Estimation of pear tree vitality based on multimodal, multitemporal optical remote sensing data

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Introduction

- Multitemporal monitoring of fruit orchard vitality with multisensor Belair data (Hypertemp)
  - The development of efficient management strategies in capital-intensive fruit crops.
  - Remote detection, mapping and monitoring of plant vitality

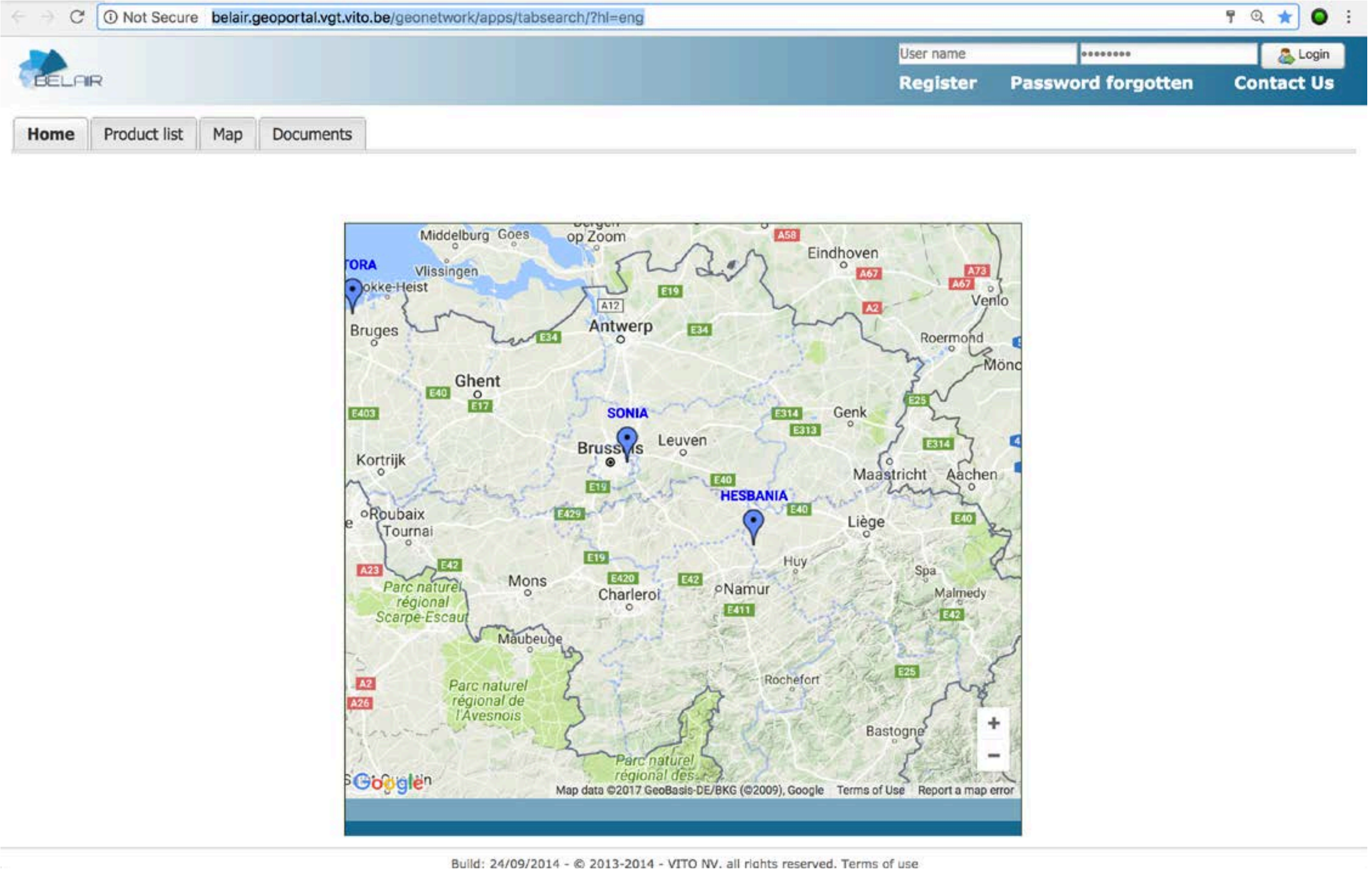
Flemish Institute for Technological Research

