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Wheat Crop Inventory Using High Spectral Resolution IRS-P3 MOS-B Spectrometer Data

R.P. SINGH, V.K. DADHWAL and R.R. NAVALGUND
Remote Sensing Applications Area
Space Applications Centre
Ahmedabad-380053

ABSTRACT

Modular Optoelectronic Scanner (MOS-B) spectrometer data over parts of Northern India was evaluated for wheat crop monitoring involving (a) sub pixel wheat fractional area estimation using spectral unmixing approach and (b) growth assessment by red edge shift at different phenological stages. Red shift of 10 nm was observed between crown root initiation stage to flowering stage. Wheat fraction estimates using linear spectral unmixing on Feb. 13, 1999 acquisition of MOS-B data had high correlation (0.82) with estimates from Wide Field Sensor (WiFS) data acquired on same date by IRS-P3 platform. It was observed that five bands (4,5,8,12,13 MOS-B bands) are sufficient for signature separability of major land cover classes viz. wheat, urban, wasteland, and water based on purely spectral separability criterion using Transformed Divergence (T.D.) approach. Higher number of bands saturated the T.D. values. In contrast, performance of sub pixel fractional area estimation using unmixing decreased drastically for eight bands (4,5,6,7,8,9,12,13 MOS-B bands) chosen from optimal band selection criteria in comparison to full set of 13 bands. The relative deviation between area estimated from Wifs and MOS-B increased from 1.72 percent when all thirteen bands were used in unmixing to 26.10 percent for the above eight bands.

Introduction

Development and operationalization of Remote Sensing based techniques using space borne sensors for monitoring crop growth over large areas for crop production forecasting has been one of the thrust areas of research in India (Navalgund *et al.* 1991). Large area crop production forecasting requires accurate area estimates as well as appropriate indicators of crop vigour and growth. High spectral resolution data makes it possible to derive

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sensitive spectral parameters like red edge and red edge shift (Collins, 1978, Demetriades-Shah *et al.* 1988) which are related to chlorophyll content (Collins, 1978, Horler *et al.* 1983, Gitelson *et al.* 1996), leaf nitrogen content, leaf area index and leaf angle distribution (Guyot *et al.* 1992). Most of the works on use of high spectral resolution on crop studies are either ground based or carried out by airborne sensors which precludes its direct applicability for regular monitoring for large areas. Satellites for global monitoring that employs narrow bandwidth sensors are generally optimised for coarser spatial resolution. High spectral resolution MOS-B sensor onboard IRS-P3 platform provides sensitive measures for estimating crop biophysical parameters but is less effective for crop inventory in Indian condition due to inadequate spatial resolution. Within the scope of above limitations for crop monitoring, there lies a need for exploring newer techniques addressing both the uses from such type of data.

This study discusses the feasibility of using MOS-B spectrometer data for crop growth monitoring as well as area estimation. High spectral information in the red – near infrared (NIR) transition domain was used for crop growth monitoring using fitted red edge parameters. Use of multi-date MOS-B data for wheat monitoring over the large homogeneous wheat belt of Northern India during 1996-97 rabi season to observe red shift, a sensitive parameter of crops biophysical properties and wheat area estimation using linear spectral unximing is reported.

Material and Methods

Data Used and Study area

MOS-B data was acquired on five dates i.e. Dec. 27, 1996, Jan. 15, 1997, Feb. 13, 1997, March 4, 1997, and March 9, 1997 which covered crop phenology from crown root initiation stage to flowering stage of crop over large homogeneous wheat tract in Punjab, India. Synchronous WiFS data of Feb. 13, 1997 (Plate 1) was also acquired for identification of endmembers as well as validation for linear spectral unmixing analysis.

