Journal of Geomatics Vol 10 No. 1 April 2016

Formosat-2 with Landsat-8 temporal - multispectral data for wheat crop identification using Hypertangent Kernel based Possibilistic classifier

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(Received: Feb 27, 2016; in final form: Apr 18, 2016)

Abstract: Agriculture plays major role in India's economy, and provides undoubtedly the largest livelihood with its allied sectors. Crop type identification serves in number of applications such as crop yield forecasting, collecting crop production statistics, facilitating crop rotation records, mapping soil productivity, identification of factors influencing crop stress, assessment of crop damage and monitoring farming activity. To identify particular crop type in a single date imagery is a challenging task. However, Classification facilitates the multi-temporal images by taking into account changes in reflectance as a function of plant phenology. This research work deals with Possibilistic c-means classifier with Hypertangent kernel for wheat (Triticumaestivum) identification in Haridwar, Uttarakhand, India. The vegetation index outputs of Formosat-2 and Landsat-8 (Operational Land Imager) sensors were arranged in chronological order of their date and prepared three temporal datasets which cover whole phenological cycle of wheat. It was evaluated that for 2.7, 2.5, and 2.5 values of weighted constant (m), images of 4 (Formosat-2: 04 Dec 2014, 30 Jan 2015, 21 Feb 2015; Landsat-8: 16 Mar 2015), 5 (Formosat-2: 04 Dec 2014, 30 Jan 2015, 21 Feb 2015; Landsat-8: 16 Mar 2015, 01 Apr 2015), and 6 (Formosat-2: 04 Dec 2014, 30 Jan 2015, 21 Feb 2015, 09 Apr 2015; Landsat-8: 16 Mar 2015, 01 Apr 2015) date combination respectively represent the nicely separated wheat crop from other vegetation and were easily differentiated between early harvested and late harvested wheat crops. This study demonstrates that 5 date combination was sufficient to discriminate late harvested wheat crops and 6 date combination was sufficient to discriminate early harvested wheat crops.

Keywords: Wheat identification, Phenology, Soft classification, Possibilistic c-means (PCM), Kernel, Weighted constant

1. Introduction

Maps of crop type are created by national and multinational agricultural agencies, insurance agencies, and regional agricultural boards to prepare an inventory of what was grown in certain areas and when? This serves in number of applications such as crop yield forecasting, collecting crop production statistics, facilitating crop rotation records, mapping soil productivity, identification of factors influencing crop stress, assessment of crop damage and monitoring farming activity.

Traditional methods of obtaining specific crop maps are through census and ground surveying. In order to standardize measurements, remote sensing offers an efficient and well-founded means to map crop type and acreage. Spectral reflectance of vegetation varies with respect to change in plant phenology, stage and crop health. In India, different crops are grown in the vicinity of each other, so spectral response of target class may overlap with other class(s). Therefore, crop mapping using single date imagery is a real challenge (Wardlow et al., 2007; Masialeti et al., 2010). The information about the varying pattern of growth cycle and the occurrence of varying crop phenology stages in the time domain can help in discriminating or identifying crops using remote sensing technique (Murty et al., 2003; Niel et al., 2004; Doriaswamy et al., 2006; Misra et al., 2012). Hence, multi-temporal approach is more beneficial to identify specific crop.

The atmospheric effect on satellite imagery is common which affects the usability of data. For temporal analysis, the data should be free of rain, haze and clouds while acquiring data covering the crop growth season. But this requirement is rarely met. This hampers the temporal analysis results and provides gaps in temporal data sampling (Steven et al., 2003). The use of multiple sensors for filling up these periods of long absence in temporal data may provide a solution to this problem (Shang et al., 2008).

