International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Impact Factor (2012): 3.358

Estimation of Growth Rate of Davanagere District using Multispectral Image using ENVI 4.7

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Abstract: ***Remote sensing (RS) in earth's perspective is the process of obtaining information about the earth surface features without being in direct contact with it, but using on board camera systems or sensors from the satellite platform. The data collected by these sensors are in the form of Electro Magnetic Energy (EME) which are emitted or reflected by the object at different wavelengths depending upon the object's physical properties. In addition, objects emit radiation depending upon their temperature and emissivity. Every pixel of the digital RS data represents an average value of the EM energy and is recorded as a Digital Number (DN) ranging from 0 to 255 in 8-bit data format. The recorded energy at different wavelengths follows a pattern which is the characteristic of the object and is known as the spectral signature of the object of class. This paper focuses mainly on urban environment and its classification. The urban context is highly complex, as cities consist of a large number of structures of different size and shapes. Most of the conditions and processes are related to space. Thus, for measuring, analyzing and classifying the urban context panchromatic high-resolution data from urban areas using morphological and neural approaches is investigated. As one data source, remotely sensed data are inherently suited to provide information on urban land cover characteristics, and their changes over time, at various spatial and temporal scales. The proposed approach is applied in experiments on high-resolution US remote sensing data from urban areas.***

Keywords: Remote Sensing, Urbanisation, sprawl, Tier II cities, LULC.

1. Introduction

Proper interpretation of the spectral signature leads to the identification of the object and further extraction of information from RS data. In the past decades, the majority of remote sensing work has been focused only on natural environment as the availability of data was restricted to low and medium resolution images. Today, the advancements in high resolution imaging system, technical advancements both in hardware and software and social needs have made urban remote sensing a field of great interest among RS community.

Classification of panchromatic high-resolution data from urban areas using morphological and neural approaches is investigated. The proposed approach is based on three steps. First, the composition of geodesic opening and closing operations of different sizes is used in order to build a differential morphological profile that records image structural information. Although, the original panchromatic image only has one data channel, the use of the composition operations will give many additional channels, which may contain redundancies. Therefore, feature extraction or feature selection is applied in the second step. Both discriminant analysis feature extraction and decision boundary feature extraction are investigated in the second step along with a simple feature selection based on picking the largest indexes of the differential morphological profiles. Third, a neural network is used to classify the features from the second step. Gaussian maximum likelihood classifier (GMLC) is applied to classify the data using the training data. GMLC uses various classification decisions using probability and cost functions and is proved superior compared to other techniques.

Land use is only one such aspect, but knowledge about land use and land cover has become increasingly important as the Nation plans to overcome the problems of haphazard, uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands, destruction of important wetlands, and loss of fish and wildlife habitat. Land use data are needed in the analysis of environmental processes and problems that must be understood if living conditions and standards are to be improved or maintained at current levels. Land use and land cover data also are needed by Federal, State, and local agencies for water-resource inventory, flood control, water supply planning, and waste-water treatment. Spatio temporal patterns of land use and land cover (LULC) based on the temporal remote sensing data would aid in understanding and visualization of spatial patterns of urban growth. This would also help in identifying the probable pockets of intense urbanization and its effects such as sprawl etc.

For the mapping of land use and land cover (LULC) remote sensing imagery is a useful source of information due to its synoptic capabilities, i.e. the acquisition of information for large areas at one time. In many cases digital mapping data for the area of interest is already available and might be used as an additional source of information.

2. Study Area

This project aims to quantify and analyze the spatial–temporal pattern of urbanization process of a tier II city – Davangere Karnataka State, India using Remote Sensing (RS) data and spatial metrics in the year 1999. Temporal remote sensing data with spatial metrics will help in understanding spatial patterns of urban sprawl. Spatial metrics will indicate a clumped and aggregated growth at the city and sprawl at the outskirts. The district lies in the center of Karnataka between the latitudes 13°5' and 14°50' N and between the longitudes 75°30' and 76°30' E.