Methodology

Data of all the five dates from Dec. 27 1996 to March 9, 1997 were registered using nearest neighbour resampling with root mean square error less than 0.5 pixel. Signatures for different land cover classes from MOS-B were generated for sites verified with WiFS data. Thirteen spectral bands (Table 1) were used to overcome the limitation of coarse spatial resolution of data using spectral unmixing technique for subpixel wheat proportion estimation. Estimated wheat proportions were

Table 1: Spectral bands of MOS-B sensor

Channel No.	*Wavelenght (nm)*
1	408±5
2	443±5
3	485±5
4	5205±5
5	570±5
6	615±5
7	650±5
8	685±5
9	750±5
10	870±5
11	1010±5
12	815±5
13	945±5

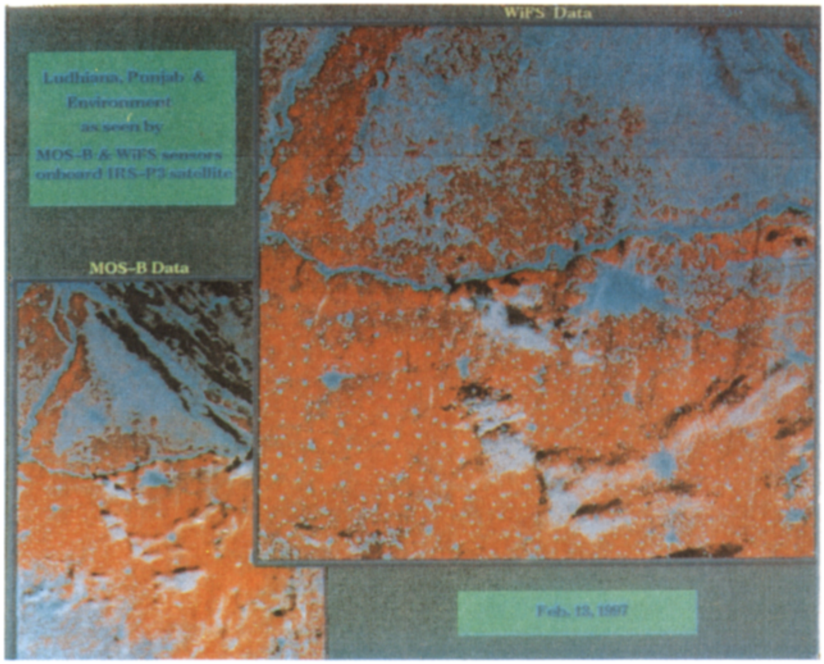

Plate 1. False colour composite of MOS-B data (Bands 11:R, 6:G, 3:B) and Wifs data showing wheat dominated region of Punjab, India.

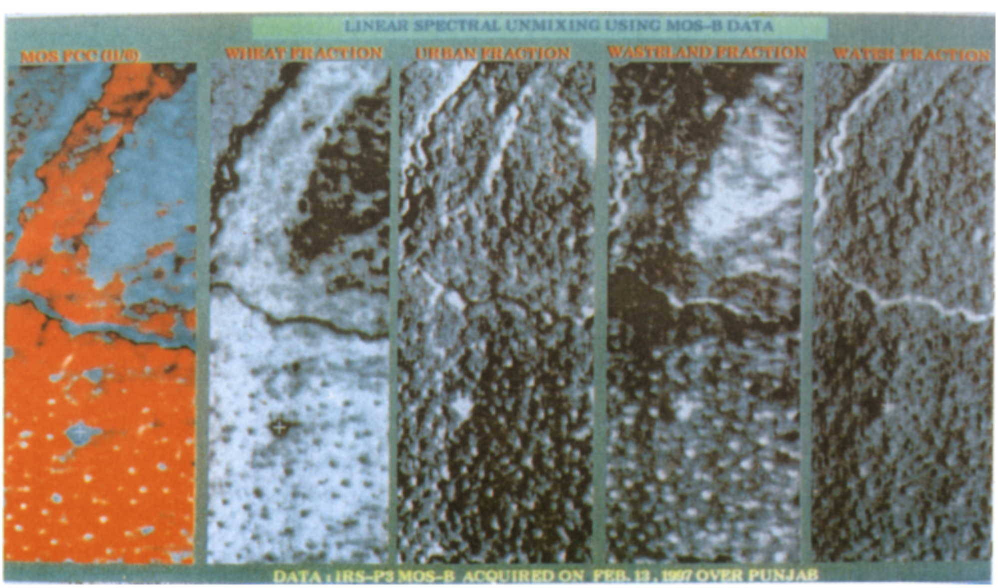

Plate 2. False colour composite of MOS-B data (Bands 11:R, 6:G, 3:B) and fraction images of different land cover classes showing proportions ranging from 0 to 100 percent.

correlated with the wheat area estimated from WiFS data acquired on same date. Comparison of unmixing was also studied with two sets of band combinations i.e. eight bands of MOS-B (4,5,6,7,8,9,12,13,) chosen from optimal band selection criteria and all 13 bands of MOS-B data. Various steps followed in analysis include (a) computation of radiance using calibration coefficients supplied in header file (b) computation of apparent reflectance using solar irradiance at top of atmosphere and solar zenith angle (c) atmospheric correction by removal of Rayleigh path radiance, (d) inverted Gaussian fitting, (e) linear spectral unnixing and (f) selection of optimum spectral bands.