For crop identification, classification facilitates the multi-temporal images by taking into account changes in reflectance as a function of plant phenology. Pixel based classification method has been traditionally used to identify specific crops. But, the technique is efficient only when the spatial resolution of sensors match the Land Use/ Land cover class on the ground and there should not exist any spectral mixing at the inter-class boundaries. The problem of occurrence of mixed pixels can be tackled by applying fuzzy based classification approach. The fuzzy set theory was proposed by Zadeh (1965) to handle the uncertainty in class assignment. Bezdek et al. (1981) improved a fuzzy based classification technique; Fuzzy *c*-means (FCM) which was put forward by Dunn, 1973. In FCM, the membership value is a measure of the "degree of sharing" of the pixel for the class. While in the case of Possibilistic c-means (PCM); the membership value represents "the degree of belongings or compatibility or typicality" (Chawla 2010). PCM was proposed by Krishnapuram and Keller (1993). PCM algorithm has the capability to extract single class and handle the problem of noises and outliers, which commonly exist in the remote sensing data.

FCM and PCM fail to give results with higher accuracy, when the classes are linearly non-separable (Wu, 2006). In such a situation, if kernels are included in the existing algorithms then it has the capability to handle mixed pixels with linearly non-separable classes. Kernels are tools which take data to a higher dimension, such that the classes are linearly separable by a hyper plane. Zhang and Chen (2002) presented a kernel based Fuzzy c-means (FCM) algorithm which was tested on spherical dataset and real iris data. Kumar et al. (2006) studied the effect of different kernels while generating density estimation using SVM with respect to overall sub-pixel classification accuracy of multi-spectral data.

A crop can be discriminated by exploiting the variations in spectral response of various crops in a multi-dimensional feature space produced by different spectral bands, or time domain or both (Dadhwal et al., 2002). Working with temporal data, the number of spectral bands also increases. Hence, to reduce the spectral dimensionality of the data, temporal indices are generated. The vegetation indices maximize the sensitivity of plant biophysical parameters and perform radiometric correction in the satellite imagery (Jensen, 2009).

Wheat has proven itself to be a highly adapted crop across the world. Wheat is main cereal crop in India and staple food of millions of Indians, particularly in the northern and north-western parts of the country. Hence, importance of monitoring crop cannot be unnoticed. Specific crop mapping has essential role for crop acreage and yield estimation.

The major objective of this research is to propose a soft classifier algorithm which has the capability to extract wheat crop with better accuracy dealing with non-linearity within the classes. Specific objectives include: (1) To implement Hypertangent kernel based Possibilistic classifier for specific crop identification in bi-sensor multi-spectral data, and (2) To evaluate number of temporal images and optimized value of weighted constant that may be best suited for wheat crop identification.

2. Temporal vegetation index and classification approach

The Normalized difference vegetation index (NDVI) layers of different date were prepared and stacked in chronological order and prepared three temporal datasets of vegetation index. The NDVI was proposed by Kriegler et al. (1969) and the mathematical expression is given by equation (1).

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \tag{1}$$

where, ρ_{NIR} represents reflectance at Near Infrared band and ρ_{Red} represents reflectance at Red band.

Possibilistic c-means algorithm is the modified form of FCM which was proposed by Krishnapuram and Keller (1993). The objective function for PCM is given in equation (2):

$$J_m(U,V) = \sum_{i=1}^{N} \sum_{j=1}^{C} (\mu_{ij})^m \left\| X_i - V_j \right\|^2 A + \sum_{j=1}^{C} \eta_j \sum_{i=1}^{N} (1 - \mu_{ij})^m \tag{2}$$

where, U is the matrix between the number of pixel and number of classes. The equation (2) is subject to constraints,

for all i	$\max_j \mu_{ij} > 0$
for all j	$\sum_{i=1}^{N} \mu_{ij} > 0$
for all i, j	$0 \le \mu_{ij} \le 1$

where, X_i is the vector denoting spectral response of a pixel i, V_j is a collection of vector of cluster centres, μ_{ij} is class membership values of a pixel, c and N are number of clusters and pixels respectively, m is a weighting component (1<m<∞), which controls the degree of fuzziness.

