Hypermix
Hyperspectral-hyperspatial fusion and unmixing techniques to tackle the spectral-spatial resolution trade-off
Hyperspectral OR Hyperspatial?

- Natura 2000 reporting
- Crop disease management
- ...
Soil and shadow difficult to distinguish from dead leaves
Spectral-spatial resolution trade-off

- High spatial resolution:
  - IKONOS (4m, Pan: 1m)
  - Quickbird (2.4m, Pan: 0.7m)
  - Worldview-2 (1.8m, Pan:0.5m)

- Low spatial resolution:
  - Hyperion (30m)
  - Chris (17m, 34m)
  - Enmap (30m)
  - Hyspiri (60m)
  - Prisma (30m)
Challenge – Combine data of available sensors

- Enhancing the accuracy of estimating biophysical parameters through narrow band vegetation indices in fruit orchards in order to better steer the orchard management
- Obtaining classification maps of higher spatial resolution.
Image data collection

- 27 June, 2011
  APEX
  KH

- 27 June, 2011
  RGB UAV
  KH

- 31 August, 2011
  RGB UAV
  Loksbergen

- September, 2011
  Thermal UAV
  Valencia

- 24 September 2011
  APEX
  Valencia

- 30 June 2012
  APEX
  Loksbergen

- 02 July 2012
  RGB UAV
  Loksbergen

- 03 May 2013
  RGB UAV
  Loksbergen
UAV flight campaign
Loksbergen
APEX quicklooks
Loksbergen
• **Decision fusion**: extract contextual, spatial information from the colour image and spectral information from the hyperspectral image, after which these two sources of information are combined to obtain detailed classification maps.

• **Subpixel mapping**: define the spatial distribution of all classes present in one mixed pixel of the high spectral, low spatial resolution image based on the high resolution image pixels.

• **Unmixing based image fusion**: unmix low-resolution images using the information about their pixel composition from co-registered high-resolution images.
High-resolution Classification Map

Attraction model

Connected Components labeling

k-means clustering

Contextual Information

SVM

Spectral unmixing

Subpixel Mapping

Contextual Subpixel Mapping

ACSPM
ACSPM: Color and downscaled HS Images
ACSPM: Pavia University Results
## ACSPM: Accuracies

### Pavia University

<table>
<thead>
<tr>
<th>Method</th>
<th>Overall accuracy</th>
<th>Average Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>86.15%</td>
<td>90.06%</td>
</tr>
<tr>
<td>ASPM</td>
<td>86.67%</td>
<td>92.05%</td>
</tr>
<tr>
<td>CSPM</td>
<td>92.61%</td>
<td>94.17%</td>
</tr>
<tr>
<td>ACSPM</td>
<td>94.12%</td>
<td>95.69%</td>
</tr>
</tbody>
</table>

### Indian Pines

<table>
<thead>
<tr>
<th>Method</th>
<th>Overall accuracy</th>
<th>Average Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>80.67%</td>
<td>80.92%</td>
</tr>
<tr>
<td>ASPM</td>
<td>91.84%</td>
<td>91.29%</td>
</tr>
<tr>
<td>CSPM</td>
<td>90.47%</td>
<td>90.79%</td>
</tr>
<tr>
<td>ACSPM</td>
<td>94.76%</td>
<td>95.93%</td>
</tr>
</tbody>
</table>
### ACSPM: Accuracies Valencia dataset

#### Clemenules

<table>
<thead>
<tr>
<th></th>
<th>Overall accuracy</th>
<th>Average Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>90.78%</td>
<td>85.41%</td>
</tr>
<tr>
<td>ASPM</td>
<td>90.75%</td>
<td>84.11%</td>
</tr>
<tr>
<td>CSPM</td>
<td>93.20%</td>
<td>92.29%</td>
</tr>
<tr>
<td>ACSPM</td>
<td>93.27%</td>
<td>92.06%</td>
</tr>
</tbody>
</table>

#### Hernandina

<table>
<thead>
<tr>
<th></th>
<th>Overall accuracy</th>
<th>Average Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>88.35%</td>
<td>86.12%</td>
</tr>
<tr>
<td>ASPM</td>
<td>88.19%</td>
<td>85.64%</td>
</tr>
<tr>
<td>CSPM</td>
<td>92.64%</td>
<td>91.72%</td>
</tr>
<tr>
<td>ACSPM</td>
<td>92.84%</td>
<td>91.95%</td>
</tr>
</tbody>
</table>

#### Marisol

<table>
<thead>
<tr>
<th></th>
<th>Overall accuracy</th>
<th>Average Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>92.01%</td>
<td>87.59%</td>
</tr>
<tr>
<td>ASPM</td>
<td>91.82%</td>
<td>83.01%</td>
</tr>
<tr>
<td>CSPM</td>
<td>96.19%</td>
<td>94.77%</td>
</tr>
<tr>
<td>ACSPM</td>
<td>96.29%</td>
<td>94.11%</td>
</tr>
</tbody>
</table>
SpU: Unmixing based fusion

Input images:
- High Spectral
- High Spatial

Classified Image:
- (n classes)

Classify

Spatial unmixing:
\[ r = f \cdot M + e \]

Pixel values \( r \) (k x k pixels)

Spectral signature for each of m classes M

Generate fraction images

Resulting Image:
- (High spatial and high spectral resolution)
The virtual environment: **PBRT: Physically Based Ray Tracing**

- **Objects:** i.e. Soil and Trees (triangle-mesh)
- **Spectral properties of objects**
  - Reflectance/Transmittance
  - Surface type (Lambertian, ...)
- **Sky map**
  - Position of the sun
  - Amount of energy per wavelength
  - Direct + indirect light

Variations in biophysical parameters:
- LAI 1.792 – 8.202
- Water content: 0.013795 - 0.021627 μg/cm²
- Chlorophyll content: 16.08161 – 58.92403 μg/cm²
Chlorophyll maps calculated by best performing SDVI

$$\frac{\lambda_{540} - \lambda_{590}}{\lambda_{540} + \lambda_{590}}$$
Water maps calculated by best performing SDVI

$$\frac{\lambda_{730} - \lambda_{1510}}{\lambda_{730} + \lambda_{1510}}$$
Output image:

- Spatially unmixed (SU): 288 bands, 0.28m spatial resolution

→ Yellow spectrum clearly reflects mixing of soil components in APEX pixel
Assumption:
• Stem water potential is indicator of water stress
• PRI is a good indicator of water stress (even better for fruit quality estimation than thermal imagery)

→ Index calculation PRI

→ Comparison of APEX (red) and SU (black) PRI index values correlated to stem potential
Assuming that the stem water potential and PRI index are good indicators of water stress levels, it can be decided that a higher spatial resolution (SU) image obtained from fusing high spatial thermal UAV images and high spectral APEX images, is better suited for detailed water stress estimation.
SpU – Loksbergen case

Elimination of understory
SpU – Results Loksbergen case
Questions?