Procedure

MOS-B data was converted into radiance and subsequently converted into apparent reflectance. Solar extraterrestrial irradiance and Solar Zenith angle were used to calculate apparent reflectance. This apparent reflectance is modulation of pure target reflectance and reflectance due to atmospheric contributions. An attempt was made to remove atmospheric effect due to Rayleigh contributions (eqn. [2] using procedure of Doerffer (1992).

Reflectance p (λ) is

$$p(\lambda) = \pi L(\lambda) d^2 / Eo(\lambda) \cos \theta_z \quad ....[1]$$

where L((λ) is radiance observed at satellite sensor, Eo(λ) is extraterrestrial solar irradiance, θ_z is solar zenith angle. And d is mean distance between sun and earth in Astronomical units.

Reyleigh path radiance L_r is

$$L_r = Eo\, \iota_r\, \omega_{or}\, p_r(\Gamma) / 4 \pi \cos \theta_v \quad ....[2]$$

Where ι_r is Rayleigh optical depth, ω_{or} is single scattering albedo, p_r (Γ) is scattering phase function and θ_v is view zenith angle.

Red Edge Using Inverted Gaussian Model

Changes in chlorophyll, carotenoid concentration and leaf area index manifest as subtle spectral change in the visible and infrared portion of reflectance curve. The slope and position of the red edge which is related to phenological and health status was modelled using inverted Gaussian model (Bonham-Carter, 1987) which is:

$$R(\lambda) = (R_s - R_0)\ \mathrm{Exp}^{-(\lambda - \lambda_0^2)/2\sigma^2} \quad ....(3)$$

where R_0 is the reflectance at the absorption maximum at λ_0, R_s is the reflectance at shoulder above 780 nm and σ is the Gaussian shape parameter (sigma) which determines the red edge value. Red edge inflection point is given by $\lambda_0+\sigma$ at which the slope is maximum.

Spectral Unmixing

Unlike high spatial resolution data which have high proportion of pure pixels, a large proportion of coarse spatial resolution data are spectrally mixed. In linear spectral unmixing analysis, it is assumed that signatures of a subset number of surface elements can reproduce the observed spectra when mixed together in various proportions. This subset may be referred to as endmembers, components, or factors; they in fact may be mixtures themselves (Gong *et al.* 1991).

Hence, given multi spectral information, it is possible to model each pixel spectrum as a linear combination of a finite set of components:

$$ri = \sum_{j=1}^{n} (aij \cdot x\, j) + ei \quad ....(4)$$

Where ri = mean spectral reflectance for the ith spectral band of the pixel containing one or more components; aij = spectral reflectance of the j th component in the pixel for the ith spectral band; x j = proportion value of the jth component in the pixel; ei = error term for the ith spectral band; j = 1, 2, ..., n is number of components assumed in unmixing and i = 1,2, ..., m is the number of spectral bands considered in the analysis. A constraint is applied, since the proportion values must be non-negative and the sum of proportions for any pixel must be one.

$x_j \geq 0$ and $\Sigma x_j = 1$, $j = 1, 2, \ldots, n$.

Proportion of each component was obtained by using singular value decomposition method with constrained least squares (Shimabukuro and Smith 1991). In order to have deterministic solution, the number of components should not exceed the number of spectral bands, i.e., $n \leq m$. Once image components (end-members) are identified, the entire image can be unmixed, pixel-by-pixel.

