it has 22 categories of land cover. From these three datasets, 307 features were obtained.

b) Training Classifiers: Two independent XGBoost (extreme gradient boosting) [22] classifiers were used for training. Classifier 1 was trained using the features derived from Landsat 8 and OSM while classifier 2 was trained with the features obtained from Sentinel 2 and OSM.

c) Co-training for classification: For larger cities, self-paced learning with co-training approach was designed [23]. Two XGBoost classifiers generated two independent maps for the target cities. On this basis, the classified samples with high-confidence of one classifier were used to improve the other classifier. Thus, the classifiers are iteratively modified and proved appropriate by adding valid samples using this co-training approach.

d) The ensemble of multi-classifiers: To further improve the overall efficiency and accuracy this co-training approach was combined with other classifiers such as multi-layer perceptron (MLP) and support vector machines (SVM).

C. Classification Using Multi-Level Ensembling [24]

The scheme based on a multi-level ensemble of Convolutional Neural Networks, Gradient Boosting and Random Forests was proposed by S. Sukhanov, I. Tankoyeu, Js. Louradour, R. Heremans, D.Trofimova and C. Debes in 2017 to develop a supervised classification system to be used across multiple cities by fusing vector data and multi-spectral imagery.

Berlin, Rome, Hong Kong, Paris and Sao Paulo were used for training the model and four cities (Chicago, Madrid, Xi'an and Amsterdam) were used as test data.

The overall methodology adapted constitutes of the following steps:

a) Feature Extraction: Features selection is an important step for developing a classifier. Set of features extracted that include 2 dimensional matrix include Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), Bare Soil Index (BSI), Advanced Vegetation Index (AVI) and Shadow Index (SI), whereas the features including 3 dimensional matric e s are Spectral Angle Mapper (SAM), Minimum Noise Fraction (MNF) and Open Street Map (OSM).

b) Cross-Validation and Classification: This methodology consists of three layers: site temporal samples combiner, first level model combiner and second level model combiner.

c) Three classifiers are used namely: Convolutional Neural Networks (CNNs) [25], Random Forest [26] and Gradient Boosting Machines.

d) Spatial Smoothing: Spatial smoothing is performed after classification and ensembling.

D. Classification using Multispectral And Panchromatic Data [26]

This methodology involved the analysis and combination of multispectral (XS) and panchromatic data from HRV (high resolution visible) sensor, GPS (global positioning system) data, land use zoning maps and OBM data. It was proposed by Paul M. T., Howarth P. J., and P Gong in 1992 as a case study for a portion of the rural-urban fringe.

The study area is a town of Markham in Canada which was the location under observation due to its changing mapping conditions [27].

The overall methodology adapted is explained below:

a) Preprocessing: To preserve the spectral and spatial information, Spot HRV and panchromatic data were combined. 5co-registered with Spot HRV XS using the nearest neighbor algorithm and first-order polynomial. Secondly, this corrected data was resampled to 10m by the nearest neighbor. Then Spot HRV data was corrected geometrically.

The point-to-point conversion was applied to the raw data of GPS. Fuzzy tolerance of 10.5m was used to clean GPS data and collapse polygons which are not required. Fuzzy tolerance is used to determine the resolution of output coverage.

Land use zoning information was digitized and imported to SPANS environment.

b) Classification: Spot HRV XS and panchromatic data wse r e classified into 8 spectral classes using supervised maximum likelihood. The frequency-based method was applied to the result of spectral classification to classify land use and land cover.

c) Classification Accuracy Assessment: The accuracy of the classified Image was done by examining training area pixels and test area.

d) Data Integration: The different data sets were imported to TYDAC SPANS and matrix overlay analysis was performed to develop a map with land zoning information and derived LULC classification from Spot HRV XS. GPS data is then integrated with matrix overlay map. The information from three data sets was output on a color plotter.

e) Map Overlay Accuracy: Zoning classes were assumed to have 100% accuracy. The accuracy of Spot HRV XS classification presents limiting factor for accuracies of resulting class. Average of these classes was taken to estimate overall accuracy of the map.

f) Spot HRV Overlay: Average accuracy (78%) indicated the individual components from two source maps and is the estimate for map's accuracy.