Project management
Data collection
Data preprocessing

Biophysical parameter extraction

Multimodal, multitemporal data analysis

Study region: Hesbania, BELGIUM



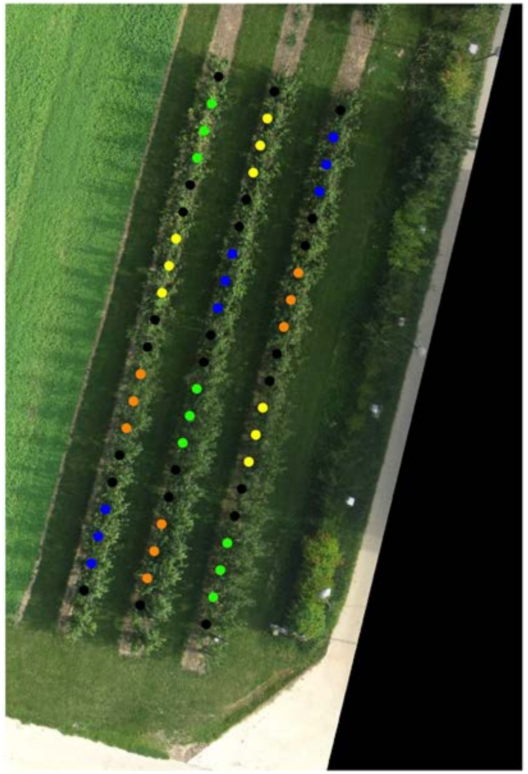
http://belair.geoportal.vgt.vito.be/geonetwork/apps/tabsearch/?hl=eng

Study site: Pear orchard

Study site: Pear orchard

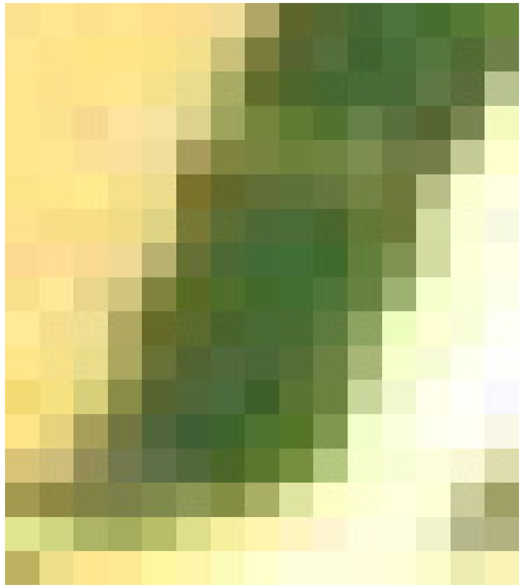
- Design
  - Pear trees under 4 different nutrient treatments
  - 3 plots per treatment
  - 3 trees per plot (2 buffer trees excluded)
  - Total number of trees: 4×3×3=36 trees with 9 trees per treatment
  - Interval of 1.5 meter
  - Center position of each tree is given by shapefile
- In-situ data
  - **Harvest** (number of pears, weight of pears per tree, 2012-2015)
  - **Chlorophyll** measurement by Chlorophyll content meter CCM-200 plus (20 leaves per tree, 2016)
  - **Mineral contents** (50 leaves, middle trees of each plots, 3 tree per treatment)
  - **Hyperspectral data** by ASD FieldSpec (leaf scale, canopy scale per tree, 2013, 2015, 2016)

