Linear Spectral Mixture Analysis of SPOT-7 for Tea Yield Estimation in Pagilaran Estate, Batang Central Java

F Fauziana 1, P Danoedoro 2, and S Heru Murti 3

1 Remote Sensing, Geography Faculty, Gadjah Mada University, Yogyakarta 55281, Indonesia
2 PUSPICS Geography Faculty, Gadjah Mada University, Yogyakarta 55281, Indonesia
3 Cartography and Remote Sensing, Geography Faculty, Gadjah Mada University, Yogyakarta 55281, Indonesia

fatmawati.fauziana@gmail.com, projodanoedoro@geo.ugm.ac.id, sigit@geo.ugm.ac.id

Abstract. Remote sensing has been utilized especially for agriculture yield estimation. Tea yield is effected by biology characteristic including crown density. The challenge of tea yield estimation uses multispectral remote sensing data is the presence of object beside tea. This mixed pixel problem can disturb spectrally to recognize tea tree, so it is necessary to use pixel approach. The aims of this research are (1) to determine fraction of tea and non-tea; (2) to estimate crown density percentage based on tea Normalized Difference Vegetation Index (NDVI); (3) to estimate tea yield based on crown density. SPOT-7 was utilized for this application. Linear Spectral Mixture Analysis (LSMA) has applied to determination fraction percentage each pixel. Each pure endmember was read the NDVI value. NDVI of tea tree has sensitivity with crown density. Counting tea NDVI was applied for NDVI mixed pixel. Linear regression analysis has applied for estimating crown density and tea yield. The results of this research are SPOT-7 which can recognize tea, tree shade, impervious and soil each pixel with accuracy 99,84%. Although it produced high accuracy, it has overestimate at certain tea estate because of the attendance of impervious. Regression analysis of crown density and NDVI showed coefficient determination 52%. This model result 4-100% crown density percentage, where crown density 4–55% were located beside tea tree or pruned-tea block. Regression analysis of crown density and tea yield relation showed coefficient determination 45%. This model produced 161,34–1296,8 kg/ha. Each this model resulted Root Mean Square Error (RMSE) 14,27% and 551,52 kg/ha.

1. Introduction

Remote sensing imagery both passive and active sensor have been used to obtain various informations on earth surface. Remote sensing imagery has potential to estimate tea yield. In Indonesia, tea (Camellia sinensis (L). O. Kuntze) is one of strategic commodity and support economic country. Traditionally, estimation agriculture yield by collecting census data and field survey. Thus will be expensive and spend a lot of time if applied at wide estate [9].

The estimation agriculture yield is necessary for making the decision like price and export and import. Tea yield is determined by wide tea estate and productivity. There is a nuisance spectrally when determining wide tea estate. The objects which exist at tea estate not only tea tree but also shade tree,
asphalt, stoned-street, soil, and tea factory. Based on estate management, tea trees need shade tree to keep stability of shoot tea growing. Fit spatial resolution SPOT-7, there are other objects beside tea tree at one pixel, hence it is necessary be resolved by separation mixed-pixel. Linear Spectral Mixture Analysis (LSMA) has been built to resolve mixed-pixel beside fuzzy classification \[10\]. LSMA assumes dominant objects (i.e. endmember) in every pixel at tea estate is linear. LSMA has successed be applied for vegetation study \[2\]. This method also can be applied like \[3\] said that tree shadow between tea canopy causes mixing interclass and nuisance remote sensing imagery effectiveness.

Tea productivity is interaction between environment condition like altitude and pruning-year. Pruning-year denotes vegetative growth including tree crown since tea trees have been pruned at certain block. Near-infrared has sensitivity to a number of leaves reflection. It is assumed that by increasing a number of leaves will increase digital number of infrared. Increasing tea leaves are interaction between branch growth and pruning year. Crown density increases along with increasing pruning year and assumed tea yield will increase. Vegetation indices (VI) are widely employed remote sensing technique for measurement crown density. The most VI which employed is Normalized Difference Vegetation Index (NDVI) \[4\]. The VI of value every pixel does not always show the pure tea tree. Hence, this research demonstrate to combine LSMA and VI to produce tea crown density.

The objectives of this study are (1) to determine the tea fraction and non-tea fraction, (2) to count the tea crown density based on NDVI, and (3) to count the tea yield based on tea crown density.