Spectral unmixing was carried out by first coding every pixel/scan line of MOS-B image with unique number. Image to image transformation equation was developed to transfer MOS code at WiFS resolution for locating the corresponding pixels on WiFS image for a given pixel of MOS image. It also helped in transferring the endmembers locations, selected from WiFS data for use in unmixing MOS data. Pure pixels of wheat, urban, wasteland and water classes were taken as endmembers. Accuracy assessment of fractional area was done at 70 random locations of 3x3 pixels from MOS image and estimated wheat proportion from corresponding WiFS pixels. Analysis was carried out using "unmix" module of a commercial software package.

Selection of optimal spectral bands

In order to determine the optimum bands for class discrimination from a given set of bands, some criteria must be established. The criteria used was based on average transformed divergence (T.D.). This was calculated from the class sample means and the class covariance matrices. The average transformed divergence is based on the exponential of the divergence (Mahalanobis distance), and reduces the dominance of classes, which have the highest divergence. A branch and bound method developed by Narendra and Fukunaga (1977) was used for feature subset selection.

Results and Discussion

Inverted gaussian model (Bonham-Carter, 1987) was fitted for MOS-B derived reflectances between 650 and 870 nm to estimate inflection wavelength and its subsequent change with crop stages i.e. red shift. Red shift of 10 nm observed from crown root initiation stage (703.8 nm) to peak vegetative stage (714.2 nm). An attempt was also made to analyze the error component and sensitivities of red edge detection by reducing the number of unknown parameters by fixing wavelength of the absorption maximum (λo). Wavelength λo was kept constant from 665 to 685 nm at the interval of 5 nm. It was observed that maximum red shift variation occurred at λo within 665 to 670 nm during crop growth cycle (Singh *et al.* 1998).

All thirteen narrow MOS-B spectral bands were used for subpixel wheat proportion estimation using spectral unximing and validation of wheat proportion was also carried out with corresponding WiFS pixels. Sub pixel wheat proportion from MOS-B data, when all the thirteen bands were used in unmixing, showed high correlation (0.82) with proportion enumerated from WiFS pixels (Fig 1). Fractional images of different landcovers viz. wheat, urban, wasteland and water are shown in Plate (2). Relative deviation between both estimates was 1.72 per cent. As is discussed in the methodology, proportion of each component

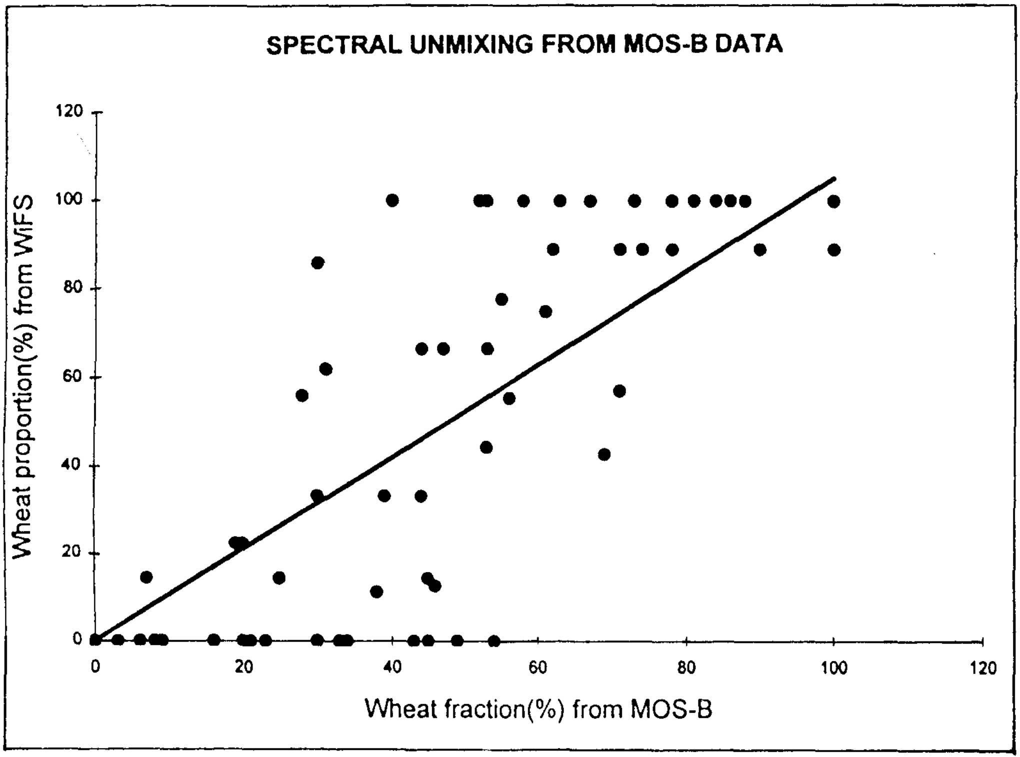

Fig. 1 Comparison of wheat proportions estimated from spectral unmixing of MOS-B data to estimated proportions from WiFS data

