

International Conference on Information and Communication Technologies (ICICT 2014)

## A Hierarchical Framework for the Classification of Multispectral Imagery

Saritha S<sup>a,\*</sup>, G Santhosh Kumar<sup>b</sup>

<sup>a</sup>Department of Information Technology, Rajagiri School of Engineering & Technology, Kochi, Kerala, India

<sup>b</sup>Department of Computer Science, Cochin University of Science and Technology, Kochi, Kerala, India

---

### Abstract

Out of the abundant digital image data available, multispectral imagery is one which gives us information about the earth we live in. To gain knowledge from multispectral imagery, it is essential to classify the data present in the image based on spectral information. Classification plays a significant role in understanding the remotely sensed data obtained from the satellites. This paper brings out a new classification scheme based on a hierarchical framework. The hierarchical model proposed in this paper helps to understand the imagery at different levels of abstractness and concreteness to serve different applications like town planning, facility management and so on. The model depicts classification of the multispectral imagery on three abstract levels. The algorithm proposed outputs classification at different levels with an average accuracy of 72.6% in level 1 and 78.3% in level 2. The time sensitivity analysis of the algorithm shows that it outperforms the traditional SVM classifier. A detailed analysis of the algorithm proposed is detailed in this paper with respect to the parameters influencing the classification accuracy.

© 2015 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license

(<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Peer-review under responsibility of organizing committee of the International Conference on Information and Communication Technologies (ICICT 2014)

**Keywords:** Multispectral imagery; Hierarchical; Image Classification

---

### 1. Introduction

The conventional method of environmental data collection and analysis is not efficient in delivering the

---

\* Saritha S. Tel.: +91-9947256711.

E-mail address: sarithas.sarithas@gmail.com

necessary information in a timely and cost effectively fashion. Hence viewing the earth from satellites has become essential to understand the usage of land in the earth. Remote sensing images from satellites provide a feasible source of data from which land cover information can be extracted efficiently and effectively. Satellite remote sensing system periodically collects spectral data and provides information in understanding and monitoring the earth's surface. Land cover refers to the biophysical cover of the earth's surface which is either natural such as vegetation and water bodies or human induced such as settlements. Land use denotes the way in which and the purpose for which land and its resources are being used by humans. The land cover/land use classification can be done on the multispectral images at different levels of abstractions depending upon the resolution of the image. For very high resolution satellite images, the classification can be achieved on a very concrete level. There are applications like town management, road facility management and so on which require the classification to happen on an abstract level also.

This paper proposes a classification technique which provides the class labelling on a hierarchical level. Here the high resolution image is classified at different levels of concepts to support different applications. An algorithm is proposed which achieves this classification. The algorithm is supported by semi-supervised learning methods to enhance its performance. The method is analyzed in terms of accuracy, and it is observed that the technique is in par with the traditional classifiers. The algorithm outperforms other classifiers in terms of time sensitivity.

The paper is organized in five sections. Section 2 describes the current state of art in the field of multispectral image classification. The design of the hierarchical classification scheme and the algorithm is presented in detail in section 3. A summary of the results and the analysis of the algorithm is illustrated in section 4. The paper is concluded in section 5.

## 2. Background

Resolution is the property of remotely sensed data most critical to their utility which refers to an imaging system's capability of resolving two adjacent features or phenomena. There are different types of resolution for remote sensing imagery, of which the most important one are spatial and spectral, radiometric, and temporal. Spatial resolution of imagery refers to its ability to distinguish two spatially adjacent objects on the ground. Spectral resolution refers to the ability of a remote sensing system to differentiate ground objects at different reflectance values. It is determined by the number of spectral bands used to record spectrally split radiant energy received from the target. Depending upon the need for which remotely sensed image is used, the appropriate resolution has to be chosen. Also the way to understand or classify the observed area depends upon the user's application needs. A fine scale classification presents every local detail inside the image. To understand/classify the image on a regional level, medium scale resolution imagery is sufficient. However to understand/classify the image on a global scale, a very large resolution imagery is enough.