2. Study area
This study area, located at Pagilaran Estate exactly Pagilaran unit production. It is located in Batang, Central Java, Indonesia (Figure 1). The estate area covers approximately 1.132,25 ha which devided three afdeling thus are Pagilaran, Kayulandak and Andongsili. Beside tea, Pagilaran also cultivates clove and quinine. Pagilaran unit production located in Kemulan mount slope at an altitude 740-1600 m above sea level. The soil type is dominated andosol that has high characteristics to binding water, loose, and structured crumb. Rainfall between 3500-6000 mm/year.

3. Data
SPOT-7 image acquired on 15th of March 2015. There is no cloud covers this area, therefore it helps to make easy interpretation the objects. SPOT-7 imagery has dynamic range acquisition 12 bit per pixel. There are 2 detectors within SPOT-7, multispectral and panrametric, each images has spatial resolution 6m and 1.5m. SPOT-7 satelite deliver images over 4 bands spectral thus are blue (0,450–0,520 μm), green (0,530–0,590 μm), red (0,625–0,695) and near-infrared (0,760–0,890 μm). Panrametric mode works on 0,450–0,745 μm. SPOT-7 satelite constellation has a revisit time every 26 days. This data has orthorectified correction. The digital numbers data were convertd to radiance data using metadata. Radiance data four images were converted to reflectance data using Top of Atmosphere (ToA). Google Earth used to assess accuracy fraction percentage.

4. Methods
4.1 Image processing
LSMA was performed on SPOT-7 image after radiometric correction using ENVI 5.2 classic (Figure 2). The important assumption SMA is spectral signature endmember each pixel is linear \[1\][\[7\]. LSMA model require two principal points. First, endmember proportion each pixel must be equal 1,00 which mathematically formulated as follows:

\[\sum_{i=1}^{N} F_{i} = F_{1} + F_{2} + \cdots + F_{N} = 1\]  (1)

Second, each spectral bands, brightness value (BV\_(\lambda)) each pixel is amount of BV pure pixel each endmember multiple by weight fraction endmember plus one.

\[BV_{\lambda} = F_{1}BV_{\lambda,1} + F_{2}BV_{\lambda,2} + \cdots + F_{N}BV_{\lambda,N} + E_{\lambda}\]  (2)
Figure 1. Location map of Pagilaran Estate showed some tea block were pruned and begin growing after pruning. SPOT-7 is displayed in false colours.
Radiometric correction

NDVI pixel

LSMA

Elevation map

Google Earth autogeoreferencing

Field data:
- crown density
- tea yield
- pruning year

Accuracy assessment

Field survey

Fraction maps

SPOT 7 orthorectified

Figure 2. Flow chart shows methodology this research

The stages of LSMA as followed:

4.1.1. Minimum Noise Fraction (MNF)
MNF was known to remove data redundancy and present good quality imagery. Disturbance identification was shown by eigenvalue. Research area covers 2 tiles, hence these were applied separately. Statistic calculated from both tiles shows MNF 1 has the highest eigenvalue and MNF 4 has the lowest eigenvalue (Table 1). It means MNF 1 has lower noise than MNF 4. Only 1 tile continued to the next step, due to the eigenvalue over 1 only 1 MNF transformation whereas expected endmembers were 4

Table 1. Statistic data of MNF transformation

| Tile | Band | Minimum value | Maximum value | Mean | St.Dev | Eigenvalue |
|------|------|---------------|---------------|------|--------|------------|
| R2C2 | MNF 1 | -10.509       | 55.023960     | -2.59 | 3.227136 | 24,987     |
|      | MNF 2 | -20.456       | 13.006959     | -2.06 | 3.728131 | 6,186      |
|      | MNF 3 | -7.157        | 26.850830     | 0.53  | 1.459634 | 3,380      |
|      | MNF 4 | -13.435       | 24.751259     | -0.65 | 1.510371 | 1,605      |
|      | Total |               |               |       |        | 36,157     |
| R3C2 | MNF 1 | -10.509       | 55.023        | -2.60 | 3.229   | 23,974     |
|      | MNF 2 | -20.456       | 13.007        | -2.07 | 3.732   | 4,888      |
|      | MNF 3 | -7.157        | 26.851        | 0.53  | 1.462   | 0,182      |
|      | MNF 4 | -13.435       | 24.751        | -0.66 | 1.512   | 0,072      |
|      | Total |               |               |       |        | 24,716     |
### 4.1.2. Pixel Purity Index (PPI)

There are two ways to select endmember, these are by spectral library and PPI process. PPI was applied to obtain pure pixel each endmember. PPI worked by the iteration to detect pure pixel. The result of this process is the pure pixel value that brightness rate denote how many pixel is recorded extremely. The advantages of MNF and PPI processes separate pure pixel and mixed pixel, decrease analyzed pixel and recognize endmember easily [1].