- Name of the City : Davanagere
- Location: 270 km from Bangalore city.
- Population i) 2011 census : 19,46,905

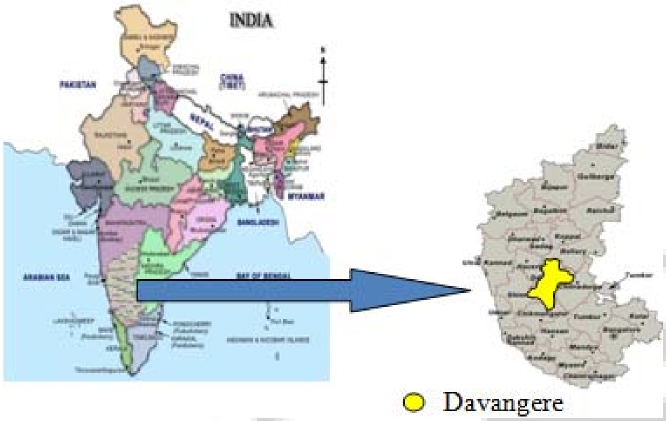

Figure 1: Shows the geographical location of Davangere district

3. Materials and Methods

Urban dynamics was analysed using temporal remote sensing data of the year during (1999-2013). The time spatial data acquired from Landsat 7 and Landsat 8 (30m) sensors for the year 1999 and 2103 respectively, were downloaded from public domain (http://earthexplorer.usgs.gov/). Survey of India (SOI) toposheet of Davangere District is ND 43-7 scales were used to generate base layers of city boundary, etc. City map with ward boundaries were digitized from the city administration map. Population data was collected from the Directorate of Census Operations, Davangere region (http://censuskarnataka.gov.in). Table I lists the data used in the current analysis. Ground control points to register and geo-correct remote sensing data were collected using hand held pre-calibrated GPS (Global Positioning System), Survey of India toposheet and Google earth.

A two-step approach was adopted to understand the dynamics of the urbanizing city (Figure 2), which includes (i) a normative approach to understand the land use and land cover, (ii) spatial metrics analysis for quantifying the growth and (iii) Compare GPS points with 2013 classified image and to find out the accuracy. Vegetation cover analysis was performed using the index Normalized Difference Vegetation index (NDVI) was computed for all the years to understand the change in the temporal dynamics of the vegetation cover in the study region.

Table 1: Materials used in Analysis

Satellite Spacecraft_Id and Data Type	*Date of Acquisition*	*WRS Path: Row*	*Spatial Resolution*
LE71450501999 336SGS00 "LANDSAT_7" *Multispectral* (Unsigned 8-bit)	02-DEC-1999	145-050	30m
"LC81450502013350LGN00" "LANDSAT_8"Multispectral *(Unsigned 8-bit)*	16-DEC-2013	145-050	30m

Various stages in the data analysis using project flow diagram shown in Figure 2.