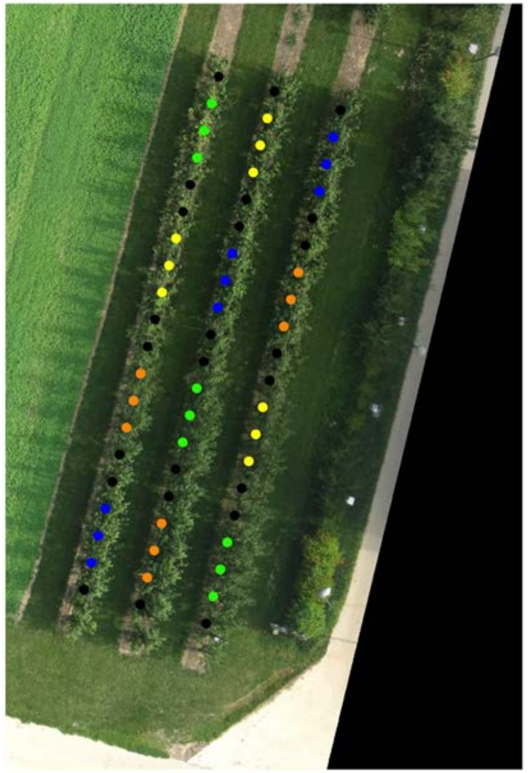
Color	**Treatment**	Number of trees
	$CaNO_3$ (artificial)	9 (3 tees × 3 plots)
	Slurry (organic)	9 (3 tees × 3 plots)
	Digestant (organic)	9 (3 tees × 3 plots)
	Liquid N (artificial)	9 (3 tees × 3 plots)
	Buffer	



Airborne image (APEX)

- Dates: 08/07/2013, 01/07/2015, 19/07/2016
- Bands: 267
- Spectral range: 400 - 2300 nm
- Resolution: 2.0 m (tree interval of 1.5 m)



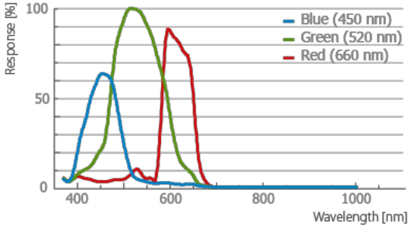


Aerial observation based on UAV

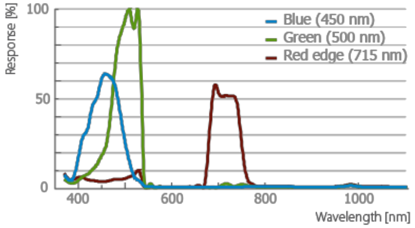
- Platform: Remotely Piloted Aircraft System (PRAS), senselFy eBee
  - Weight: approx. 0.69 kg
  - Cruise speed: 40-90 km/h
  - Maximum flight time: 50 min.
  - Maximum coverage: 12 km^2

- Optical sensors (multimodal)
  - S110 RGB (r,g,b), RE (b, g, red edge), Multispectral (g, r, red edge, NIR)

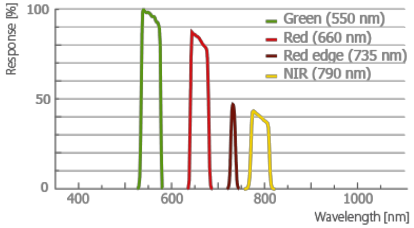
S110 RGB



S110 RE



multiSPEC 4C



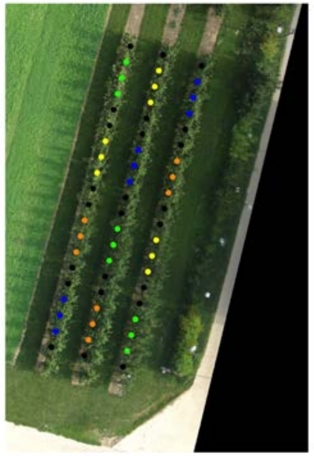
Aerial images

- Observation: 6 dates in 2015
- Georeferenced images (Geotiff format)
- Center position of each tree is given by shapefile
- Extraction of each canopy: within 0.7 m radius of center position