E. Using Multimodal, Multitemporal and Multisource Global Data Fusion [28]

This methodology is based on ensembling techniques and fusion of multimodal data for local climate zone classification and was adapted by Naoto Yokoya, Pedram Ghamisi and Junshi Xia in 2017.

The overall methodology adapted constitutes of the following steps:

a) Preprocessing: On the Landsat 8 images atmospheric correction was done for removal of haze and the images were upsampled using bicubic interpolation. To reduce the computational cost, OSM images were normalized between 0 and 1 and downgraded to GSD of 10m.

b) Feature Extraction: 44 features were extracted that comprised of spectral indexes, spatial features and spectral reflectance. 22 of them (44 features) were found by calculating the mean and standard deviation of pixels of a patch of 10×10. 6 features included NDWI, NDVI and BSI. Spatial information was extracted from 10 m GSD NDVI OSM by using Morphological profiles (MPs).

c) Classification: For classification two methods i.e. Canonical Correlation Forests (CCFs) and Rotation Forest (ROFs) [94] were used. Both classifiers are advantageous due to their accuracy, processing time and capability.

d) Post Processing: To lessen the wrong labeling of classification maps and remove the salt and pepper noise,

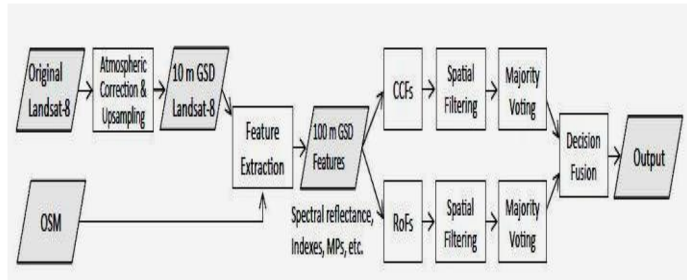


Fig. 3. Overview of the complete process [28].

spatial filtering using 3 3 median filters was applied. Majority

voting on 15 × N classification maps was used for the final

classified map. N is the number of images of Landsat8. Results of ROFs was used for Madrid and CCFs for Chicago, Amsterdam and Xi'an.

The process discussed above is shown in Figure 3.

F. Using ASTER And Landsat Data [29]

Different classification techniques using different data sets give good results. But they do not perform well for dataset of densely populated and compact cities [30]. ASTER data is now freely available, a combination of Landsat8 and ASTER data can produce better results for urban areas. This methodology was adapted by Y. Xu, C. Ren, N. Y. Edward, M. Cai and T. Wu in 2017. For this study densely populated and large area cities of China chosen were Wuhan (8,494 km²) and Guangzhou (7433 km²). The steps involved are:

a) Feature Extraction: For generating Local Climate Zone maps, the authors proposed the use of spectral and texture features. Spectral features included Landsat bands (1-7 and 10-11) and ASTER bands (1-3) whereas texture features included gray level co-occurrence matrix (GLCM) that represented the mean,

variance, contrast, similarity, homogeneity, correlation, entropy and second moment.

b) Training: Training of selected area was manually done with Google Earth.

c) Classifiers: Three classifiers used included Neural Network (NN), Random Forest (RF) and support vector machines (SVM).

Neural network classifier is feed forward classifier in which input nodes correspond to features and output layer shows the classified result. Different nodes process different information and then generate a final result.

SVM makes the data linearly separable by projecting it into high dimensional space. A kernel function is used as a hidden layer which separates original data in high dimensional space.

RF is an extension of decision tree classifier. The final classification is the integration of the results of different trees by voting. RF was used in SAGA GIS software. It is computationally efficient and has good prediction accuracy.

d) Performance Evaluation: The accuracy was tested via Google Earth and rechecked by Baidu D map (available at www.baidu.com).

G. Study Of Local Climate Zone Using Improved WUDAPT Methodology [31]

Local Climate Zone Study using improved WUDAPT methodology was done by M. Cai, C. Ren, Y. Xu, W. Dai & X. M. Wang in 2016 for Sustainable Megacities Development as a case study in Guangzhou.

The Greater Pearl River Delta (GPRD) includes the economic zone of Guangdong province apart from other regions. The study area, Guangzhou, is one of the nine municipalities of Guangdong province. It is the densely populated (more than 8.5 million) [32] area of China with a total area 7434km^2 and is facing rapid climatic changes due to land use changes. Hence UHI effect is more prominent.