η_j is dependent on the shape and average size of cluster j and is computed as in Eq. (3):

$$\eta_j = K \frac{\sum_{i=1}^{N} \mu_{ij}^m d_{ij}^2}{\sum_{i=1}^{N} \mu_{ij}^m} \tag{3}$$

The class memberships, μ_{ij} are obtained from equation (4):

$$\mu_{ij} = \frac{1}{1 + \left(\frac{d_{ij}^2}{\eta_j} \right)^{\frac{1}{m-1}}} \tag{4}$$

where, d_{ij} represents the distance between the pixels value i and mean of the class j.

PCM is robust to handle mixed pixels but it fails to correctly classify the pixels when the classes are linearly non-separable (Wu, 2006). Kernel methods provide a compatible and reliable framework for developing nonlinear technique of classification and have useful properties when dealing with low number of training data, presence of heterogeneous land cover and different noise sources in the data.

In this paper a robust supervised fuzzy classification technique, Kernel based Possibilistic c- Means algorithm (KPCM) has been presented. Its basic idea is to transform the low dimensional input data into a higher dimensional feature space via a kernel method. After the implementation of kernels, the classes become linearly separable and PCM is performed on the feature space.

The mathematical expression of Hypertangent kernel used in this study is given in equation (5) (Kaur et al., 2012):

$$K(x, x_i) = 1 - tanh\left(-\frac{\|x_i - x_j\|^2}{\sigma^2}\right), \sigma > 0 \qquad (5)$$

Hence, the objective function of Kernel based Possibilistic c-Means (Zhang and Chen, 2003) is given by equation (6):

$$J_m(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{c} \mu_{ij}{}^{m} K(X_i, V_j) + \sum_{j=1}^{C} \eta_j \sum_{i=1}^{N} (1 - \mu_{ij})^m \qquad (6)$$

The updated membership value can be computed as given by equation (7):

$$\mu_{ij} = \frac{1}{1 + \left(\frac{K(X_i, V_j)}{\eta_j}\right)^{\frac{1}{m-1}}} \qquad (7)$$

where,

$$K(X_i, V_j) = \left\|\emptyset(X_i) - \emptyset(V_j)\right\|^2 \qquad (8)$$

where, $\emptyset$ represents the kernel function. And

$$\left\|\emptyset(X_i) - \emptyset(V_j)\right\|^2 = K(X_i, X_i) + K(V_j, V_j) - 2K(X_i, V_j) \qquad (9)$$

The Hypertangent Kernel equation (5) helps to evaluate the above kernel function.

3. Study area and data used

The study area under this research is East side of Haridwar, Uttarakhand, India towards National Highway 74 as shown in fig. 1. Uttarakhand is a state in the northern part of India. The Haridwar district shares its boundaries by Dehradun in the north, Pauri Garhwal district in the east while, west and south are bounded by districts of Uttar Pradesh state. The central latitude and longitude of the study area taken are 29°52'20.3124"N and 78°10'25.0998"E respectively. The land is fertile with river Ganga flowing through the district and tourism and agriculture remains the backbone of the district. The major crops grown in the study area are rice, wheat, lentil, groundnut, mustard and plantations like citrus fruits, mango, litchi etc. In this study, remotely sensed temporal images of Formosat-2 and Landsat-8 (Operational Land Imager) were used for wheat crop identification. The sensors specifications are shown in Table 1(a) and 1(b).

Wheat (Triticumaestivum) is the Rabi season crop in India. The sowing window of wheat is 2nd week of November to 4th week of December in Haridwar district. Then it passes through a series of developmental phases from sowing to harvest. The harvesting period for wheat crop is mid-March to first week of April.

The combination of Formosat-2 and Landsat-8 (OLI) images NDVI outputs have been combined and prepared three datasets which cover major five growth phases (Tillering, Stem extension, Heading, Flowering and Ripening) of wheat crop. The datasets for Formosat-2 and Landsat-8 are shown in Table 2(a) and 2(b) respectively.