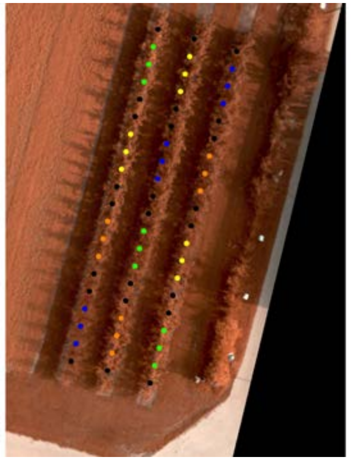
Spatial resolution (m)

Date	Time	RGB	RE	MultiSpec
		DN value (uint8)	DN value (uint8)	reflectance
11/05/2015	unknown			0.0900
21/05/2015	11h00	0.0261	0.0334	
12/06/2015	15h35	0.0195	0.0239	
01/07/2015	16h04	0.0190	0.0232	0.0943
13/08/2015	09h56	0.0189	0.0238	0.0945
09/09/2015	15h16	0.0275	0.0343	0.0900

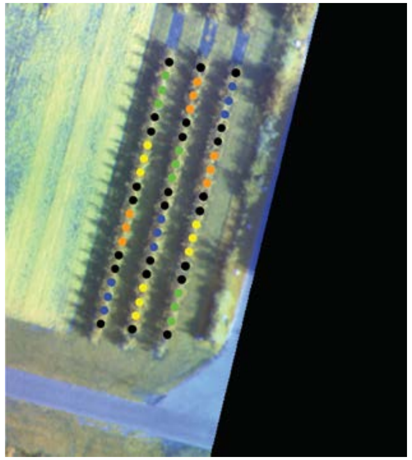
RGB



RE



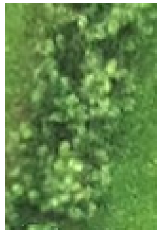
multispectral



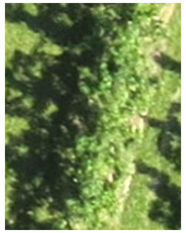
16h04
(01/07)

15h35
(12/06)

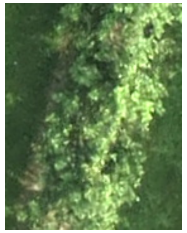
15h16
(09/09)



11h00
(21/05)



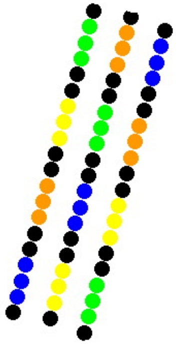
9h56
(13/08)



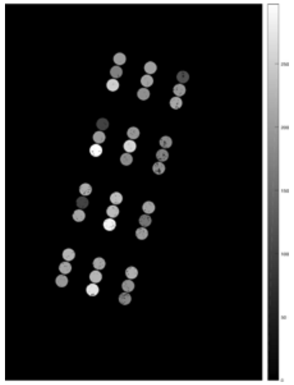
Brief verifications

- No significant difference caused by nutrient conditions

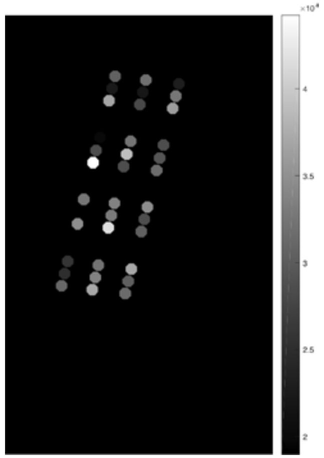
No.	Color	Treatment
1		CaNO3 (artificial)
2		Slurry (organic)
3		Digestant (organic)
4		Liquid N (artificial)