The steps involved in this methodology are:

a) Preprocessing: Atmospheric and seamless mosaic corrections were applied to the above mentioned four Landsat images and combined into single. Then resampled the resolution from 30m to 100m.

b) Digitization of training areas: Each LCZ class was selected by polygons (5 for each class) as training samples and then saved as kml file. Training of selected area was manually done with Google Earth and training samples included Shenzhen, Huizhou, Hong Kong and Guangzhou. 50 polygons were used for every class of LCZ.

c) Classification in SAGA GIS: The preprocessed Landsat data and whole GPRD was fed to SAGA GIS and LCZ map of GPRD was generated.

d) Extraction of cities inside the region: The boundaries of municipalities were used to extract the municipalities (11 municipalities were generated) in the region separately.

H. Expert Classification Algorithm Using Digital Aerial Photographs [33].

This study was done by A. Perea, J. Meroño, M. Aguilera and L. Cruz in 2010 using spectral information of digital sensor for classifying land cover. The study area used for this purpose was Pedroches, Spain. It has a Mediterranean climate with mild winters and dry summers.

Vexcel UltracamD photogrammetric sensor was used to capture 64 frames on 23rd May 2006 with 7500 × 11500 pixels. The spatial resolution of frames was 0.5m which consisted of red, green, blue and infrared bands.

Erdas Imagine 9.0 system was used for expert algorithm classification.

The overall processing has the following steps:

a) Obtaining the principal components: To summarize numerous variables into a small set without losing any information, PCA (principal component analysis) is used. It constructs images to increase their capacity of differentiating cover types.

b) Obtaining NDVI: Vegetation absorbs red and reflects near infrared wavelength. NDVI was calculated to know the spectral behavior and calculating reflectivity image.

c) Supervised classification: Several images were obtained from different band combinations. The Bayesian classifier was used in ERDAS Imagine for classification due to a variety of classes.

d) Object-oriented classification: This classification is based on objects instead of using pixels. This processing uses less time.

e) Expert classification algorithm: The algorithm used in this classification consisted of assigning the classes. The pixels of each class (of the classified image of PC and NDVI), when coincided with the classified image from principal components, they were assigned to this class. Where there was no coincidence found the pixels were assigned by object-oriented classification. 75000 verification points were used to analyze the quality of classifications.

I. High-Resolution Remote Sensing Imagery Classification Using Fully Convolutional Network [34]

This classification approach, based on improved Fully

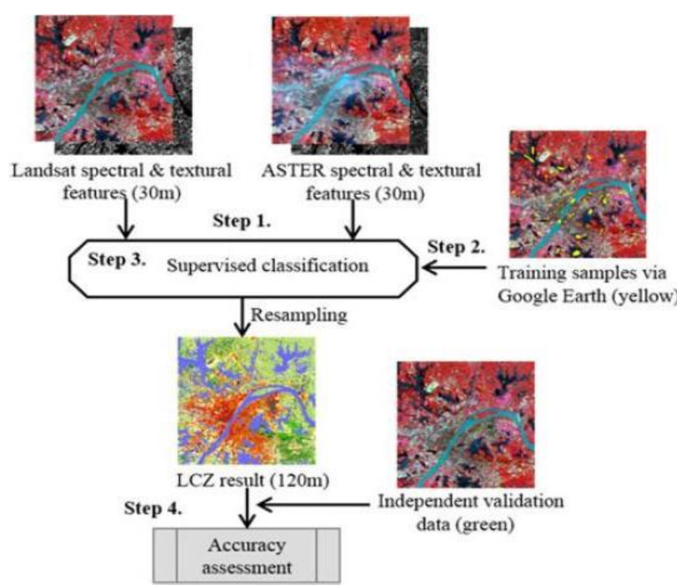


Fig. 4. Overall classification process using Landsat and ASTER data [29]

Convolutional Neural Network (FCN) model was proposed by Gang Fu, C. Liu, R. Zhou, T. Sun, and Q. Zhang in 2017. It is a supervised classification approach.

The study area comprisesf northeastern Beijing, China. Dataset was collected from 2 GF-2 high-resolution images with 0.8m resolution of 2nd September 2015 and 5th December 2014.