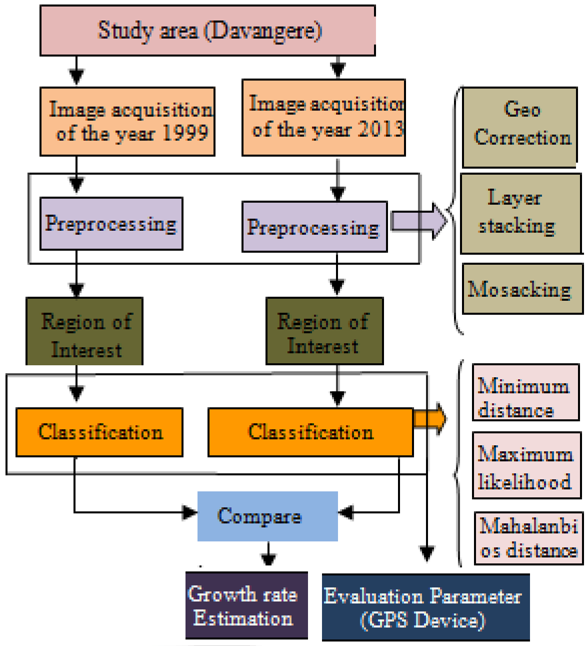

Figure 2: Project Flow

3.1 Preprocessing

There are three steps in preprocessing and first one is Geocorrection in Image preprocessing may include the detection and restoration of bad lines, geometric rectification or image registration, radiometric calibration and atmospheric correction, and topographic correction. If different ancillary data are used, data conversion among different sources or formats and quality evaluation of these data are also necessary before they can be incorporated into a classification procedure. Second one is layer stack and Layer stacking is often used to combine separate image bands into a single multispectral image file. Layer stacking is also commonly used to combine image derivatives with spectral bands for further analysis (i.e., layer stack an NDVI image with spectral bands for input to an image classification). Third one is Mosacking If we take pictures of a planar scene, such as a large wall, or a remote scene (scene at infinity), or if we shoot pictures with the camera rotating around its center of projection, we can stitch the pictures together to form a single big picture of the scene. This is called image mosaicking.

3.2 Region of Interest (ROI)

Supervised Classification uses a set of user defined spectral signatures to classify an image whereas unsupervised classification uses computer-derived clusters. The spectral signatures are derived from training areas (or sets) that are created by interactively delineating features of interest on an image. The spectral properties of the training sets along with previous knowledge, data from field studies and higher resolution images are all combined to perform a supervised classification. Care must be taken to create effective training signature sets. Important points to keep in mind include: i) Each training set should appear homogenous (percent crown closure, species mix, etc...); ii) Delineate several training sites within each information class; iii) If the same information class appears different in two or more locations (e.g., sunny vs. shady locations), consider collecting separate training sites for each. Signatures for each of the classes in the classification scheme that are found within the imagery—and in some cases more than one signature per class are collected. Goals of ROI are Collect Signatures to classify the RS image, Collect at least one signature using Region Grow ROI and Collect remaining signatures manually using the ROI Tools.

3.3 Classification

There are three methods in classification one is Minimum distance classification, Maximum likelihood classification and Mahalanbios distance classification. Minimum distance classification is a "centroid" for each class is determined from the data by calculating the mean value by band for each class. For each image pixel, the distance in n-dimensional distance to each of these centroids is calculated, and the closest centroid determines the class. Any pixel in the scene is categorized using the distances between:

- The digital number vector (spectral vector) associated with that pixel, and
- The means of the information classes derived from the training sets.

If minimum distance is greater than the threshold, the pixel will be considered unclassified. It is a faster technique than the maximum likelihood classification.

Maximum likelihood classification Maximum likelihood classification uses mean and variance-covariance in class spectra to determine classification scheme. It assumes that the spectral responses for a given class have normal distribution. A pixel with the maximum likelihood is classified into the corresponding class. The aforementioned classifiers were based primarily on identifying decision boundaries in feature space based on training class multispectral distance measurements. The maximum likelihood decision rule is based on probability. It assigns each pixel having pattern measurements or features X to the class i whose units are most probable or likely to have given rise to feature vector X. In other words, the probability of a pixel belonging to each of a predefined set of m classes is calculated, and the pixel is then assigned to the class for which the probability is the highest. For each pixel to be classified:

- The probability of assuming that this pixel belongs to each of the classes is computed.
- The pixel is designated to the class with the largest probability.

However, this probability should be larger than a given threshold Probability that a pixel with signal (s) belongs to a class (i) with mean (Mi) and standard deviation (σi):

$$Pi = \frac{1}{\sqrt{(2\pi)}*\sigma i} e^{-((s-Mi)*(s-Mi))/2(\sigma i*\sigma i)} \qquad (1)$$

Mahalanbios distance classification is similar to minimum distance classification, except that the covariance matrix is used in the equation. Variance and covariance are figured in so that clusters that are highly varied lead to similarly varied classes, and vice versa. For example when classifying urban areas-typically a class whose pixels vary widely-correctly classified pixels may be farther from the mean than those of a class for water, which is usually not a highly varied class. The Mahalanbios distance algorithm assumes that the histograms of the bands have normal distributions. If the histograms of the bands do not have normal distributions, better results can be obtained with the use of parallelepiped or minimum distance decision rule, or by performing a first-pass parallelepiped classification.