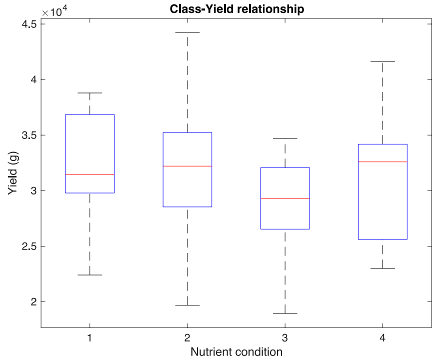
number of pears



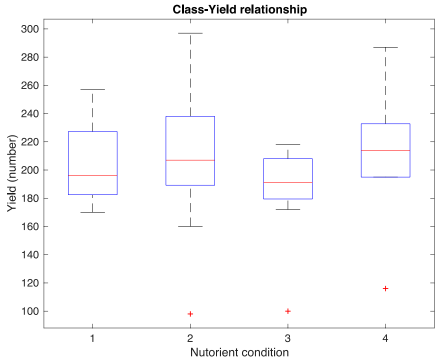
total weight



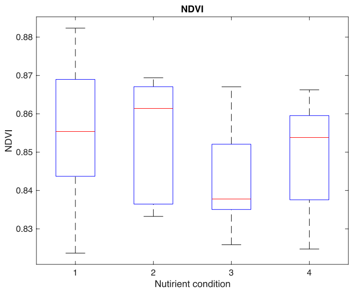
number of pears

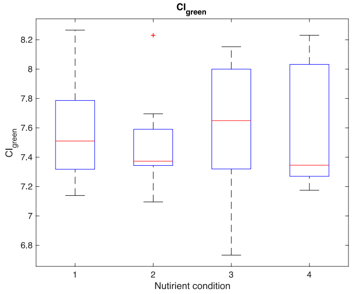


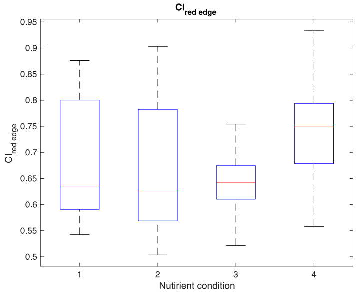
total weight



- Mean optical info is not sufficient for estimating growth states







$$NDVI = \frac{NIR - R}{NIR + R}$$

$$CI_{green} = \frac{NIR}{G} - 1$$

$$CI_{rededge} = \frac{NIR}{RE} - 1$$

Correlation

	NDVI	CI_{green}	$Ci_{red\ edge}$
Number	0.1902	-0.0037	0.0274
Weight	0.3241	0.0549	0.0980

*Each band information is an averaged value within canopy

Estimation based on machine learning

- Objective
  - Classification: four different nutrient treatments
  - Regression: yields (number, weight)
- Features: single sensor on a single date
  - Mean value
- Estimation
  - Classifiers: LDA, SVM
  - Regression: linear regression, SVM, neural network
- Validation
  - 9-fold CV
  - Classification: overall accuracy
  - Regression: correlation

Classification (overall accuracy)

(yellow)	over 0.6
(red)	over 0.5

	RGB (dim = 3)	RE (dim = 3)	Multispec (dim = 4)
11/05/2017			0.62972
21/05/2015	0.34694	0.35667	
12/06/2015	0.42806	0.29556	
01/07/2015	0.28944	0.26	0.54139
13/08/2015	0.31833	0.53778	0.52639
09/09/2015	0.33222	0.18806	0.42111

Yield (number, correlation)

(purple)	over 0.4
(green)	over 0.35

	RGB (dim = 3)	RE (dim = 3)	Multispec (dim = 4)
11/05/2015			-0.12104
21/05/2015	0.4502	0.25264	
12/06/2015	0.38375	0.31152	
01/07/2015	0.12502	0.45651	0.051739
13/08/2015	0.17649	0.21582	0.33369
09/09/2015	0.34256	0.061575	-0.15193