The methodology adapted has the following steps:

a) Training: Training dataset contained 70 images with a size 1024 × 1024 for each of which there existed a label map of the same size. Image-GT label pairs were used as training samples and fed into multiscale classification network. Softmax function was used to predict the class distribution. Cross-entropy loss was calculated and then network parameters were updated by SGD momentum (Stochastic Gradient Descent). 4 images were used for testing.

b) Classification: Up-sampling was performed and then classification boundaries were blurred. To refine the results, post-processing using CRFs was performed.

J. Classification Based On Multiple Features And Ensemble Learning [35]

The method for land use/ cover change detection in urban areas from high spatial resolution images based on multiple features and ensemble learning was proposed by X. Wang, S. Liu, P. Du, H. Liang, J. Xia and Y. Li in 2018.

Different areas were chosen for performing multiple experiments that include: Xuzhou and Jiangyin (China). QuickBird satellite was used to acquire images of 15th September 2004 and 2nd May 2005.

It involves the following steps:

a) Pre-processing: To reduce the discrepancies between images and reflectance differences, pre-processing (radiometric correction and atmospheric correction) is done. Orthorectification, Pan-sharpening and Co-registration is also performed.

b) Segmentation: Images are divided into small regions using spectral, spatial, textural information and shape. Segmentation maps are generated for bi-temporal images.

c) Difference image: Differencing process is done using pixel-based feature extraction process to calculate difference vectors of bi-temporal images and then they are used as input to classifiers.

d) Classification: Different classifiers used and integrated include: Support vector machines, KNN, Extreme Learning Machines (ELM), random forest. The accuracy of each classifier was calculated, the largest value obtained among them was defined as the final result.

4. RESULTS AND DISCUSSION

The results of all the methods discussed in the previous chapter are summarized and compared in Table I.

The supervised [38] methods require a lot of effort in training the classifier using high-quality imagery [39].

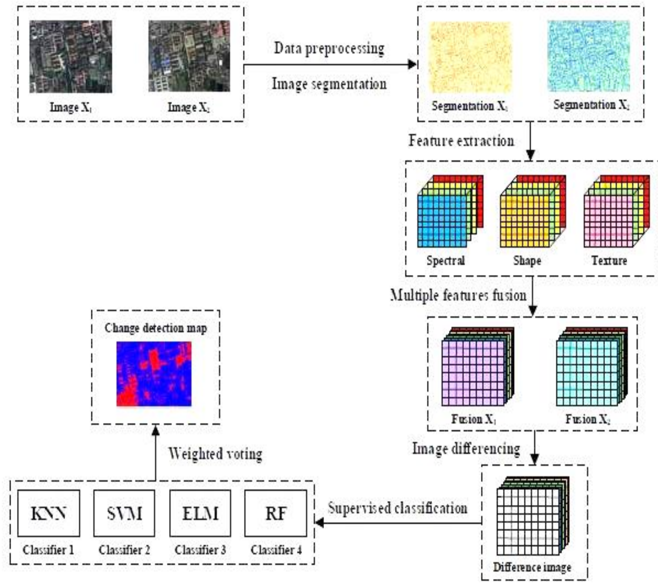


Fig. 5. Workflow for classification [35]

TABLE 1. COMPARISON OF METHODS

Sr. No.	Method	Overall Accuracy	Kappa Coefficient
1	Classification using World Urban Database and Access Portal Tools (WUDAPT) and Random Forest Classifier.	For Wuhan 75.2 For Hangzhou 75.5	For Wuhan 0.75 For Hangzhou 0.72
2	Classification with Multi-Source Data using Co-Training approach.	73.2	0.66
3	Classification using Multi-level Ensembling.	72.63	0.68
4	Classification using Multispectral and Panchromatic data.	74.4	0.7
5	Classification using Multimodal, Multitemporal and Multisource Global Data Fusion.	74.49	0.71
6	Classification using ASTER and Landsat Data.	For Wuhan 84 For Hangzhou	For Wuhan 0.83 For Hangzhou 0.64
7	Study of Local Climate Zone using Improved WUDAPT Methodology.	83.93	0.774
8	**Expert Classification Algorithm using Digital Aerial Photographs.**	**95**	**0.911**
9	High-Resolution Remote Sensing Imagery Classification Using Fully Convolutional Network.	81	0.83
10	**Based on Multiple Features and Ensemble Learning.**	**93.15**	**0.858**

A. Supervised Classification

]. There is less availability of ground truth data for supervised classification. Sometimes the land regions are highly ambiguous and complex to recognize. Therefore, it is quite difficult to characterize them and attain reliable results [40]. Also, a lot of knowledge is required to differentiate overlapping classes such as dense residential, sparse residential and medium residential [41].