The aspect of classification is changing from pure aspect to semantic mode to facilitate the applications so as to aid human understanding. This contributes to the motivation of such a work. Following literature describes the current state of art in image classification. A sub pixel based mapping strategy of the remote sensing images is presented which establishes the spatial distribution of land cover<sup>1</sup>. It is necessary to dip down into the sub pixel as the pixel is a mixed one, and hence the classification is achieved at a sub pixel level to give more semantics to the image under consideration. A semantic annotation of objects in the remotely sensed satellite image is done through deep learning methods<sup>2</sup>. In this paper, the image features are represented in terms of hierarchies, so that higher levels are formed by combining features in the lower levels. There exists also an efficient technique of combining Support Vector Machines and Support Tensor Machines to classify image data<sup>3</sup>. The decision boundaries and the margin functions are based on a ranking method. There are also classification techniques present in literature which uses mid level features for classification purposes<sup>4</sup>, in which the mid level features are relevant patterns from dense low level features.

It is also observed that image classification on semantic level is highly supported by learning dictionaries<sup>5</sup>. Learning dictionaries are usually linear combinations of vectors which are stored in a sparse space to increase the learning capacity of the classifier. As and when the image becomes complex, graph based representation of the images are sought at to achieve image classification<sup>6</sup>. This work models images as graphs to integrate high level

information to the low level information present in the image. This model shows an appreciable accuracy over existing methods.

### 3. Design of the Proposed Hierarchical System

The general model of the remotely sensed image classification is depicted in Fig. 1. The multispectral image is first preprocessed. Raw satellite image data may require geometric, radiometric and atmospheric corrections. Errors in geometry can be caused by the relative motion of satellite, its scanners and the earth. Errors in measured radiance values of pixels are called radiometric errors. Effect of atmospheric particles can contaminate the surface reflectance of ground objects recorded by the sensors of satellites. All these errors should be corrected appropriately. After preprocessing, the hierarchical classification technique is applied to the corrected image to perform classification at different concept levels. Finally the accuracy is assessed using different prevailing methods.

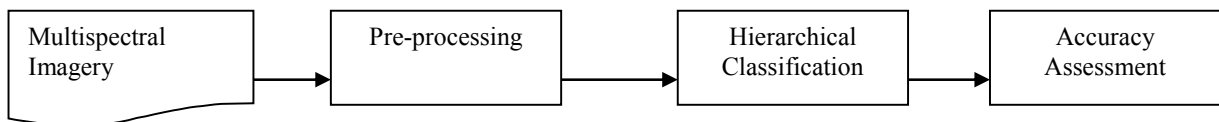


Fig.1. General Model for Image Classification

The steps in the proposed hierarchical model are detailed in the Fig. 2 and the steps are outlined in detail as follows. The algorithm is also explained.

#### A. Choosing a multispectral imagery

The multispectral imagery has to be chosen by considering the resolution. Resolution determines up to which level the classification can be attained. For example to obtain classification on level 2, the multispectral imagery should be high resolution type. Level 3 classification can be achieved only with the aid of very high resolution multispectral imagery.

#### B. Hierarchical Levels

The hierarchical levels are determined from Anderson's classification system<sup>7</sup>. A subset of the same is used for classification in the proposed which is represented in the following Table 1. Although this paper considers two hierarchical levels in the discussion, a sample representation of what constitutes level 3 is presented in Table 2. This Level 3 classification of "Residential" class employs criteria of capacity, type, and permanency of residence as the discriminating factors. However this type of classification requires supplement information.

#### C. Assigning Class Labels at different levels

The algorithm follows a top down approach, i.e., it proceeds with an abstract classification at level 1 and proceed towards concreteness at level 2. The method is a greedy one. In the first step, a window of random size is chosen within the image, say  $N \times N$ . It is to be made certain that  $N$  can be expressed as a power of 2. Inside the window, find a group of pixels at the centroid of the window. At the centroid the group should contain  $\log_2 N$  pixels. In the next phase, classification starts. Choose a pixel at the centroid of the group of pixels and assign a class label to it, depending on its spectral value. Run a neighbourhood growing technique on the region and assign class labels. At the same time, store it in the spectral knowledge base to aid classification in the next levels. Assign the group of pixels as the class with more number of occurrences and move to the next window in the image. The classification terminates when the whole image is covered. A contraction factor,  $k$ , is applied on the window size for classification at level 2. The process at level 2 classification is accelerated with the aid of spectral knowledge base created at level 1. When the classification at level 2 is completed, classification at level 3 can be initiated. There is a spectral knowledge base which works as a kind of dictionary and serves as input for applying the classified category at level 3. For example, for the 'Residential' class can be further categorized as Single- family unit, Multi-family units, group quarters, residential hotels, mobile parks and lodging. The level 3 classification thus gives a semantic approach to the classification. However, the aid of a supporting knowledge base is necessary to achieve the classification in level 3. The window is further resized in level 3 with the help of a tightening factor, say ' $v$ '. By varying ' $v$ ' over a range of values, an optimum classification at level 3 can be achieved.