Yield (weight, correlation)

(purple)	over 0.4
(green)	over 0.35

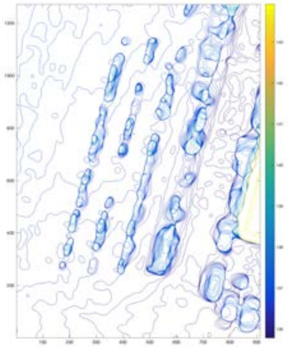
	RGB (dim = 3)	RE (dim = 3)	Multispec (dim = 4)
11/05/2015			-0.36464
21/05/2015	0.26093	0.25191	
12/06/2015	0.2032	0.32681	
01/07/2015	00.32049	0.27679	0.060387
13/08/2015	0.15629	0.27663	0.16699
09/09/2015	0.43531	-0.36829	0.078858

Estimation using high-order statistics

- Canopy structure
  - DSM is not reliable
  - Shading is helpful
  - High-order statistics

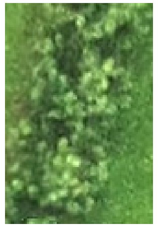
RE image
(21/05)

DSM

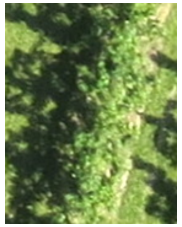


- Brief summary
  - Mean optical information is not sufficient
  - Shading represents canopy structure
  - Temporal shading images

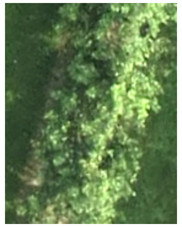
15h16
(09/09)



11h00
(21/05)



9h56
(13/08)



16h04
(01/07)

15h35
(12/06)

Comparison of estimation accuracies based on high order statistics (multispectral data: 4 bands)

(yellow)	over 0.6
(red)	over 0.5

Classification

	Mean value	Variance	Skewness	Kurtosis
11/05/2017	0.62972	0.31361	0.52028	0.26083
21/05/2015				
12/06/2015				
01/07/2015	0.54139	0.37333	0.27639	0.25528
13/08/2015	0.52639	0.31806	0.35056	0.31444
09/09/2015	0.42111	0.36278	0.36333	0.29639

(yellow)	over 0.6
(red)	over 0.5
(purple)	over 0.4
(green)	over 0.35

Regression (yield, number of pears per tree)

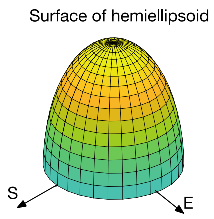
	Mean value	Variance	Skewness	Kurtosis
11/05/2015	-0.12104	0.17494	0.57952	0.61796
21/05/2015				
12/06/2015				
01/07/2015	0.051739	-0.067606	-0.099876	0.02339
13/08/2015	0.33369	0.17382	0.34362	0.16762
09/09/2015	-0.15193	0.19629	0.22777	0.14162

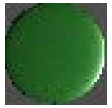
Regression (yield, weight of pears per tree)

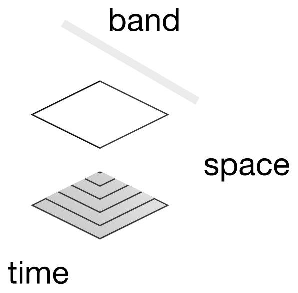
	Mean value	Variance	Skewness	Kurtosis
11/05/2015	-0.36464	-0.26265	0.57641	0.45551
21/05/2015				
12/06/2015				
01/07/2015	0.060387	0.12788	0.080978	0.023766
13/08/2015	0.16699	0.29685	0.2957	0.21613
09/09/2015	0.078858	0.10918	0.19566	0.093726