### 4.1.3. Endmember selection

Endmember selection is the important step to obtain meaningful classification of spectral mixture analysis. Endmember output depends on input bands that are used. Selected endmember including tea tree, shade tree, impervious and soil. Four objects are assumed to represent object at Pagilaran, note that the clove and quinine are ignored. PPI leads to choose endmember based on the majority iteration each endmember. Tea tree was derived at tea block, shade tree was derived at \textit{(Albizia saman (Jacq.) Merr)}, impervious was derived at tea factory and soil was derived at pruned-tea block. Although at the pruned-tea block was not found majority soil due to residu pruning tea at local block.

### 4.1.4. LSMA implementation

The result of LSMA process is the fraction percentage each endmember and error imagery shown by root mean square error (RMSE). Based on this map fraction percentage, it can be recognized pure pixel and mixed pixel. Constraint unmixing was applied for this process that the total fraction of every pixel is 1.

### 4.1.5. Normalized Difference Vegetation Index (NDVI) Transformation

NDVI has sensitivity to vegetation density. This index is applied to near infrared and red. Near-infrared portion shows higher reflectance in multiple leaves than single leaf. This is due to addictive reflectance from second and next layer of leaves (Howard, 1991). This condition is found on tea tree, the old leaves participate reflectance portion, whereas only shoot tea which is plucked, it can add NDVI and likely does not indicate high plucking. NDVI equation can be expressed as,

\[
NDVI = \frac{NIR - \text{red}}{NIR + \text{red}}
\]

where NIR is near-infrared reflectance shown at band 4 in SPOT-7 and Red is red reflectance shown at band 3 in SPOT-7.

The result of this equation is NDVI pixel that indicate mixed-pixel, hence to compute tea NDVI should be expressed by formula which adapted from Brown, 2001,

\[
VI_{\text{pixel}} = f_{\text{tea}} \cdot VI_{\text{tea}} + f_{\text{shade tree}} \cdot VI_{\text{shade tree}} + f_{\text{impervious}} \cdot VI_{\text{impervious}} + f_{\text{soil}} \cdot VI_{\text{soil}} + \epsilon
\]

Where VI denotes NDVI each endmember \( f_s \) denotes fraction each endmember and \( \epsilon \) is RMSE. Based on Eqs. (4) can be expressed the equation as,

\[
VI_{\text{tea}} = VI_{\text{pixel}} - f_{\text{shade tree}} \cdot VI_{\text{shade tree}} - f_{\text{impervious}} \cdot VI_{\text{impervious}} - f_{\text{soil}} \cdot VI_{\text{soil}} - \epsilon
\]

Eqs. (5) was obtained from the spectral mixture analysis which each pixel is linear. NDVI pure pixel of endmember were displayed in table 2. The highest value is tea and the lowest is impervious.

| Table 2. NDVI each pure endmember |
|-----------------------------------|
| **Endmember** | **NDVI pixel** |
| Tea             | 0.635938       |
| Shade tree      | 0.367396       |
| Impervious      | -0.001394      |
| Soil            | 0.323242       |
4.1. Crown density and tea yield computation
Empirical relation between the NDVI and crown density were investigated, whereas relation between the crown density and tea yield was tried to be investigated. Model was applied by correlation and regression analysis. Crown density was obtained from field measurement, which ignore soil, tree shadow and branch. Field measurement was executed by plotting 12x12 meters and samples were determined by altitude. Sampling method was proportional stratified sampling. The informations obtained from each samples beside tea crown density and tea yield are pruning-year and clon.

5. Results
5.1 Fraction accuracy assessment
The result of LSMA process shows there are minus value and value more than 1. Ideally, each pixel from constraint unmixing is 1 or 100%. It is due to the objects at the Pagilaran estate not only four objects based on endmember and they have characteristics spectrally. Figure 4 displays the endmember percentage.