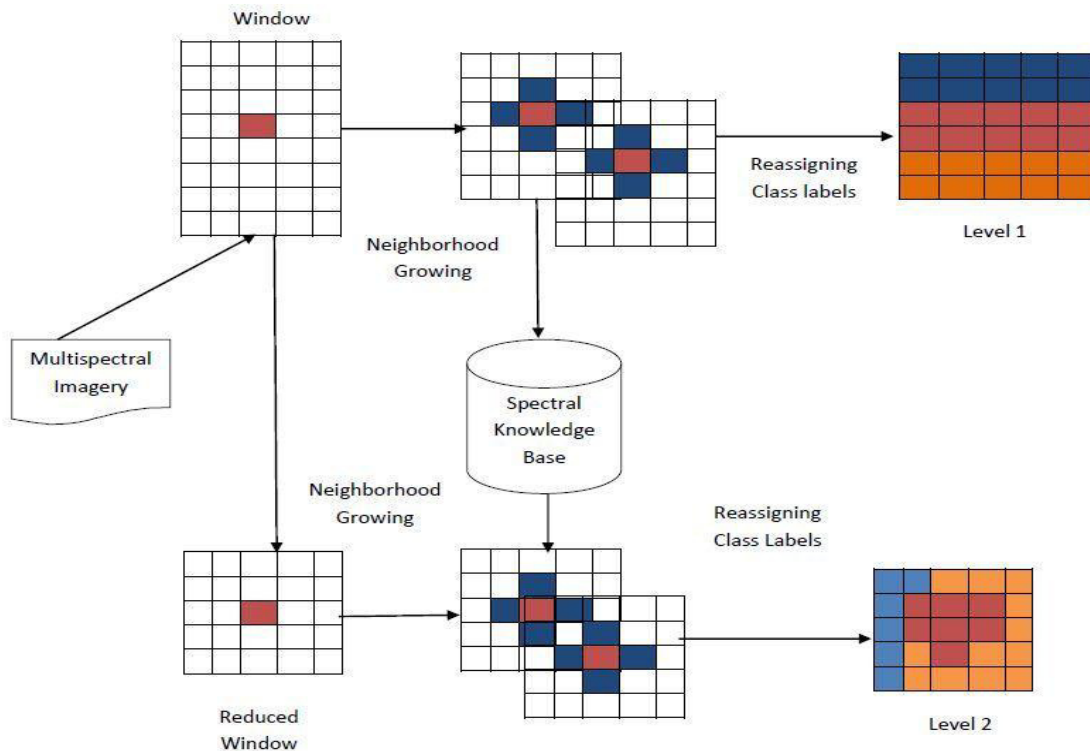


Fig. 2. Hierarchical Model Framework for Image Classification

### Algorithm

Input: Corrected Multispectral Imagery of size  $X \times Y$

Output: Hierarchical class labeling of the imagery

1. Let the multispectral imagery be  $D$  of size  $X \times Y$
2. For classifying the image on level 1
  - 2.1 Choose a random window of size as  $N \times N$
  - 2.2 Find a group of pixels at the centroid of the window, whose size is determined by  $\log_2 N$
  - 2.3 Assigning the class labels to the group of pixels
    - 2.3.1 Assign class label  $C_i$  for the centroid pixel from its spectral value
    - 2.3.2 Find its neighbourhood region class labels, say,  $C_j$ , for  $j=1,2,3,4$
    - 2.3.3 Store the neighbourhood region class labels in the spatial knowledge base
    - 2.3.4 if number of occurrences of  $C_j \neq C_i$  do, then  $C_j \leftarrow C_i$
3. Recursively perform step 2 for the whole image  $D$
4. For classifying the image on level 2
  - 4.1 Iterate on step 2 & 3 by reducing the window size to  $(N-k) \times (N-k)$  //  $k$ : contraction factor
  - 4.2 Use spectral knowledge base to find the class labels of neighbourhood classes
5. For classifying the image on level 3
  - 5.1 Iterate on step 2 & 3 by reducing the window size to  $(N-k-v) \times (N-k-v)$  //  $v$ : tightening factor
  - 5.2 Use spectral knowledge base to find the class labels of neighbourhood classes