Shape from shading based on Tensor decomposition

- Objective: retrieve <u>canopy structure</u> and <u>inherent leaf color</u> from multitemporal shading images







3 order tensor

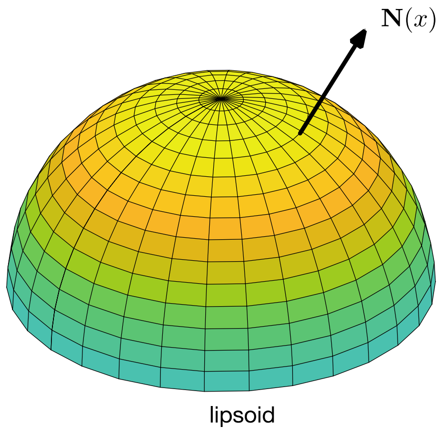
Simplification of tensor structure
(Tensor decomposition)

- Canopy structure
- Leaf color

- Assumption (Reflection model)
  - Direct solar illumination is dominant
  - Leaves are under direct illumination

Dichromatic reflection $$\rho(\lambda_i) = \mathbf{N} \cdot \mathbf{L}\ k(\lambda_i) + S_s(\mathbf{N}, \mathbf{L}, \mathbf{V})$$

Simplification $$\rho(x, t, \lambda) \approx \mathbf{N}(x) \cdot \mathbf{L}(t)\ k(\lambda)$$

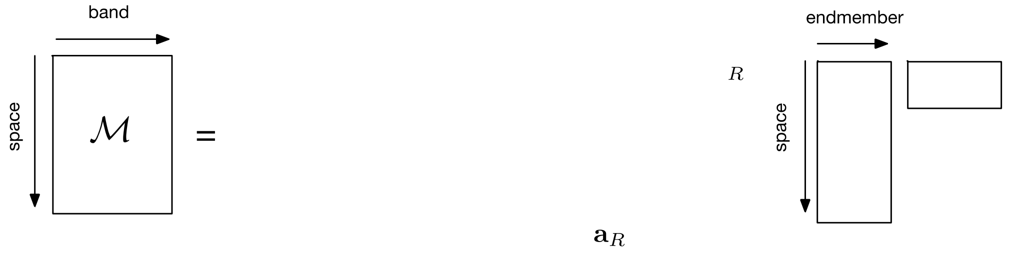


Tensor decomposition for HS data

- Expansion of matrix decomposition to higher-order arrays
    - Typical example of matrix decomposition (unmixing)

$$\underset{\mathbf{A},\mathbf{B}}{\operatorname{argmin}} ||\mathcal{M} - \mathbf{A}\mathbf{B}^T||$$

A: abundance
B: endmember



- Three-order array (canonical polyadic (CP) tensor decomposition)

$$\mathcal{D}_{ijk} = a_i b_j c_k$$

$$\underset{\mathbf{A},\mathbf{B},\mathbf{C}}{\operatorname{argmin}} ||\tau - (\mathbf{A},\mathbf{B},\mathbf{C})||$$

A: abundance
B: endmember
C: additional array

- Examples 1: time-series of MODIS hyperspectral sensor (Alps during 2012 snow season) ⇒ abundance, endmember (snow, ice, debris, forest, etc.), temporal evolution