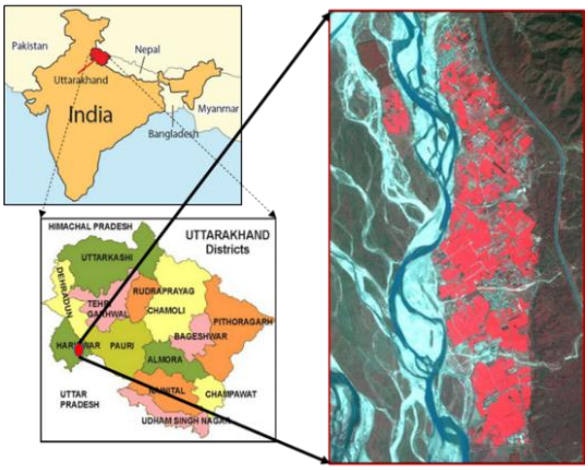


Figure 1: Study area: East Haridwar, Uttarakhand, India

Table 1(a): Formosat-2 Sensors Specifications (http://www.satimagingcorp.com/satellite-sensors/other-satellite-sensors/formosat-2/)

Band	Wavelength (in µm)	Spatial Resolution (in m)
Band 1 –Blue	0.45 – 0.52	8
Band 2 –Green	0.52 – 0.60	8
Band 3 –Red	0.63 – 0.69	8
Band 4 – Near Infrared (NIR)	0.76 – 0.90	8
P - Panchromatic	0.45 – 0.90	2

Table 1(b): Landsat-8 OLI Sensors Specifications (Landsat-8 Data User Handbook-June 2015)

Band	Wavelength (in µm)	Spatial Resolution (in m)
Band 1- Coastal/ Aerosol	0.433-0.453	30
Band 2- Blue	0.450-0.515	30
Band 3- Green	0.525-0.600	30
Band 4- Red	0.630-0.680	30
Band 5- Near Infrared (NIR)	0.845-0.885	30
Band 6-Short Wave Infrared	1.560-1.660	30
Band 7- Shot Wave Infrared	2.100-2.300	30
Band 8- Panchromatic	0.500-0.680	15
Band 9- Cirrus	1.360-1.390	30

Table 2(a): Formosat-2 temporal datasets

Formosat-2	
Date	Reference code
04 Dec 2014	F1
30 Jan 2015	F2
21 Feb 2015	F3
09 Apr 2015	F4

Table 2(b): Landsat-8 temporal datasets

Landsat-8 (OLI)	
Date	Reference code
16 Mar 2015	L1
01 Apr 2015	L2

Reference data for wheat was identified on the imagery from the GPS data collected during a field visit on 16 March 2015. During field survey the early sowing and late sowing wheat crop samples were collected based on the information provided by concern farmers. Further, this reference data was used as a training and testing data for classification and validation.

4. Methodology

Four temporal data of Formosat-2 from 04 Dec 2014 to 09 April 2015 and two temporal data of Landsat-8 (OLI) of 16 March 2015 and 01 April 2015, sensors have been used. These data were geometrically corrected for both sensors by using reference image as Formosat-2 21 Feb 2015 date. The Temporal Images were atmospherically corrected by ATCOR. The NDVI images were generated and linearly stretched in the scale of 0 to 255 by image enhancement technique, because of good visibility. The SMIC (Sub-Pixel Land Cover Mapping Image Classifier), a JAVA based image processing package (Kumar et al., 2006) supports 8 bit as well as 16 bit scale imagery has been used.

The vegetation index outputs of Formosat-2 and Landsat-8 (Operational Land Imager) sensors were arranged in chronological order of their dates and prepared three temporal datasets of 4 (Formosat-2: 04 Dec 2014, 30 Jan 2015, 21 Feb 2015; Landsat-8: 16 Mar 2015), 5 (Formosat-2: 04 Dec 2014, 30 Jan 2015, 21 Feb 2015; Landsat-8: 16 Mar 2015, 01 Apr 2015), and 6 (Formosat-2: 04 Dec 2014, 30 Jan 2015, 21 Feb 2015, 09 Apr 2015; Landsat-8: 16 Mar 2015, 01 Apr 2015) date combination, which cover whole phenological cycle of wheat.