3.4 Compare

In this classification considering the signatures which are useful to compare year of 1999 classified image with year of 2013 classified image to estimate growth rate of Davangere district are Aquatic Weed, Water, Forest, Rock, Agriculture, Waste Land, and Build Up.

3.5 Evaluation Parameter (GPS Device)

It defines the efficiency of the proposed classifications (Minimum Distance, Maximum Likelihood, and Mahalanbios distance) by comparing with actual points obtained by GPS device. The signatures which we are obtained by GPS device of particular place Longitude and Latitude value are checked in proposed classified image. The results obtained for set of training sets. If the GPS device and classified image signatures are same then the accuracy will be 100%, considered 20 points the accuracy for three methods of classification by taking average of obtained indusial results is shown in results part.

4. Results and Analysis

The shown above Figure 3 satellite raw image year of 1999 and year of 2013 Davanagere district. This image taken by the Landsat 7 and Landsat 8 archive satellite sensor. Minimum distance classification, Maximum Likelihood classification and Mahalanbios Distance classification these three classifications are applied to the raw image. The output and change detection of each classification are shown below. The table 2, table 3, and table 4 shows area (Square Kilometer) covered by the classes/signatures classified under the minimum distance classification.

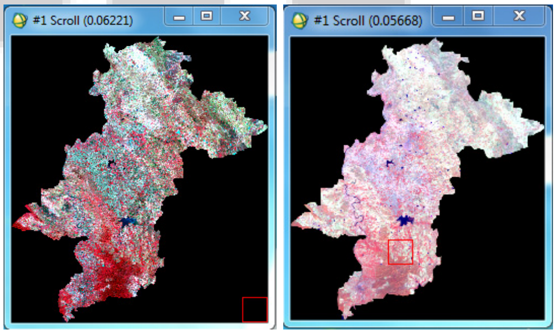

Figure 3: Year of 1999 and 2013 year Raw satellite Image

4.1 Minimum Distance Classification

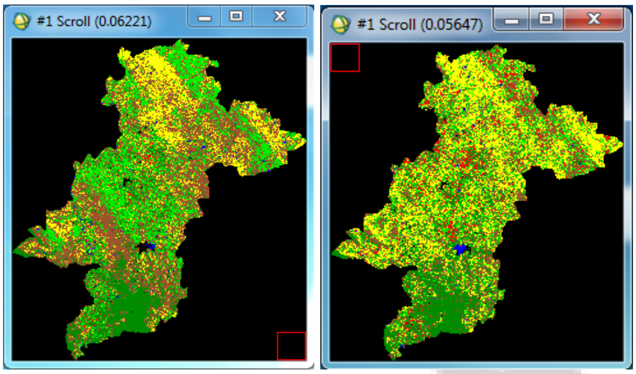

Figure 4: Year of 1999 and year of 2013 Minimum Distance Classified Satellite Image

Table 2: Class names area in Square Kilometer

Class Name	*Color*	*Year of 1999 area in Sq. Km*	*Year of 2013 area in Sq. Km*
Aquatic Weed		43.4853	43.8606
Water		45.7992	34.8075
Forest		1145.8	1297.73
Waste Land		1068.34	2037.34
Rock		2558.57	1540.3
Agriculture		1658.2	1318.76
Build-Up		93.2535	340.654