Table 1 .Level 1 & Level 2 Classification derived from Anderson et.al<sup>7</sup>

Level 1	Level 2
Builtup Land	Residential Commercial Industrial Transportation Mixed Urban land
Agricultural Land	Cropland Horticultural
Forest Land	Deciduous Forest Land Evergreen Forest Land Mixed Forest Land
Barren Land	Sandy Areas Bare Exposed Rock Play Grounds

Table 2 .Level 3 Classification derived from Anderson et.al<sup>7</sup> for Residential Class

Level 2	Level 3
Residential	Single-family Units Multi-family Units Group Quarters Residential Hotels Mobile Home Parks Lodging

#### 4. Results and Discussions

The performance of the hierarchical system model is evaluated using the dataset available at <sup>8</sup>. The system is implemented in MATLAB and is tested for various factors.

At first, the classification accuracy in terms of Kappa coefficient is computed for level 1 and level 2. The classification accuracy at level 1 is 72.6% whereas for level 2 it is 78.3%. The accuracy is compared against the ground truth image given in <sup>8</sup>. The accuracy of the proposed model is compared with the traditional SVM classifier. The classification map acquired in level 1 and level 2 is depicted in Fig. 3.a and Fig. 3.b respectively. Level 1 Classification on the data set is done on Builtup Land, Forest Land, and Barren Land. A further classification of barren land and forest land is achieved in level 2 image classification. Level 3 can be achieved only when we can supplement information for performing the classification. After the classification on level 1, the spectral knowledge base is update to accommodate the neighboring pixels. This information can be utilized for level 2 classifications which will reduce the computation time for level 2 classification.

The ROC curve (TPR Vs FPR) curve for the hierarchical model for levels 1 and 2 is depicted in the Fig. 4 to evaluate the performance. The curve shows that significant performance is achieved on level 2 than in level 1, as it is clear that the level 1 is an abstract mode of classification. The comparison of Kappa coefficient values is depicted in the Fig. 5. The bar graph shows the variation of Kappa coefficient for SVM, Hierarchical Classification Level 1 and Level 2. It is observed that the classification accuracy of the Level 2 mode of the proposed system is 78.3% which is in par with SVM classifier whose accuracy is 77.9%.

The computation time involved for this model at different levels is compared with the traditional classifier and the result is depicted in Table 3. The traditional SVM classifier takes 22.6 s to classify the image, whereas for the proposed models, it is 11.3 s and 18.9 s for level 1 and level 2 classifications respectively. It is seen that the computation time is less for the model proposed. As level 1 method strives for an abstract classification, the algorithm tries for an approximate classification rather than a pixel wise mode. For the level 2 classification, as it

uses spectral knowledge base, the time is further reduced as compared with SVM.