Hypertangent kernel based PCM soft classifier has been applied on the all three date combination of temporal vegetation index datasets. By using testing data the optimized weighted constant and best temporal vegetation index datasets were evaluated by observing the difference in membership between the target class and other class(s). The maximum membership difference containing weighted constant value will be the optimized weighted constant. Best temporal vegetation index datasets to identify two classes of early harvested and late harvested wheat crops were evaluated by using the maximum membership difference between both classes among all three NDVI temporal datasets. The Flowchart of the methodology adopted is shown in Fig. 2:

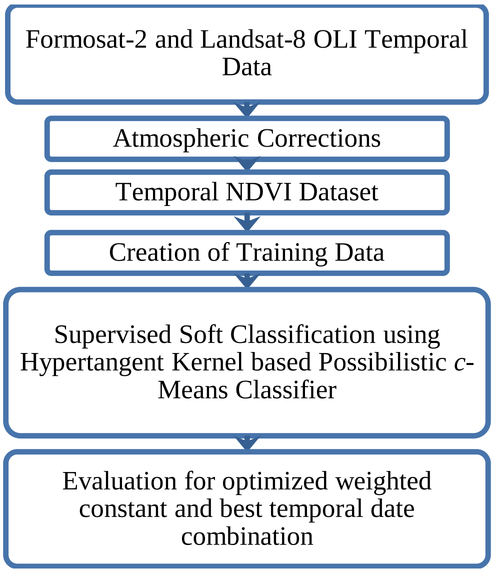


Figure 2: Methodology adopted

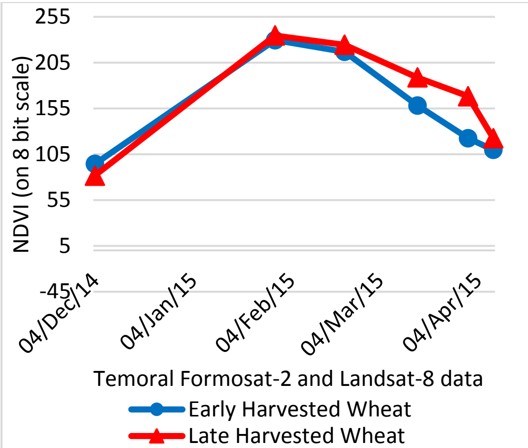


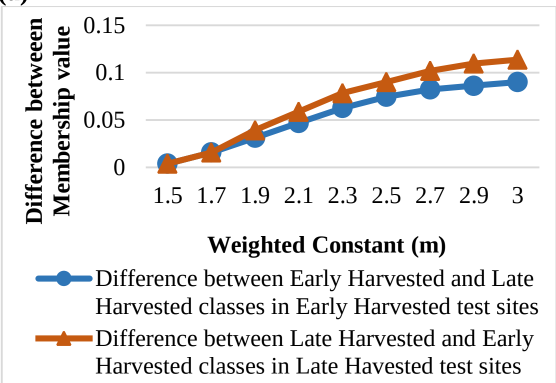
Figure 3: Spectral growth curve of wheat at training sites

5. Result and discussion

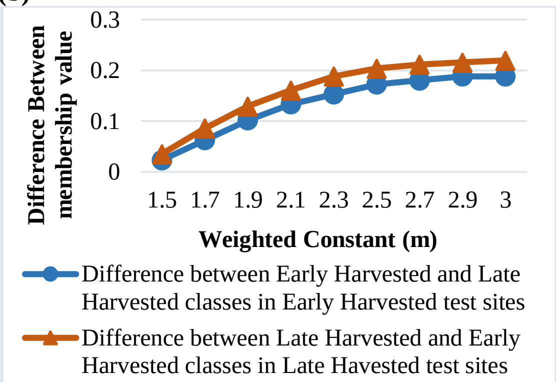
The spectral growth curve of early harvested and late harvested wheat crop has been shown in fig.3. The graph is showing the variation of NDVI between both classes with respect to time.

