Testing the Sensitivity of Vegetation Indices for Crop Type Classification using RapidEye Imagery

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About me

• From Istanbul, Turkey
• BSc & MSc degree in Geomatic Engineering
• Currently pursuing PhD in Remote Sensing
• Member of RSPSoc and ISPRS
• Working as a research assistant in Geomatic Engineering in YTU
OUTLINE

• Introduction
• Objectives

• Study area
• Data (RapidEye Imagery)

• Vegetation Indices
• Image Classification

• Results&Conclusion

INTRODUCTION

REMOTE SENSING AND AGRICULTURE

• increasing necessity of the food
• high population growth
• global climate change

Sustainable management of agricultural resources

Economy!
INTRODUCTION

REMOTE SENSING AND AGRICULTURE

- Crop pattern identification
- Crop yield estimation
- Precision Agriculture
- Monitoring crop status
- Adaptation to Common Agricultural Policy (CAP)
  - Sustainable agriculture
  - Accurate and appropriate planning

IMAGE CLASSIFICATION

INFORMATION FROM IMAGES

- Maximum Likelihood,
- Support Vector Machines and many more

- Which is the best?
- Accurate Information?

Which is the best?
- Maximum Likelihood,
- Support Vector Machines and many more

- Accurate Information?
- Vegetation Indices

- Appropriate band selection
- Training/testing data
- Classification Methods
- Resolution
- Ancillary Data
Image Classification Accuracy + Vegetation Indices = Classification Accuracy?
Data (Satellite Imagery)

RapidEye Imagery

• 5m spatial resolution
• Orthoimage (Level 3A)

Prior (Common) Application Areas

✓ Agriculture
✓ Vegetation
✓ Forestry

Crop types
Vegetation Indices

<table>
<thead>
<tr>
<th>Vegetation Index</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>[ \text{NDVI} = \frac{(R_{\text{band5}} - R_{\text{band3}})}{(R_{\text{band5}} + R_{\text{band3}})} ]</td>
</tr>
<tr>
<td>GNDVI</td>
<td>[ \text{GNDVI} = \frac{(R_{\text{band5}} - R_{\text{band2}})}{(R_{\text{band5}} + R_{\text{band2}})} ]</td>
</tr>
<tr>
<td>NDRE</td>
<td>[ \text{NDRE} = \frac{(R_{\text{band5}} - R_{\text{band4}})}{(R_{\text{band5}} + R_{\text{band4}})} ]</td>
</tr>
</tbody>
</table>

The band numbers of 2,3,4,5 refer to green (520 – 590nm), red (630 – 685nm), red edge (690 – 730nm) and near-infrared (760 – 850nm), respectively.

Image Classification

- Maximum Likelihood
- Support Vector Machines

<table>
<thead>
<tr>
<th>ROI Name</th>
<th>Color</th>
<th>Pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st_corn</td>
<td>Red3</td>
<td>363</td>
</tr>
<tr>
<td>2nd_corn</td>
<td>Red</td>
<td>555</td>
</tr>
<tr>
<td>well_cotton</td>
<td>Yellow1</td>
<td>391</td>
</tr>
<tr>
<td>moderate_corn</td>
<td>Yellow3</td>
<td>462</td>
</tr>
<tr>
<td>week_cotton</td>
<td>Green1</td>
<td>345</td>
</tr>
<tr>
<td>wet_soil</td>
<td>Purple</td>
<td>319</td>
</tr>
<tr>
<td>moist_soil</td>
<td>Aquamarine</td>
<td>355</td>
</tr>
<tr>
<td>dry_soil</td>
<td>Chartruese</td>
<td>627</td>
</tr>
<tr>
<td>water_surface</td>
<td>Blue</td>
<td>218</td>
</tr>
</tbody>
</table>

Training Data

In-situ data collection
Support Vector Machines

K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)

Radial Basis Function Kernel
(C, \gamma) = (100, 0.125)

Optimum Parameters

Accuracy Assessment

<table>
<thead>
<tr>
<th>Analysis</th>
<th>Overall Accuracy (%)</th>
<th>Kappa coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLC_5 (5 spectral band)</td>
<td>80.21</td>
<td>0.77</td>
</tr>
<tr>
<td>MLC_8 (5 band+ 3 vegetation indices)</td>
<td>73.38</td>
<td>0.70</td>
</tr>
<tr>
<td>SVM_5 (5 spectral band)</td>
<td>83.96</td>
<td>0.82</td>
</tr>
<tr>
<td>SVM_8 (5 band+ 3 vegetation indices)</td>
<td>86.01</td>
<td>0.84</td>
</tr>
</tbody>
</table>
### Accuracy Assessment

\[
\text{Image Classification Accuracy} + \text{Vegetation Indices} = \text{Classification Accuracy ?}
\]

#### Support Vector Machines

#### Maximum Likelihood

### Classified Images

**Legend**
- Unclassified
- First crop corn
- Second crop corn
- Wheat developed cotton
- Moderate developed cotton
- Poor developed cotton
- Wet soil
- Moist soil
- Dry soil
- Water surface

Map Scale 1:100,000
Conclusions

- RapidEye imagery for crop classification and satisfactory results
- Efficient use of SVM for crop classification
- Vegetation indices (VIs) have different sensitivity on classification methods
- SVM increase, MLC decrease when VIs added

Acknowledgements

The authors would like to thank Prof. Dr. Yusuf Kurucu and Dr. Ing. M. Tolga Esetlili from the Department of Soil Science and Plant Nutrition in Ege University for the data providing as well as their assistance in the analysis and interpretation of the crop types for the study area.
Thank you for your attention!

Contact

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Questions & Answers