Deep hierarchical structure easily extracts features from labeled and unlabeled data and provide promising results [42]. Several existing datasets have limitations such as lack of image variation, accuracy, and number of images per class hence limit the new algorithm development for scene detection.

B. Problem In WUDAPT Methodology

The WUDAPT methodology is simple and universal. It aims to become a global protocol to gather information about the form and function of different cities from freely available Landsat data by the use of Google Earth and SAGA GIS. It classifies cities globally and then produces a database of urban form and structure and this overall process consumes excess time in preprocessing of images and selecting training samples in case of each city hence difficult to analyze them one by one [43].

C. Improved WUDAPT Methodology

The improved WUDAPT methodology includes more training samples and the atmospheric correction of the satellite images hence it eliminates the atmospheric and solar influences as compared to normal WUDAPT method. Therefore, the classification results, overall accuracy and kappa coefficient is more accurate.

D. Use Of Digital Aerial Photographs

The use of digital aerial photos to give geometrically corrected products is ideal to assess the environmental processes instead of using satellite imagery [44]. Remote sensing faces a technical problem of extracting useful information from satellite images because of non-sufficient spectral information [45]. In high-resolution images each pixel refers to a portion of components instead of an object which limits the use of pixel-based classification [46]. Therefore, the use of group of pixels as an object is beneficial.

E. Fully Convolutional Networks (FCN)

High-resolution images contain more information about ground details. Land use land cover has many types and can be affected by illumination, noise, seasonal changes and several other reasons hence make classification difficult.

Among many deep learning techniques, Convolutional Neural Networks are found to produce excellent results for image classification. In 2015, J. Long et al. [47] presented the fully convolutional network model. Keeping in view the advantages of FCN different authors proposed different related frameworks for large-scale classification.

FCN model has the benefits of easy implementation, higher accuracy and less expensive computation as compared to convolutionalneural networks (CNN). CNN involves redundant computations due to overlapped regions for dense class [48].

Object-oriented classification involves segmentation-classification. Segmentation is done in an unsupervised manner and that can lead to the wrong classification. For classification, it is difficult to choose features for an object and requires experience. In FCN, the class information controls the processes such as feature extraction and classification. The methodology adopted in [49] combines both stages i.e. segmentation and classification and presents good quality classification.

F. Use Of Multiple Sensors Multiple Features

Experiments show that height features derived from LIDAR produce low classification accuracy i.e. 83.17%, adding intensity information improves the accuracy by 3.92% points which wse r e improved 87.69% by adding multiple return features. Classification accuracy for SPOT5 images is 86.51% which is further improved by 6.03% by combining it with LIDAR data [50].

Combining LIDAR and multispectral data compensate the drawbacks of one another and produce more accurate classification results as compared to their individual use.

G. Computing LCZ From OpenStreetMap (OSM) Data

OSM data has enough information required to derive LCZs and has the advantage of direct calculating geometric properties with the disadvantage of the weak derivation of previous surfaces as compared to image-based methods.

H. SAGA GIS Based Classification

In SAGA GIS the images acquired from Landsat and vector file containing training areas must be preprocessed. GIS-based methods need tremendous data as input thus, it is difficult to use it worldwide.

I. Ensembling Multiple Classifiers

Integrating different classifiers yields better results than that of their individuality. The technique of combining support vector machines (SVM) and multi-layer perceptron (MLP) with the co-training approach (discussed in section 3.2) shows that accuracy improves by 2-3%.

J. Random Forest

The Random Forest classier is very fast and efficient as compared to other classifiers and hence it is used mostly for classification including WUDAPT method.

K. Co-Training Approach

This approach is efficient in saving time consumption. It uses multi-source data and new features for better performance and hence produces better LCZ mapping results.