The weighted constant; m was optimized for 4, 5 and 6 date combination for two classes; early harvested wheat crop and late harvested wheat crop. The value of m was varied from 1.5 to 3.0 for each classification. However, the testing sites data were used to find the difference between membership values of both output fraction images. As the difference tends to be constant the corresponding value of m can be considered as its optimized value. The graphs shown in figure 4(a), 4(b) and 4(c) depict the difference between the membership values of classes as m was varied for 4, 5 and 6 date combination at unbiased sites. While in the case Hypertangent kernel based PCM optimized m was observed at 2.7, 2.5 and 2.5 respectively.

(a)



(b)



(c)

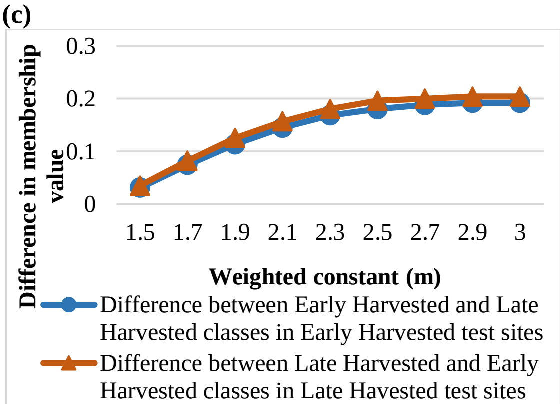
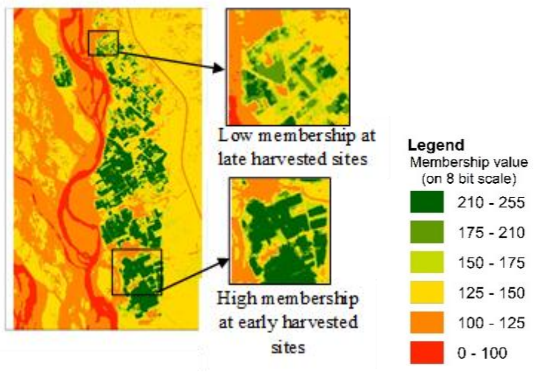


Figure 4: Weighted Constant (m) vs Difference between membership values for (a) 4 date combination datasets; (b) 5 date combination datasets; (c) 6 date combination datasets

The four dates classified results were not appropriate to discriminate both wheat classes. The Five dates and six dates classified results were represented the high difference between membership values of both classes at unbiased sites (The wheat crop area, which have not been used as training sites). However, five dates were found sufficient to discriminate late harvested wheat crops. The six dates classified results were also evaluated for good discrimination of early harvested wheat crop from other non-interest classes. Figure 5(a) and 5(b) represent nicely separated membership values in late harvested and early harvested wheat crop fields for 5 and 6 date combination temporal images. The classified images membership values have been stretched up in 8 bit scale for good visibility.

(a)



(b)

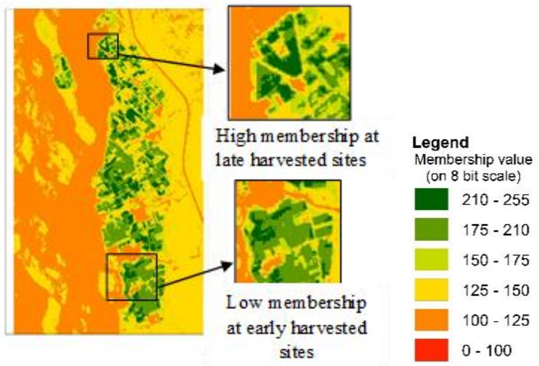


Figure 5: Classified images extracted by using Hyper Tangent Kernel based PCM classifier, (a) Class1- Early harvested wheat crop (Six date; optimized m= 2.5); (b) Class2- Late harvested wheat crop (Five date; optimized m= 2.5)