![Endmember Collection Spectra](image)

**Figure 4.** Spectral reflectance each endmember
Tea tree has the highest spectral reflectance in green and near-infrared region, it means healthy tea on good condition and tea leaves reflectance in some layers and also was controlled by tea internal structure. Tea curve reflectance is higher than shade tree because tea crown is denser than shade tree crown. Impervious reflectance increase in green region and constant in red and near-infrared. Soil reflectance increase along with the increasing of band region especially until near-infrared.

Accuracy assessment to exam fraction estimation is mean absolute error (MAE). Validation process was based on Google Earth image with higher spatial resolution. Accuracy was applied in permanent object. MAE for tea was 0.28, shade tree 0.16, impervious 0.10 and soil 0.11. Overall accuracy was 99.84. Although overall accuracy was high but there are pixels had impervious overestimate due to brightness pixel indicate tea or impervious.

5.2 Crown density computing based on NDVI
Tea crown density on field was input to produce crown density map based on NDVI. Statistic analysis show crown density was influenced 52% by tea NDVI. NDVI is a simple vegetation index to computing vegetation density, almost majority of researches used it. Figure 5 (left) tends to show interaction between pruning-year and crown density that can be divided into two classess. First class has characteristics, majority from seed and pruning-year is 1 which on going to vegetative growth. Pruning year 1 denote a few tea branch and has gap in tea tree. Second class was dominated seed and pruning-year 2 until 4. This is the optimum condition of tea growth. Any amount whatever of NDVI, if at tea block with optimum growth will produce same crown density. Pruning-year 2 experienced growing branch and additive dense leaves, until reach constant growth in pruning-year 4. Crown density was measured by ignoring plant disease and weather condition. The similarity seed for first and second class
is tens old moreover hundreds old. Any amount whatever of tea age will produce good vegetative growth if in a good estate management.

![Figure 5.](image1.png)

**Figure 5.** Regression graphic between tea NDVI and tea crown density (left) and map of distribution of the tea crown density estimation (right)

![Figure 6.](image2.png)

**Figure 6.** The average condition of first class tea crown density (left) and second class tea crown density (right)

The lowest estimated tea crown density was 4% and the highest tea crown density was 100%. Crown density 4% until 55% were found at shade tree and pruned-tea block (Figure 5 (right)). RMSE was 14.27% and accuracy assessment 86.37%. The model was accepted to be input tea yield estimation model, although there are overestimate and underestimate crown density percentage. Overestimate denote different pruning-year tea block that was before pruning, while field measurement on pruning-year 1.

5.3 *Tea yield computing based on crown density*

Different tea yield although at the same pruning-year is non-uniformity of the shoot tea growth. Although tea block has dense leaves but the distribution shoot tea growth is not uniform, will produce different tea yield. It is due to unfit plucking technique by shear. Sometimes tea pluckers do not pluck young shoot because limits of scope or they leave drop young shoot in gaps of tea tree. Tea yield was
influenced 45% by crown density, it means not only crown density influence tea yield. Figure 7 (left) displayed 2 classes tea yield. First class was dominated by pruning-year 1 tea trees and over but vegetative growth do not produce enough dense shoot tea. Second class was dominated by pruning-year 2 tea trees and over.

**Figure 7.** Regression graphic between tea crown density and tea yield (left) and map of distribution of the tea yield estimation (right)
The overall model result caused pixels beside tea fraction has participation to tea yield. Hence, masking was applied in 56%-100% crown density. It assumed that minimum 56% crown density is enough to produce tea yield. The effect of masking is remove tea yield at slope tea block. Actually, this tea block has leaves density but LSMA of SPOT-7 recognize this place as shadow. Minimal tea yield was 161.34 kg/ha produced by 56% crown density and maximum tea yield was 1296.8 kg/ha produced by 100% crown density (Figure 7 (right)). RMSE was 551.52 kg/ha and accuracy assessment 35.65%. Difference tea block between acquisition image and field survey produce high standard deviation. The examples, Pulosari II block was not pruned on March 2015 yet but on December 2015 was pruning-year 1, it produce low tea yield. Pekandangan IA 1 block was like pruned on the image whereas based on field data this block did not produce tea yield from last March until April.

