Chapter 4

Problem formulation

4.1 General

Chapter 4 outlines the present-day-challenges in RS classification, motivation to the present study, problem statement and research objectives of the work. The literature survey discussed in chapter 2 identifies image fusion, classification algorithms and effective integration of ancillary data into classification as the three important areas need to be explored to enhance the classification accuracy. This chapter, to arrive at the problem statement, once again briefly reviews the previous work and discusses the major limitations of the conventional classification techniques. Accordingly, the study to be carried out is narrowed down to the evaluation of image fusion techniques, behavioural study of decision tree classification algorithm, and effectiveness of integration of band transformation, band ratioing and texture features into classification process. The study is also carried out to examine the reliability of using statistical distance measures as feature selection criteria in non-Gaussian environment and to observe border-effect in texture-based classification. Therefore, the objectives of the study are formulated under three major phases.

4.2 Problem statement

From sections 2.2, 2.4, 2.5 and [6] it is intuitive in a broader way that obtaining satisfactory classification accuracy over urban or semi-urban LU/LC classes, particularly in high spatial resolution images, is deemed to be a present day challenge in remote sensing and is attributed to the following reasons. For classification of features in urban area, the spatial resolution of the data should be at least 5m or less. [26]. The enhanced spatial detail which is available from the high resolution imagery allows mapping of individual objects and contains larger within-class spectral variation. It is evident from the simple visual observation that the urban/semi-urban areas comprising of the ground covered with parking lots, highways, interior tar roads, vegetation, lawn, garden, tree crowns, water bodies, soil, construction sites, built-up areas having rooftops made of RCC, clay tiles, corrugated plastic, fiber and asbestos sheets, etc. show abundant sub-classes within classes. Apart from the above, various man-made structures made of similar materials but having different colours stand spectrally distinct even though they belong to the same class. For example, rooftops having different colours or the sunlit and
the shady sides of the same rooftop constructed of the same material and colour would exhibit vastly different spectral responses even though they belong to the same class. Also, the urban landscapes composed of features that are smaller than the spatial resolution of the sensors lead to mixed pixel problem in medium spatial resolution data (between 10m to 100m spatial resolution) [6]. In addition to providing higher spatial details, most of the high resolution imagery sources suffer from low spectral resolution, typically containing only three or four spectral data bands. Therefore, when the spatial resolution of the satellite imagery is increased, the higher within-class variability reduces the statistical separability between the land cover classes in spectral space and tends to diminish the classification accuracy [103]. A similar conclusion is also drawn by Danielle et al. on SPOT imagery [5] and Aaron and Curt on IKONOS data [101]. The two major reasons for this negative impact on the classification accuracy are viewed as below.

- The assumption of Gaussian distribution of spectra is often violated especially in the high resolution MS data comprising of urban/ semi-urban LU/ LC features [3], [72], [101]. The existing traditional hard classification techniques (per-pixel classifiers) are parametric in nature and they assume datasets to follow Gaussian distribution for their reliable performance, which cannot be ensured when the spatial resolution of the data becomes finer. In addition to the above, insufficient, non-representative or multimodal distribution of training samples further introduces uncertainty into the classification procedure.

- Another major drawback of the parametric classifiers lies in the difficulty of integrating ancillary data [3], [9] like digital elevation model [18], size and structural information [100], [174], slope, texture [164], NDVI [165], surface temperature [72], demographic information, agricultural and population density census data [166], [167], and contextual information, etc. with spectral data. Despite the fact that the ancillary data are found to be useful in bringing out enhanced separability between the classes, the difficulty arises when the ancillary data violate the normal distribution of the resulting data. In some context, ancillary data are also called add-on data and addressed under data fusion to derive greater information from classification. If the data to be fused is not in a common representation format and bears no compatibility in representation format (data type) and scales, then fusion of supportive data with the original multi-spectral bands, and subsequent analysis and knowledge extraction is difficult to execute [87], [167] (Example: The spectral information is in image format and the demographic information or census data are in statistical format).
Therefore, the traditional per-pixel classifiers which are confined to examine only the spectral variance of the pixels ignore the spatial and ancillary data information corresponding to the class distribution and are unable to ensure accurate classification results. As a consequence, the above potential problems make parametric classifiers fail to exploit the best use of information available through today’s advanced sensor systems and various ancillary data.

On the contrary, from section 2.4.3.3, it is known that non-parametric classifiers are independent of the properties of distribution of data and found to be suitable for the incorporation of non-spectral data (ancillary data or add-on data) into a classification procedure. Despite the fact that neural networks and SVM (belong to the family of non-parametric classifiers) show superior learning accuracy [76], they do suffer from longer training time [87], [89], [95], [168], and the classification time is linearly proportional to the size of the image. Hence their practical implementation is still unattractive and not feasible in RS data analysis. In this situation, the decision tree learning algorithm evolved from the field of data mining is emerging as a potential candidate for non-parametric classification in handling data of non-Gaussian distribution.

