Suitability Mapping For Locating Special Economic Zone

by

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Abstract

A Special Economic Zone (SEZ) is a geographical region that has economic laws more liberal than a country's typical economic laws. In the recent years, India has witnessed a confrontation between farmers and the state, the reason being use of highly productive land for setting up SEZs with some of the cases occupying a centre stage in the World fora (Nandigram violence). In this paper, we propose an integrated solution for identifying non-agricultural lands for setting up SEZs using MODIS NDVI product and remote sensing techniques. The study also identifies multi- cropping practices and reinforces the potential of time-series MODIS data for mapping and land cover classification at regional scales.

Keywords: *SEZ, MODIS, Land cover, LMF*

1. Introduction

The Indian government introduced the policy of Special Economic Zone in April 2000. Out of the total land area of 2973190 sq km in India, total agricultural land is of the order of 1620388 sq km (54.5%) and agriculture is still the most important occupation employing 70% of the rural population though contributing a little over 2% to the GDP. The balanced growth of the nation calls for an appropriate distribution of resources between the farmers and the industrialists for the benefit of all. We have aimed to achieve this through remote sensing by deriving maps that identify unproductive lands most suitable for setting up industry. We have christened these maps as SEZ suitability maps. Such maps are of great utility to the policy makers who sanction the SEZ projects.

Though the present problem definition is unique, much work has been done to analyze the time series of satellite data for various purposes. We have tried to adapt the existing methods to provide a solution to this problem. Time series analysis of satellite data such as standardized principal component analysis (Eastman and Fulk 1993) or Fourier analysis (Andres et al. 1994, Azzali and Menenti 2000), are useful technique to obtain the information of seasonal vegetation changes characterized by phenology. Jakubauskas (2001) used the harmonic analysis to characterize seasonal changes for natural and agricultural land use/land cover. Sawada et al. 1998 have devised a process called local maximum fitting to fit time series satellite data that can reduce the influences of noise such as cloud, haze and system noise. Further, they have taken forward this concept to fit AVHRR time series NDVI data to obtain the agricultural map of Asian region (Sawada et al, 2001).

The system to be operational has to span the entire country and hence the need for a regional approach. This necessitates the use of moderate spatial resolution imagery with a temporal and spectral resolution that is fair enough to aid land cover/use classification. Also, the high spatial resolution imagery has a disadvantage of being poor in spectral resolution. The use of Moderate Resolution Imaging Spectroradiometer (MODIS) 250-m NDVI data for state level crop mapping in the US Central Great Plains has been demonstrated (Wardlow and Egbert 2005).

This paper focuses on the production of the SEZ suitability map using the local maximum fitting technique on MODIS 250-m NDVI data with a decision tree classifier. The case study region for this is Hassan district located within the Cauvery river basin.

2. Land Cover Classification

The remote sensing community has been challenged to produce regional- to global-scale data sets on a repetitive basis that characterize 'current' LULC patterns, document major LULC changes, and include a stronger land use component (Turner *et al.*, 1995; NRC 2001; NASA 2002). For the system that we envisage, it needs to be near real time in operation. The objective of land cover classification was to find the temporal pattern of the land cover with particular emphasis on agricultural landscapes mainly in identifying the multi-cropping patterns. The land use classifier produced five classes 1) Double Crop 2) Single Crop 3) Forest 4) Water and 5) Waste land. This land use map is one of the important inputs to find SEZ suitability map.

2.1 Data

The MODIS 250-m Vegetation Index (VI) product (MOD13Q1), which consists of NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index) data composited at 16-day intervals is used in this study. It holds considerable promise for regional-scale crop mapping given its resolutions, large area coverage, and cost free status.

2.2 Local Maximum Fitting

Local Maximum Fitting (LMF) is a time series model filter and is composed of a linear combination of cyclic functions controlled by a time-dependent co-efficients. LMF consists of three steps, 1. Revision of data 2. Fitting with the time series model by a combination of cyclic functions 3. Automatic decision to determine the optimum combination of cyclic functions.

2.2.1 Revision

Revision of data is necessary before fitting of the cyclic functions especially in the case in which noise has a strong influence on the data or if there are some periods without observations. The value of a vegetation index or of thermal infrared radiation decreases with clouds and hazes. In that case, time series filter processing is applied, extracting the local maximum value. Equation (1) describes the time series filter

$$d_t^{'} = Min\left[Max\left(d_{t-w+1}, d_{t-w+2}, \ldots\ldots, d_t\right), Max\left(d_t, d_{t+1}, \ldots. d_{t+w-1}\right)\right] \qquad (1)$$

This filter does not affect the values if it is maximum at time '*t*' or if it has a monotonous change in the window '*w*'. The data value is replaced only if it locally decreases at time *t*.