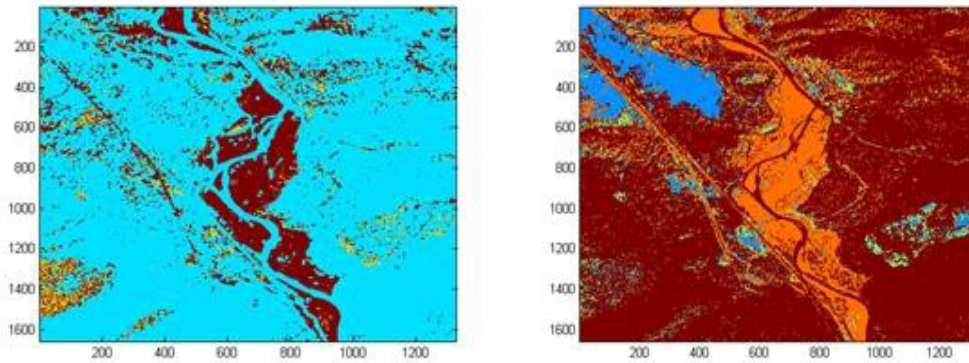


Fig. 3. Classification Map (a) Level 1 (b) Level 2

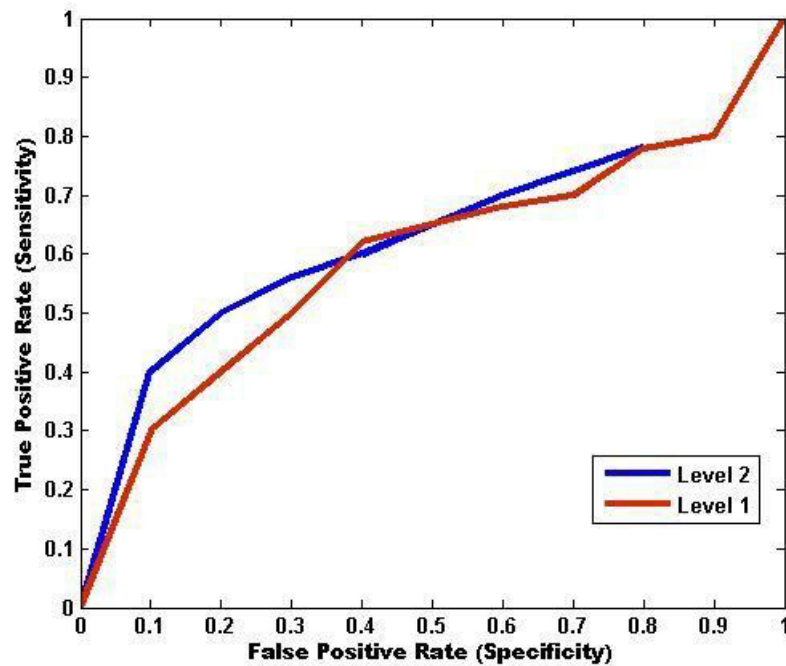


Fig. 4. ROC curve for the proposed hierarchical model

Table 3. Comparison of Computation Time

Classifier	Computation Time	
SVM	22.6 s	
Hierarchical Model	18.9 s (Level 2)	11.3 s (Level 1)

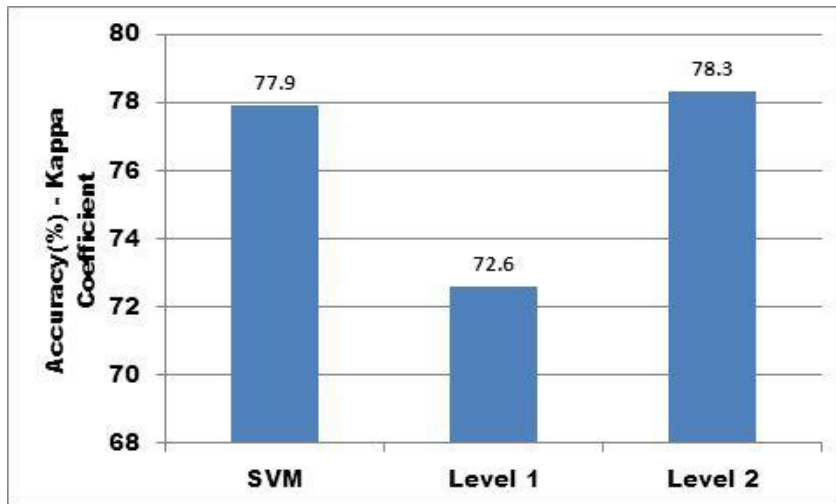


Fig. 5. Kappa Coefficient for SVM, Hierarchical Level 1 and Level 2 classification

A detailed examination of the proposed algorithm is done by considering various parameters chosen in the same. The performance of the algorithm in the first level of classification is observed by varying the window size. The observance is shown in Fig. 6 (a). From the figure it is clear that the algorithm performs optimally in terms of accuracy for particular window sizes and the accuracy deteriorates at higher window size. In terms of time, the smaller window sizes are highly time consuming, as it takes more entries into the spectral knowledge base. For an optimum window size of 2048 X 2048, the group of pixels is fixed as 12. The optimal window size of the algorithm has to be fixed as that which gives highest discriminative power between the categories of classification.