in a pixel was obtained using constrained least square method. In order to have deterministic solution, requirement of bands are such that it should either equal to (worst case) or more than the components (number of classes) considered. Accuracy of estimated proportion of different components depends on the number of bands considered vis a vis number of component used in analysis. To study the influence of number of bands on sub pixel fraction estimation, unmixing result was compared at two sets of band combination i.e., all thirteen bands as described above and eight bands (4,5,6,7,8,9,12,13) of MOS-B data. There are many eight-band combinations that can be selected out of full thirteen bands of MOS-B data. Optimum band combination procedure was used to arrive at the above eight-band combination. Details on the optimum band combination are discussed in the next paragraph. It was found that correlation between subpixel wheat proportion estimated from MOS-B data and enumerated WiFS pixels area reduced to 0.72 when only above eight bands were used in unmixing. Relative deviation observed between WiFS and MOS enumeration for this combination of bands increased to 26.1 per cent. This decrease in performance was also visually verified when false colour composite of WiFS was compared with Pseudo colour composite generated by giving red colour to wheat fractions and green and blue colours to non wheat fractions.

Selection of optimal bands becomes crucial for feature space reduction in analysis or deciding the relative importance of spectral bands when the large number of bands is to be analysed. Although the choice of bands is associated with scope of applications and the level of classes considered. In the present work, very broad classes, viz., wheat, urban, wasteland and water bodies which were used in unmixing were taken into consideration. The idea was to get the best subset of bands (eight) for comparison of unmixing analysis. Average transformed divergence (T.D.) criterion was used for the determination of best subset of bands optimum for discrimination of above classes.

It was observed that five bands (4,5,8,12,13 out of all MOS-B bands) are sufficient for signature separability (T.D. 1.979) of above described land cover classes (Table 2). These bands with central location at 520, 570, 685, 815 and 945 nm cover green, red and NIR spectral region. With higher number of bands, T.D. values get saturated for these classes. On the contrary, performance of unmixing approach in sub pixel fractional area estimation decreased when the results of analysis carried out using all the 13 bands of MOS-B data when compared with the results of analysis using eight (4,5,6,7,8,9,12,13) MOS-B bands chosen from optimal band selection criteria. It can be inferred that high separability of the components in the signature domain for a given number of bands, need not be a sufficient condition of efficient unmixing.

Conclusion

Feasibility study was carried out for assessment of wheat crop over the parts of northern India using IRS-P3 MOS-B data. It showed encouraging results for its use in crop monitoring in homogeneous conditions at regional scale. High spectral resolution MOS-B spectrometer data provided an opportunity for the assessment of vigour of wheat crop using red edge technique from space platform. Attempt was made to overcome the limitation of coarse spatial resolution by taking advantage of large number of bands (13) of narrow spectral resolution for spectral unmixing. Wheat area estimated from MOS-B data using unmixing approach showed good correlation (0.82) when it was compared with the corresponding area estimated using WiFS data. Though MOS-B spectrometer is originally designed for oceanic applications, still provided an opprtunity to

Table 2: Selection of optimal bands for land covers discrimination

No. of optimal bands	*Average T.D.*	*MOS-B Bands and its central wavelength in (nm)*
2	1.811	5(570), 12(815)
3	1.936	5(570), 8(685), 12(815)
4	1.959	5(570), 8(685), 12(815), 13(945)
5	1.979	4(520), 5(570), 8(685), 12(815), 13(945)
6	1.980	4(520), 5(570), 7(650), 8(685), 12(815), 13(945)

effectively handle such type of high spectral resolution data for agricultural applications. Techniques used can further be utilized in future for the analysis of data from MODIS and MERIS sensors.

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