Decision tree classifier has not been explored as widely as other statistical classification methods within the remote sensing community. In spite of its faster learning time, easier understanding of decision rules and ability to handle data of higher dimensionality, the problems associated with DT are the selection of splitting criterion, generation of larger tree size and associated rule sets at various data dimensionality, spatial resolution and noise. Most of the research works conducted on decision tree algorithm in the context of classification of remote sensing data have confined themselves to just LU/LC classification. Only few studies have reported the performance of the algorithm in respect of training dataset size [91], choice of splitting rules (attribute selection measures) [7], [91], variation in the number of features, and various pruning methods [157] to provide greater insight into the employability of the algorithm on data recorded by various types of RS sensors [18], [95], [169].
Nevertheless, it is also observed from the literature survey that performance of the decision tree classifier for changes in training strata and training data set size, varying amount of inter-class noise and different class hierarchy levels over urban or semi-urban environment would provide better understanding of the classifier. Furthermore, the effect of band ratioing and band transformation (add-on data) on the tree structure and training time would make the behavioural study of the classifier more substantive.

Another area which poses challenge to the analysts is the choice among the various image fusion techniques. The literature mentions about the various image fusion algorithms and the conventional image quality measuring metrics to assess fused images, but they are not application-specific. The application may be classification, change detection, mapping, etc. The fusion technique which performs well in mapping need not be suitable for classification. As far as classification is concerned, it is difficult to arrive at a common plausible conclusion from the comparative study made in some of the major investigations carried out to determine the best fusion method for RS data [22], [25], [27], [28], [30], [40], [170]. Hence, the major research questions that the image fusion techniques still need to answer are:

- Which is the best RS image technique to meet the objectives/ application of the user, and which combination of data is the most successful one?

As a matter of great interest, it is observed from the previous studies that ancillary information and texture features are able to reduce the ambiguities within the spectrally overlapping LU/ LC classes and improve classification accuracy. Various methods have also been developed to blend spectral and spatial information into classification, wherein the class texture is considered to be a potential information source in improving interpretability and accuracy of the classified data. Researchers have unanimously opined that texture improves classification accuracy when integrated with multi-spectral data [5], [8], [9], [81], [95], [135], [171].

However, the success of using texture images into classification depends on the types of texture measures, texture variables like interpixel distance (displacement), quantisation level and window size, texture combinations, and the image bands used to derive texture. However, for a specific study, no rules have been recommended for identifying suitable texture measures, because texture varies with the characteristics of the landscape under
investigation and the spatial resolution of the image data [6]. Only a countable number of studies [5], [171] have quantitatively explored the performance of various texture measures in classification at varying window sizes and quantisation levels with multispectral data, but have not given a satisfactory finding on the displacement parameter. Danielle et al in 1990, and again recently Shahid Kabir et al. in 2006 have suggested the study of the GLCM based texture at different interpixel distances and directions, and separate assessment of the individual texture measures and window sizes to examine their relationship to different types of urban LU/ LC classes at high resolution imagery [5], [8].

LU et al. remarked that BTC, a statistical separability measure, which makes use of the JM and correlation coefficient, provides an effective feature selection metrics to identify the best combination of textures in their study [120]. On the contrary, Gong et al. and, Shaban and Dikshit remarked that separability measures like TD, JM and Bhattacharya distance would not serve as reliable feature selection measures in texture analysis [15], [161]. Further, there is also a lack of consensus reflected off the study carried out to know the effect of employing various band combinations of texture measures on classification accuracy [17], [171]. Of course, it is intuitive that the success of employing any feature selection measure depends on the suitability and reliability of the measures employed; otherwise interpretation of such measures may be misleading when a large number of texture features are to be combined with spectral bands. Hence, the literature survey identifies that

- There is no comprehensive study and no common agreement available with regard to the application of texture information in classification over urban/ semi-urban LU/ LC features. A study to quantify the size of the moving window, the optimum texture measures, displacement, and feature selection criteria to determine the best texture and multi-spectral band combinations for optimal accuracy would resolve some of the conflicts observed in integrating texture features into multi-spectral RS image classification.
4.3 Motivation

The ultimate goal in all classification techniques is to best exploit the spectral, spatial, temporal resolutions and polarisation signature of the data, and other inherent characteristics associated with it. In this direction, over the years, scientists and researchers with the evolution of high end computing systems and the availability of data of higher resolution (spatial, spectral, radiometric and temporal) have been devising many classification strategies to explore the image processing and data mining techniques to exploit their potential in extracting the desired information efficiently from the RS data by way of improving classification accuracy [108]. But, till date, literature has not ranked any of the classifiers as the best of all situations, because characteristics of each image and the circumstances for each study varies greatly with regard to the spectral, spatial, temporal, dimension and volume of the data under investigation.

Therefore, the general motivation behind this work is the fact that the accurate classification of remotely sensed data into various LU/LC is the foremost requirement in the study and proper management and monitoring of natural as well as man-made resources on the Earth. Hence, employing advanced classification approaches and techniques of image processing has opened new avenues to carry out ample research work in remote sensing with a great deal to develop newer classification procedures to make the best use of ancillary data so as to achieve higher classification accuracy over fine resolution satellite imagery.