6. Conclusion

The study carried out in this research indicates the potential of bi-sensor approach in the temporal analysis studies. It has been observed that to identify wheat crop, the 5 growth phases covering images are enough. The Formosat-2 temporal data shows less spectral mixing than Landsat-8 because of the finer resolution of its sensor. Therefore, five and six date combination have more spectral mixing than four date combination because of coarser resolution Landsat-8 images contribution in datasets. The results indicate that 5 date combination was sufficient to discriminate late harvested wheat crops and 6 date combination was sufficient to discriminate early harvested wheat crops. Therefore, the study conclude that the Hypertangent kernel based Possibilistic c-means classification approach is robust to handle the mixed pixels to identify wheat crop. This selected best date can help in providing a temporal window for monitoring the wheat crop. This approach would help in generating accurate maps with the help of optimum number of strategically selected temporal remote sensing images covering the growing season of the crop, and help in saving resources spent in mapping too.

Acknowledgements

The authors would like to thank Sponsors the National Space Organization, National Applied Research Laboratories and jointly supported by the Chinese Taipei Society of Photogrammetry and Remote Sensing and the Center for Space and Remote Sensing Research, National Central University of Taiwan for providing Formosat-2 temporal images of Haridwar district, Uttrakhand, India. The first author is thankful to IIRS ISRO for allowing ten month M. Tech project on study of specific crop identification by using kernel based fuzzy classifier.

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India's Journey Towards Excellence in Building Earth Observation Cameras

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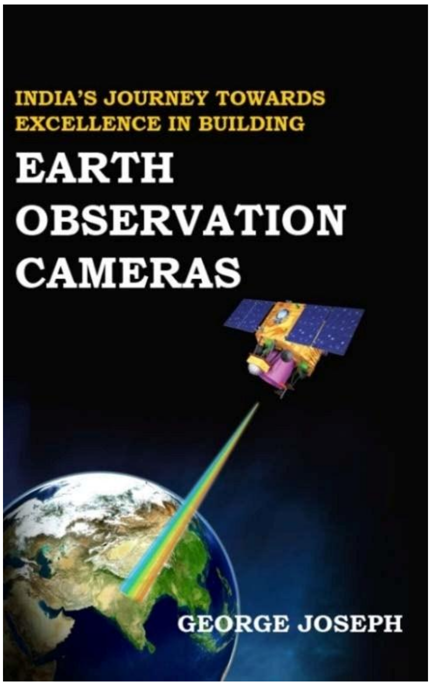

The book traces the evolution of earth observation cameras in Indian Space Research Organization (ISRO); how from a humble beginning of a two band framing camera ISRO went on to developing world class imaging system from space and the innovations carried out in the course of development of these sensors. The book also discusses the rational to choose various camera specifications based on the application needs.

The book starts with the beginning of the space program in India and systematically chronicles the journey of the development of advanced space based imaging system. The book also provides some basic technical insights into the building of space based remote sensing cameras, which have been presented in a way that can be understood by non-specialists too. In addition the book brings out the management aspects and the role played by leadership which make ISRO stand out as a successful high-tech organisation.

In addition to students and professionals in the field who will get a broad account of the functioning of space based camera systems and the nuances in the design, development and deployment of them, those in policy making and technical management in space agencies across the globe will also find the book useful to understand the path taken by India to achieve pre-eminence in this field.

"I hope the book will interest a broad range of readers both within and outside the country. Those who were part of the journey will feel a sense of satisfaction and proud of what they could achieve and the younger readers will be inspired and encouraged to be part of this excitement. The book should interest all those who want to know how India has achieved preeminence in space based remote sensing."

A.S. Kiran Kumar
Chairman ISRO/Secretary DOS
(In the foreword to the book)

Author: Dr. George Joseph was director of the Space Applications Centre (ISRO), Ahmedabad. Under his overall guidance the development of electro-optical sensors started in ISRO.