5. CONCLUSION

Mapping and classification of local climate zones is the most essential area of research in remote sensing as it is important for observing the environmental processes. Local climate zone change detection is important to understand the relationship between natural phenomena and human beings for decision making. Local climate zones classify rural and urban areas for temperature studies and can improve accuracy in reporting climatic changes.

In this study, the results of numerous techniques used with different approaches for local climate zone mapping are being discussed and compared. The results show that each method applied produces totally different results either in case of mapping LCZs or overall accuracy values.

The results of these techniques vary on the basis of the study area, data sets used, feature selection and their number, feature calculation, different kind of spatial and spectral data, sensors used for acquiring data, post classification filtering, software used, training data, training method, size of training set, classification method and classifiers used for generating the final LCZ maps.

Supervised object-based land cover/use classification mostly uses high-spatial resolution imagery. Hence, Landsat imagery is frequently used. Neural networks (NN) is not a good technique for object-based classification though it is the frequently used classifier. Random forest (RF) performs best in this case as compared to SVM.

Features selection is one of the most important tasks in image classification and classification accuracy is dependent on it. It is not good to use too many features as it can introduce uncertainties.

Each method has its own benefits and disadvantages. Some are efficient in case of time-consuming, some for producing accurate results of classification, others may be advantageous in saving time. The integration of best properties of different techniques can be done to develop a new technique that is more useful and can enhance the classification performance and can be used globally in any area of interest.

REFERENCES

[1] A.O Zubair, "Change detection in land use and land cover using Remote Sensing data and GIS", Department of Geography, University of Ibadan, October 2006.

[2] J.S. Deng, K. Wang, Y. Hong, J.G. Qi, "Spatio-temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization". *Landsc. Urban Plan*. 2009, 92,187-198, doi:10.1016/j. landurbplan. 2009.05.001

[3] M. Vizzar, "Peri-Urban transformation in agricultural landscapes of Perugia, Italy". *J.Geogr.INF.Sysyt*.2011, 3, 145-152.

[4] S. Van Asselen, P. H. Verburg, "Land cover change or land-use intensification; simulating land system change with a global-scale land change model". *Glob. Chang. Biol*. 2013, 19, 3648-3667.

[5] T.R. Oke, "The energetic basis of the urban heat island". *Quart. J. Roy. Meteor. Soc., 108*, 1-24, 1982.

[6] I.D. Stewart, & T.R. Oke, "Local Climate Zones for Urban Temperature Studies". *Bulletin of American Meteological Society*, 93, 1879-1900, 2012.

[7] B. Bechtel, C. Daneke, "Classification of local climate zones based on multiple earth observation data". *IEEE J.Sel. Top. Appl. Earth Obs. Remote sensing*, 6, 2102-2131, 2013.

[8] Q. Weng, "Global Urban Monitoring and Assessment through Earth Observation"s; CRC Press: Boca Raton, FL, USA, 2014.

[9] P. Gamba, G. Lisini, P. Liu, P. Du, H. Lin, "Urban climate zone detection and discrimination using object based analysis of VHR scenes". In Proceedings of the 4th GEOBIA, Rio e Janeiro, Brazil, 2012.

[10] E. Lelovics, J. Unger, T. Gl, C. V. Gl, "Design of an urban monitoring network based on local climate zone mapping and temperature pattern modelling". *Clim. Res*, 60, 51-62, 2014.

[11] R.O. Duda, P.E. Hart and D.G. Stork, "*Pattern Classification"*. John Wiley & Sons, New York, 2001.

[12] C.P Lo and J. Choi, "A hybrid classification approach to urban land use/cover mapping using Lansat 7 Enhanced Thematic Mapper Plus (ETM+) images". *International Journal of Remote Sensing*, 25(14): 2687-2700, 2004.

[13] M. Guler, T. Yomralioglu and S. Reis, "Using Landsat data to determine land use/cover changes in Samsun, Turkey". *Environmental Monitoring Assessment*, 127(1-3): 155-167, 2006.

[14] B.C. Foster, "An examination of some problems and solution in monitoring urban areas from satellite platforms". *International Journal of Remote Sensing* 6:139-151, 1985.