2.2.2 Fitting with Cyclic functions

The cyclic functions were introduced to model seasonal changes over a year for a time-series of satellite data. The functions used in this study are given by equation (2)

$$f(t) = c_0 + c_1 t + \sum_{l=1}^{N} \left\{ c_{2l} \sin\left(\frac{2\pi k_l t}{M}\right) + c_{2l+1} \cos\left(\frac{2\pi k_l t}{M}\right) \right\} \qquad (2)$$

where c_i is a coefficient, t is time interval, N is the pair number of the cyclic function, M is the data number in a period and k_l is the periodicity of each cyclic function in a period. The optimal coefficients, c_i, are obtained by the least squares method. The optimum number of functions for these models is obtained when the AIC (Akaike's Information Criteria) is at its minimum. The combination of functions for which AIC is minimized is automatically selected so that model functions for a pixel are determined. Figure (1) shows an example of local maximum fitting.

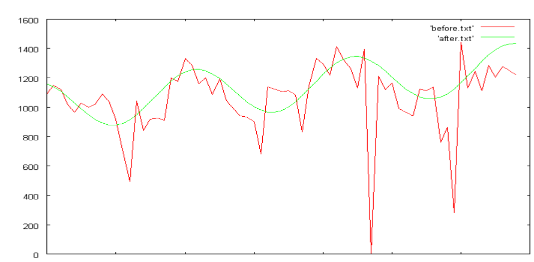

Figure 1: *Example of Local Maximum Fitting*

2.3 Classifier

The amount of vegetation present at particular geographical area is encoded as NDVI values in our input data. However the accurate range of values that NDVI assumes for vegetated area is not known. This uncertainty holds for any other land cover entity like water. Since these ranges are important parameters that influence the accuracy of our classifier, a reliable way to find them is essential. We employed the Nelder-Mead nonlinear optimization algorithm to arrive at optimal values for these parameters. The method uses the concept of a simplex, which is a polytope of $N + 1$ vertices in N dimensions; a line segment on a line, a triangle on a plane, a tetrahedron in three-dimensional space and so forth. The method approximately finds a locally optimal solution to a problem with N variables when the objective function varies smoothly.

Our decision tree classifier has four parameters, starting and ending values of crop area, starting value for forest area and ending value for water. The optimization algorithm produces a set of solutions iteratively which are later used by classifier. Since we have not taken the period of vegetation into account, sugarcane (annual crop) which is grown in this area is classified as a single crop. More classification accuracies can be obtained by employing other important features that can be derived from time-series curves.

2.4 Validation

We compared our results with 56-m resolution classified image obtained from National Remote Sensing Agency (NRSA). This image had sixteen classes which were merged to obtain the required five classes. After appropriate scaling, it was compared with the derived map. To further validate the decision tree classifier and the parameters, the algorithm was applied on another district of Karnataka, Mysore. The classification accuracy in both cases was above 70% which can be further improved by including some more discriminating variables in the classifier design.

Figure (2) shows the reference map obtained from NRSA and figure (3) land use map derived by us for Hassan district. Figure (4) shows the land use map derived for Mysore district.