Figure 8. The average condition tea of first class tea yield (left) and second class tea yield (right)

6. Discussion
Digital number of SPOT-7 is mixed-pixel of the objects in the tea estate. The separation fraction of each pixel help to remove the error determination of tea width and vegetation index transformation. This model show high accuracy of LSMA even though there are overestimate impervious pixel in tea block. It is caused high albedo fraction including stoned-road between tea blocks, non-uniformity topography and endmember selection which do not include all objects in tea planation. [10] remove soil from high albedo fraction and distinguish impervious with water and high dense vegetation. The lack LSMA of this study is unavailable spectral library to recognize spectral particular endmember, it trade on how many iteration show pure pixel whereas there is tea block which considered uniform. [5] summarize hyperspectral data can distinguish tea growing in sunlit and shade condition in green and near-infrared region. Blue region distinguish tea growth and healthy condition. Red and near-infrared regions can discriminate pruned and unpruned-tea.

Tea block with high tree population and high dense leaves contribute higher reflectance energy than shade tree in near-infrared region. Actually, high reflectance tea estate do not related with tea yield directly, due to only plucking tea shoot might not reach 20% from leaves population every tea tree. Crown density is an approach that assume many tea leaves will increase tea yield. Crown density has stronger correlation with NDVI than TVI (Transformed Vegetation Index) and RVI (Ratio Vegetation Index) [7].

Tea yield produces from young leaves which increase from pruning-year 1 until 3 and constant in pruning year 4. This condition does not prevail in all tea block. Tea shoot can not be plucked in unhealthy condition, long dry season and error of plucking. The periodicity of tea plucking depend on altitude. High altitude causes long plucking cycle, it is due to lack of sunlit and slow photosynthesis.

7. Conclusion
LSMA can separate objects in tea estate using SPOT-7 image including tea tree, shade tree, impervious and soil and produce accuracy 99.84%. Crown density was computed based on NDVI, it produce 4%
until 100% crown density and RMSE 14.27% and accuracy assessment 86.37%. Tea yield estimation based on crown density produce 161.34 kg/ha until 1296.8 kg/ha and RMSE was 551.52 kg/ha and accuracy assessment 35.65%. Low accuracy is caused plucking and human interference including pruning.

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References
[1] Asis A M De and Omasa K 2007 Estimation of vegetation parameter for modeling soil erosion using linear Spectral Mixture Analysis of Landsat ETM data Photogrammetry and Remote Sensing 62 309–324
[2] Brown D G 2001 A Spectral Unmixing Approach To Leaf Area Index (LAI) Estimation At The Alpine Treeline Ecotonein GIS and Remote Sensing Applications in Biogeography and Ecology A. C. Millington, S. J. Walsh, and atrick E. Osborne (New York: Springer Science and Bussiness Media)
[3] Dutta R 2011 A Spatio - Temporal Analysis of Tea Productivity and Quality in North East India Dissertation University of Twente The Netherlands
[4] Jensen J R 2014 Remote Sensing of the Environment An Earth Resource Perspective Second Edition (New York: Pearson)
[5] Kumar A, Manjunath K R, Meenakshi, Bala R, Sud R K, Singh R D and Panigrahy S 2013 Field hyperspectral data analysis for discriminating spectral behavior of tea plantations under various management practices International Journal of Applied Earth Observations and Geoinformation 23 352–359
[6] Muningsih R, Indradewa D and Sulistyaningsih E 2014 Karakter Fisiologis dan Hasil Pucuk Teh pada Beberapa Umur Pangkas Produksi dan Tinggi Tempat. Ilmu Pertanian.17(1) 25–36
[7] Rohman A S 2002 Analisis Digital Data Citra Landsat TM dan SIG untuk Estimasi Produksi Teh di Sebagian Wilayah Bogor, Cianjur dan Sukabumi Propinsi Jawa Barat Skripsi Gadjah Mada University
[8] Somers B, Asner, Gregory P, Tits L, and Coppin P 2011 Endmember Variability in Spectral Mixture Analysis: A review Remote Sensing of Environment 115(7) 1603–1616
[9] Tripathi N K, Rajapakse S S, and Honda K 2004 Tea Yield Modeling Based on Satellite Derived LAI Geocarto International 19(3) 51–54
[10] Weng Q 2010 Remote Sensing and GIS Integration: Theories, Methods, and Application (New York: McGraw-Hill)