[15] D.K. Gordon, R.P. Warren and William D.P., "Fruit Tree Inventory with Landsat Thematic Mapper Data". *Photogrammetric Engineering and Remote Sensing*, 52:1871-1876, 1986.

[16] R.N. Jadhav, M.M Kimhoti and A.K. Kandya, "Grassland Mapping/Monitoring of Banni, Kachchh (Gujrat) using Remotely Sensed Data". *International Journal of Remote Sensing*, 14:3093-3103, 1993.

[17] R. Balak and A. S. Kolakar, "Remote sensing application in monitoring land use changes in Arid Rajasthan", *International Journal of Remote Sensing*, 14(17),3191-3200, 1993.

[18] R. Chao, C. Meng, W. Ran, X. Young and N. Edward, "Local Climate Zone Classification using World Urban Database and Access Portal Tools (WUDAPT) method: A case study in Wuhan and Hangzou", *The Fourth International Conference on Countermeasure to Urban Heat Islands*, 4th IC2UHI, Singapore, 2016.

[19] X. Yong, M. Fan, D. Meng, C. Ren., and L. Yee, "IEEE GRSS Data Fusion Contest: A Co-Training Approach to the classification of Local Climate Zines with multi source data", *IEEE Geosci. Remote Sens. Mag*, 2017.

[20] D. Tuia, G. Moser, B. Le Saux, B. Bechtel, and L. See, "IEEE GRSS Data Fusion Contest: open data for global multimodal land use classification", *IEEE Geosci. Remote Sens. Mag*. 2017.

[21] X. Cao, L. Xu, D. Meng, Q. Zhao, and Z. Xu, "Integration of 3-dimensional discrete wavelet transform and Markov random field for hyperspectral image classification", *Neurocomputing*, vol.226, pp. 90-100, 2017.

[22] J. H. Friedman, "Greedy function approximation: A gradient boosting machine", Annals of statistics, vol.29, pp. 1189-1232, 2000.

[23] F. Ma and D. Meng, "Self-paced Co-training", International Conference on Machine Learning (ICML.), 2017.

[24] S. Sukhanov, I. Tankoyeu, J., Louradour, R. Heremans, D.Trofimova and C. Debes, "IEEE GRSS Data Fusion Contest": Multilevel Ensembling for Local Climate Zones Classification, *IEEE Geosci. Remote Sens. Mag*, 2017.

[25] N. Seivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting", *Journal of Machine Learning Research*, vol. 15, 2014.

[26] P. Trietz, Howarth, P. and P. Gong, "Application of satellite and GIS Technologies for Land-Cover and Land-Use Mapping at the Rural-Urban Fringe": A case Study, *Photogrammetric Engineering and Remote Sensing*, 58(4), pp. 439-448, 1992.

[27] P.M. Trietz, P. J. Howarth, D. J. Gratton, G. H. Holder, and C. A. Greatrex, "GPS and SPOT data for Map Revision in the Rural Urban Fringe". *Proceedings, GIS for the 1990s, second National Conference on GIS,* Ottawa, Ontario, Canada, pp 1539-1545, 1990.

[28] N. Yokoya, P. Ghamisi, and J. Xia, "IEEE GRSS Data Fusion Contest: Multimodal, Multitemporal and Multisource Global Data Fusion for Local Climate Zone Classification", *IEEE Geosci. Remote Sens. Mag.* 2017.

[29] Y. Xu, C. Ren, N. Y. Edward, M. Cai, and T. Wu, "Classification of Local Climate Zones Using ASTER and Landsat Data for High-Density Cities", *IEEE journal of selected topics in Applied and Remote Sensing.* 10(7), 3397-3405, 2017.

[30] M. Cai, C. Ren, Y. Xu, W. Dai and X. M. Wang, "Local climate zone study for sustainable megacities development by using improved WUDAPT methodology": A case study in Guangzhou, Int. Conf. Geograph. Health Lining Cities, Making cities healthy for all (H-City), Hong Kong, 2016.

[31] M. Cai, C. Ren, Y. Xu, W. Dai and X. M. Wang, "Local Climate Zone Study for Sustainable Megacities Development by Using Improved WUDAPT Methodology"–A Case Study in Guangzhou. *Procedia Environmental Sciences*, *36*, 82-89, 2016.