4.2 Maximum Likelihood classification

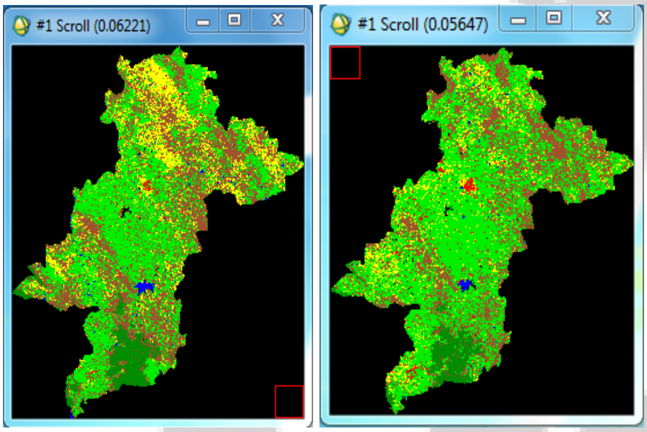

Figure 5: Year of 1999 and year of 2013 Minimum Distance Classified Satellite Image

Table 3: Class names area in Square Kilometer

Class Name	*Color*	*Year of 1999 area in Sq. Km*	*Year of 2013 area in Sq. Km*
Aquatic Weed		16.7652	32.8545
Water		62.271	28.1457
Forest		369.133	306.598
Waste Land		927.256	621.77
Rock		2175.28	1635.48
Agriculture		2986.2	3806.02
Build-Up		76.536	182.581

4.3 Mahalanbios Distance Classification

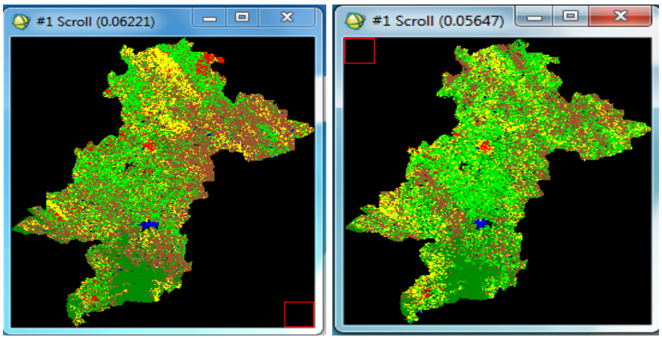

Figure 6: Year of 1999 and year of 2013 Mahalanbios Distance classified satellite image

Table 4: Class names area in Square Kilometer

Class Name	*Color*	*Year of 1999 area in Sq. Km*	*Year of 2013 area in Sq. Km*
Aquatic Weed		53.0136	83.4399
Water		46.4967	32.4261
Forest		797.288	1160.8
Waste Land		835.861	1056.66
Rock		2732.72	7090.09
Agriculture		1850.97	2386.79
Build-Up		297.101	103.253

Table 5: Evaluation Parameter

Classification	*Accuracy*
Minimum Distance	75%
Maximum Likelihood	90%
Mahalanbios Distance	70%

From the table 5 we conclude that the best classification can be achieved by the method maximum Likelihood classification. The classification made for two images of the years 1999 and 2013 by maximum likelihood classification is shown in table 3. From this table the observations can made that Build up area is increased by 106.045 Sq. Km, Agriculture area is increased by 538.82 Sq. Km, Water content area decreased by 34.1253 Sq. Km and forest area is decreased by 363.512 Sq. Km in 2013 classified image compare with 1999 classified image.

5. Conclusion

Karnataka government's initiative and focus to develop the major tier II cities such as Davangere in order to decongest the burgeoning Tier 1 city, Bangalore, has posed challenges to the district planners to accommodate the developmental activities at a higher speed while ensuring sustainability of natural resources. Availability of temporal spatial data has aided in monitoring the temporal land use dynamics. Spatial metrics in conjunction with the density gradient approach have been effective in capturing the patterns of urbanization at local levels.

The techniques would aid as decision-support tools for unraveling the impacts of classical urban sprawl patterns in Davangere. A set of spatial metrics describing the morphology of unplanned areas have been extracted along with temporal land uses. The extracted indices have indicated the areas of high likelihood of 'unplanned growth' considering the three dimensions (size/density/pattern).

6. Acknowledgement

It is a pleasure to recognize the many individual who have helped me in completing this technical paper. Mr Shivakumar .B.R (GMIT Davangere) and Mr. Raghudathesh G P for all the technical guidance, encouragement and analysis of the data throughout this process.

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