4.4 Aim of the work

The aim of this research work is to achieve higher classification accuracy over semi-urban LU/LC features in high resolution multi-spectral data and to develop a framework to exploit the spectral and spatial information content of the data.
4.5 Objectives of the present study

Keeping in mind the observations made in the literature survey and the problems summarised under section 4.2, the present study has been carried out in three phases with specific objectives as mentioned below in the context of classification of semi-urban LU/LC features in high resolution multi-spectral data.

Phase-I

For classification of urban features, the required spatial resolution should be at least 5m or less where buildings and roads can be easily distinguished [26]. The above requirement can also be fulfilled through image fusion, which enables combining multiple images into a composite product so as to derive the best features of both the sensors than that of the individual. Accordingly, the objective of the phase-I work is set as follows.

**Objective 1:** To carry out image fusion at pixel level to integrate a multi-spectral image of 5.8m and a panchromatic image of 2.5m spatial resolution by employing at least any three of the commonly available data fusion algorithms and evaluate the algorithms quantitatively based on visual analysis, statistical analysis and derived classification accuracy so as to determine the best fusion algorithm which yields greater overall classification accuracy for semi-urban features, which is also a pre-requisite for further studies.

Phase-II

Since, the existing traditional hard classification techniques are parametric in nature and show limited success in the complex environment of the urban area on high resolution data, the research interest is focused on employing a decision tree classifier (DTC) based on non-parametric learning algorithm. The behavioural study of the DTC algorithm would provide a greater insight into the performance of the classifier on RS data. Hence, in continuation of the studies carried out so far in literature with regard to DT, the following objective has been set in phase-II of the work.

**Objective 2:** To investigate and study the behavioural response of the decision tree classifier at various training dataset sizes and at two different classification hierarchy levels over a semi-urban area. The objective is also extended to investigate the effect of integration of image band conversion, band ratioing and image smoothing techniques on classification accuracy and associated rule sets in DTC algorithm.
Phase-III

Since, texture represents the intrinsic spatial variability of the radiometric data and is a valuable feature in RS data to discriminate different LU/LC types, a study is required to investigate the effect of texture feature extraction and their combinations in LU/LC feature classification, which is found quite relevant in the context of classification of RS data [5]. Moreover, since the reliability of employing the statistical distance measures as feature selection criteria in classification holds contradictory opinions [9], [15], [120], [161], an assessment of the measures in non-Gaussian environment (texture integrated into high resolution MS data) is believed to be worthy of study. Hence, the following objectives have been formulated in phase-III of the study.

**Objective 3:** To develop a methodology to investigate and to effectively integrate the GLCM derived texture measures in classifying panchromatic sharpened data of 2.5m resolution at various window sizes and interpixel distances at class hierarchy level I and II, and to examine border-effect in the classified images.

**Objective 4:** To understand how single and combinations of more than one texture measure perform simultaneously with multi-spectral data in parametric and non-parametric classification.

**Objective 5:** To assess the reliability of employing conventional statistical distance measures- the TD and JM as feature selection criteria in selecting the optimal combinations of texture and multi-spectral bands in parametric and non-parametric classification.
4.6 Summary

To sum up, the review of literature clearly indicates that the finer spatial resolution data poses challenge in generating a satisfactory classified image over urban/ semi-urban areas using traditional classifiers, and the task is not as straightforward as classification of low resolution imagery (30m or more).

The major challenges in RS data processing and classification are related to the classification process. Remote sensing data has spectral, spatial, temporal, polarisation and other related characteristics. Making full use of this RS information and ancillary data may be the most efficient and effective way of improving classification accuracy. In relevance to this, the classification algorithm, the type of texture measures and the associated variables, the algorithm adopted for image fusion, the type of ancillary and add-on data, etc. play major role in improving classification accuracy; and their application need to be studied extensively. Further, one of the critical steps in remote sensing is the selection of suitable RS data variables and ancillary data for classification. Research is ongoing in this direction to devise appropriate selection and quality assessment measures; which must necessarily be reliable and time-efficient.

The motivation behind this research is the fact that accurate classification of remotely sensed data into various LU/ LC is very essential in proper management and monitoring of natural as well as man-made resources on the Earth. The aim of this research is to improve the classification accuracy over semi-urban LU/ LC features in high resolution satellite image by adopting advanced classification algorithm and exploiting the spatial information inherent to the high resolution data by employing advanced image processing techniques. In this direction, a machine learning algorithm called the decision tree classification algorithm–a member of the family of non-parametric classifiers - has been selected for the study. Besides multi-spectral data, the texture images, the band transformed and band ratioed images are also introduced to bring in additional class-discriminatory power to the classifier. The objectives 2, 3 and 4 represent the core motivation to this research work and, objectives 1 and 5 are the pre-requisite that serve as collateral study.