[32] J. Xu., "Analysis of the Guangzhou urban heat island effect". Robotics and Applications (ISRA). IEEE Symposium on (pp. 555-557.) 2012.

[33] A. J. Perea, J. E Merono, M. J. Aguilera & J. L. Cruz, "Land-cover classification with an expert classification algorithm using digital aerial photographs". *South African Journal of Science*, *106*(5-6), 92-97, 2010.

[34] G. Fu, C. Liu, R. Zhou, T. Sun, & Q. Zhang, "Classification for high resolution remote sensing imagery using a fully convolutional network". *Remote Sensing*, *9*(5), 498, 2017.

[35] X. Wang, S. Liu, P. Du, H. Liang, J. Xia, & Y. Li, "Object-Based Change Detection in Urban Areas from High Spatial Resolution Images Based on Multiple Features and Ensemble Learning". *Remote Sensing*, *10*(2), 276, 2018.

[36] V. Walter, "Object-based classification of remote sensing data for change detection". *ISPRS Journal of photogrammetry and remote sensing*, *58*(3-4), 225-238, 2004.

[37] B. Bechtel, C. Deneke, "Classification of local climate zones based on multiple earth observation data". IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 5(4), 1191-1202, 2012.

[38] G. Mills, J. Ching, L. See, B. Bechtel, "An introduction to WUDAPT Project". Paper Presented at the 9th International Conference on Urban Climate. 2015.

[39] G. Cheng, J. Han, & X. Lu, "Remote sensing image scene classification: benchmark and state of the art". *Proceedings of the IEEE*, *105*(10), 1865-1883, (2017).

[40] L. Gomez-Chova, D. Tuia, G. Moser & G. Camps-Valls, "Multimodal classification of remote sensing images: A review and future directions". *Proceedings of the IEEE*, *103*(9), 1560-1584. (2015).

[41] H. Wu, B. Liu, W. Su, W. Zhang, & J. Sun, "Deep filter banks for land-use scene classification". *IEEE Geoscience and Remote Sensing Letters*, *13*(12), 1895-1899. (2016).

[42] Q. Zhu, Y. Zhong, B. Zhao, G. S. Xia, & L. Zhang, "Bag-of-visual-words scene classifier with local and global features for high spatial resolution remote sensing imagery". *IEEE Geoscience and Remote Sensing Letters*, *13*(6), 747-751. (2016).

[43] A. Krizhevsky, I. Sutskever, & G. E. Hinton, "Imagenet classification with deep convolutional neural networks". In *Advances in neural information processing systems* (pp. 1097-1105). (2012).

[44] C. Ren, R. Wang, M. Cai, Y. Xu, & E. Ng, "Accuracy Comparison between LCZ map Generated by GIS-based Method and World Urban Database and Access Portal Tools Method". In *The Fourth International Conference on Countermeasure to Urban Heat Islands (4th IC2UHI).(Under review)*. (2016).

[45] J. Moreira and J. Environ "Digital orthophotos of Andalusia, an important environmental value". 49:35-37. Spanish. 2005.

[46] G. Wilkinson, I. Kanellopoulos, C. Kontoes, R. Schoenmakers "Advances in the automatic processing of satellite images". Paper presented at: Conference on the Application of Remote Sensing to Agricultural Statics; Villa Carlotta, Belgirate, Lake Maggaiore, Italy. Luxembourg: Office for Publications of the European Commision; p.125-132. 1991.

[47] N. Sanchez, "Current overview of mixed techniques of image classification using spectral and texture segmentation". Application to high spatial resolution images. Mapping 88:32-37. 2003.

[48] J. Long, E. Shelhamer and T. Darrel "Fully Convolutional Networks for Semantic Segmentation". In proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, USA. 2015.

[49] M. Lagkvist, A. Kiselev, M. Alirezaie, A. Loutfi 2016. Classification and Segmentation of Satellite Orthoimagery Using Convolutional Neural Networks. Remote Sens. 6,329.

[50] J. Chen, P. Du, C. Wu, J. Xia and J. Chanussot, "Mapping Urban Land Cover of a Large Area Using Multiple Sensors Multiple Features". Remote Sens. 10,872; doi: 10.3390. 2018.