The value of  $k$  has to be varied from 1 to 11 to observe the performance at level 2 classification. The same is shown in Fig. 6 (b). The value of the contraction factor,  $k$  is varied from 1 to 11; the optimum value of 78.3 % accuracy is obtained when the value of  $k$  is 11. It is understood that the value of  $k$  has to be fixed by trial and error methods within the range to get appreciable classification accuracy.

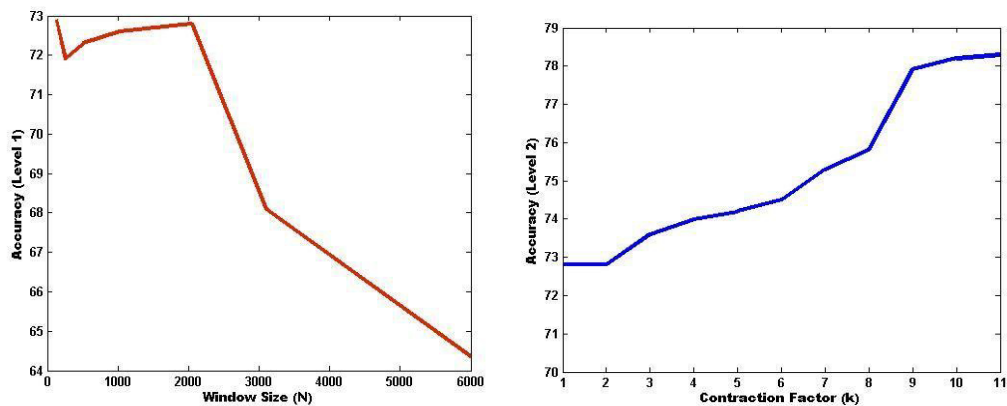


Fig. 6 (a) Analysis of Level 1 Classification (b) Analysis of Level 2 Classification



## 5. Conclusion

This paper proposed a classification scheme built on a hierarchical model. Different levels of classification of the multispectral imagery are achieved through this framework. The classification scheme was done on Level 1 and Level 2 of Anderson Classification scheme. The designed system gave an accuracy of 72.6% and 78.3 % in terms of Kappa coefficient for level 1 and level 2 classifications respectively. A comparison of the proposed method is done with SVM classifier. The algorithm proposed here works on a greedy mode and depends on parameters, like window size, contraction factor and tightening factor. The effect of window size and contraction factor on the classification accuracy is clearly illustrated in the discussion. The effect of tightening factor has to be analyzed as a future enhancement work, as the classification at level 3 requires supplement information like density estimation of the spatial area, space usage in annotated mode and so on. Also an extension of performing classification more effectively by the usage of randomized algorithms can be sought for.

## References

1. Zhong, Y., Zhang, L., Pingxiang, L., & Shen, H. A sub-pixel mapping algorithm based on artificial immune systems for remote sensing imagery. In *Geoscience and Remote Sensing Symposium, 2009 IEEE International, IGARSS 2009*; 2009 .Vol. 3, p. III-1007.
2. Vaduva, C., Gavati, I., & Datcu, M. Deep learning in very high resolution remote sensing image information mining communication concept. In *Signal Processing Conference (EUSIPCO), 2012 Proceedings of the 20th European*; 2012. p. 2506-2510.
3. Hou, C., Nie, F., Zhang, C., Yi, D., & Wu, Y. Multiple rank multi-linear SVM for matrix data classification. *Pattern Recognition* 47(1); 2014. p. 454-469.
4. Fernado, B., Fromont, E., & Tuytelaars, T. Mining mid-level features for image classification. *International Journal of Computer Vision*, 108(3); 2014. p. 186-203.
5. Liu, B. D., Wang, Y. X., Zhang, Y. J., & Shen, B. Learning dictionary on manifolds for image classification. *Pattern Recognition*, 46(7); 2013. p. 1879-1890.
6. Morales-González, A., Acosta-Mendoza, N., Gago-Alonso, A., García-Reyes, E. B., & Medina-Pagola, J. E. A new proposal for graph-based image classification using frequent approximate subgraphs. *Pattern Recognition*, 47(1); 2014. p. 169-177.
7. Anderson, James Richard. A land use and land cover classification system for use with remote sensor data. Vol. 964. *US Government Printing Office*, 1976.
8. <http://vision.ucmerced.edu/datasets/landuse.html>