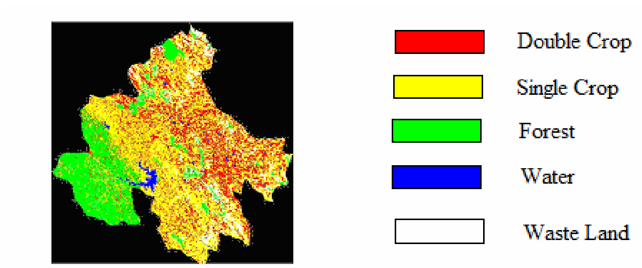

Figure 2: *Reference land use map of Hassan*

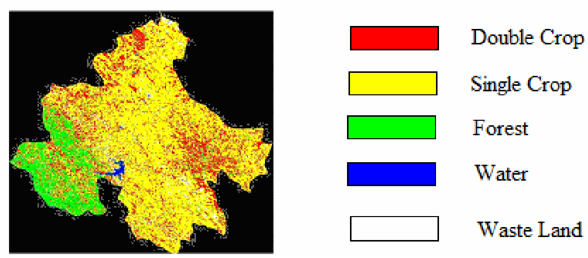

Figure 3: *Derived land use map of Hassan*

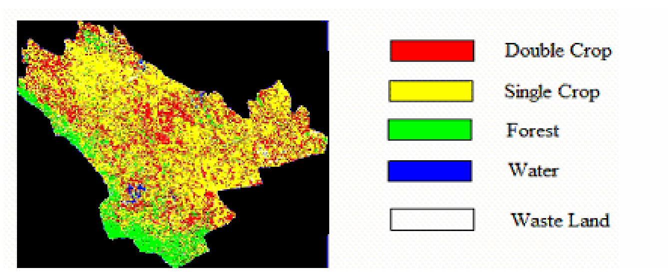

Figure 4: *Derived land use map of Mysore*

3. SEZ Mapping

Land use map is one of the main inputs to the SEZ mapping protocol because prevention of use of highly productive agricultural land for setting up SEZs was the main aim of this study. Road maps, urban centres and river map were digitized and used as other inputs to the SEZ mapping protocol. Certain conditions enacted by the government in the form of legislation to protect the farmers interests and some others desired by the industrialists are enforced. The former are negative in nature such as prevention of using multi cropping lands while the latter are positive in nature such as accessibility in terms of road network and urban centres. The enforcement of these conditions produces the desired SEZ suitability map. Figure (5) summarizes the SEZ suitability mapping process.

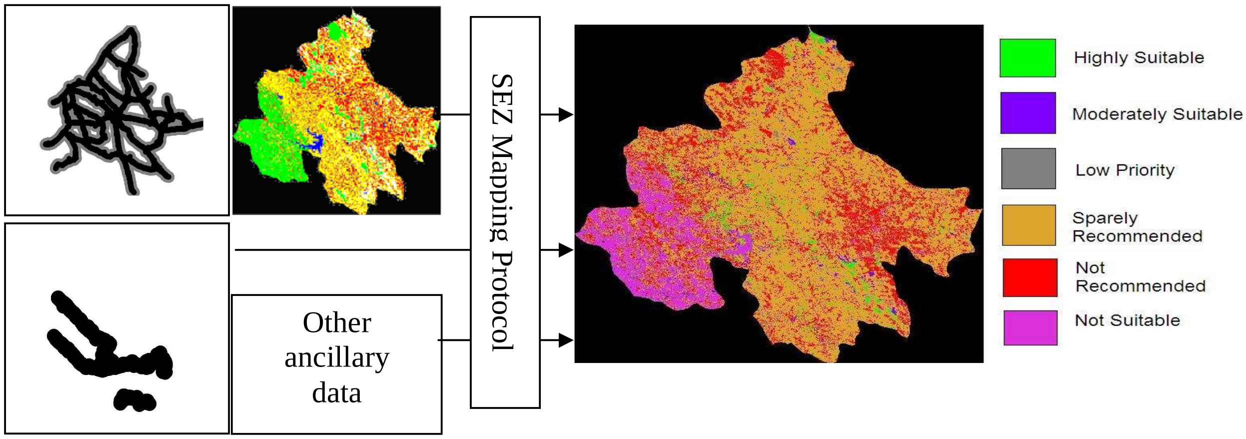

Figure 5: *Overview of SEZ Mapping Process*

4. Discussion and Conclusions

Local maximum fitting used with AVHRR data is successfully adapted to MODIS data. Also, 16 day composites are useful to study the seasonal patterns and derive the curves. Most of the images during monsoon have cloud cover and LMF has been able to reduce its effects considerably. The assumption that peaking of NDVI twice is a result of the pixel being a double crop area is valid only if the pixel in question is a "pure pixel". Such an assumption may not be perfectly valid in regions of high heterogeneity in farming practices and presence of small fragmented landholdings - making it necessary for identifying mixed pixels, unmixing the spectra and then using an appropriate classifier. An attempt is made here to relate the time-series with crop growth, which can improve classification of major crops grown in the area, thus providing for a reliable system that produces crop maps and also helps in better estimation of crop yields.

In our study we have successfully taken forward the idea of deriving LULC map from NDVI data to derive SEZ maps. The LULC classifier here displayed promising accuracy when compared to the map provided by NRSA thereby demonstrating the viability of time-series MODIS 250-m NDVI data. The conditions we have used to identify lands for setting up SEZs is not comprehensive and is not based on a systematic study of industrial requirements which can vary with the kind of industry. However, we have established a framework for incorporating more such information which influences the decision.

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