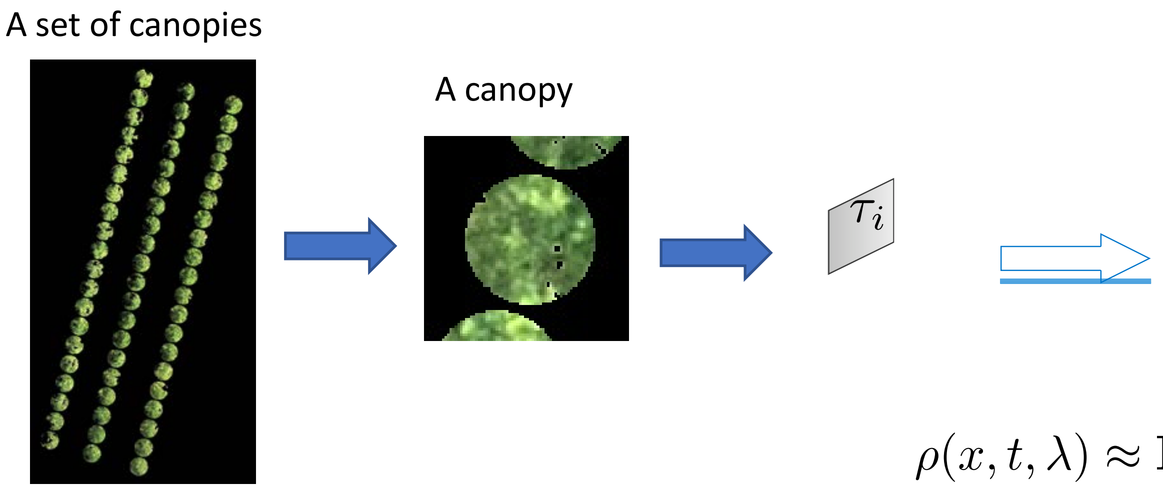
M.A. Veganzones, et. al., Nonnegative Tensor CP Decomposition of Hyperspectral Data, TGRS, vol. 54, no. 5, pp.2577-2588, 2016

- Example 2: multi-angle images of Compact Reconnaissance Imaging Spectrometer for Mars (outskirts of south permanent polar cap in Mars) ⇒ abundance, endmember, observation

M.A. Veganzones, et. al., Nonnegative CP Decomposition of Multiangle Hyperspectal Data: A Case Study on CRISM Observations of Martian Icy Surface, WHISPERS, 2016

Tensor decomposition for canopy shading

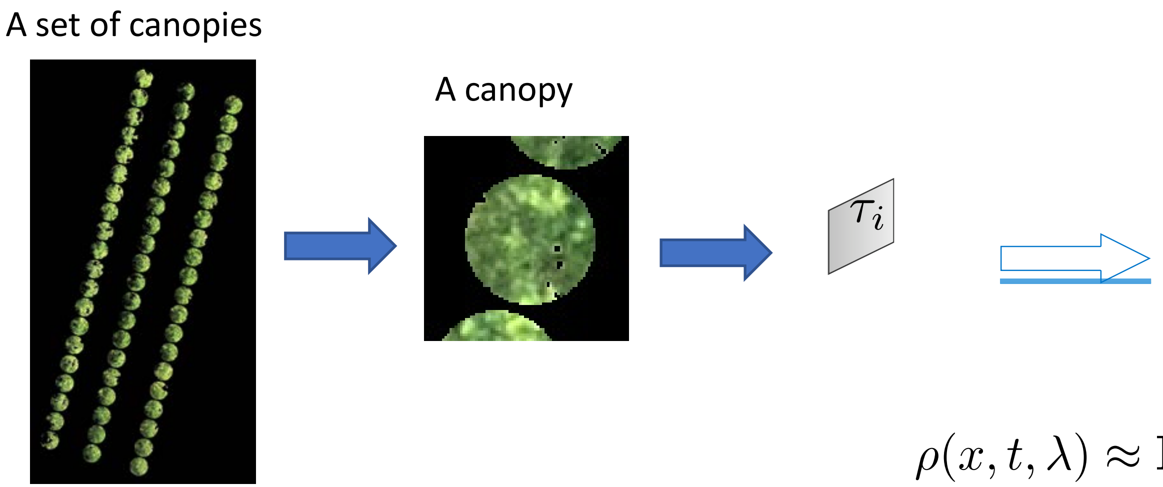
- Assumption
  - One endmember per canopy
  - Leaves are under direct sunlight
  - Direct illumination is dominant
  - Snapshot decomposition



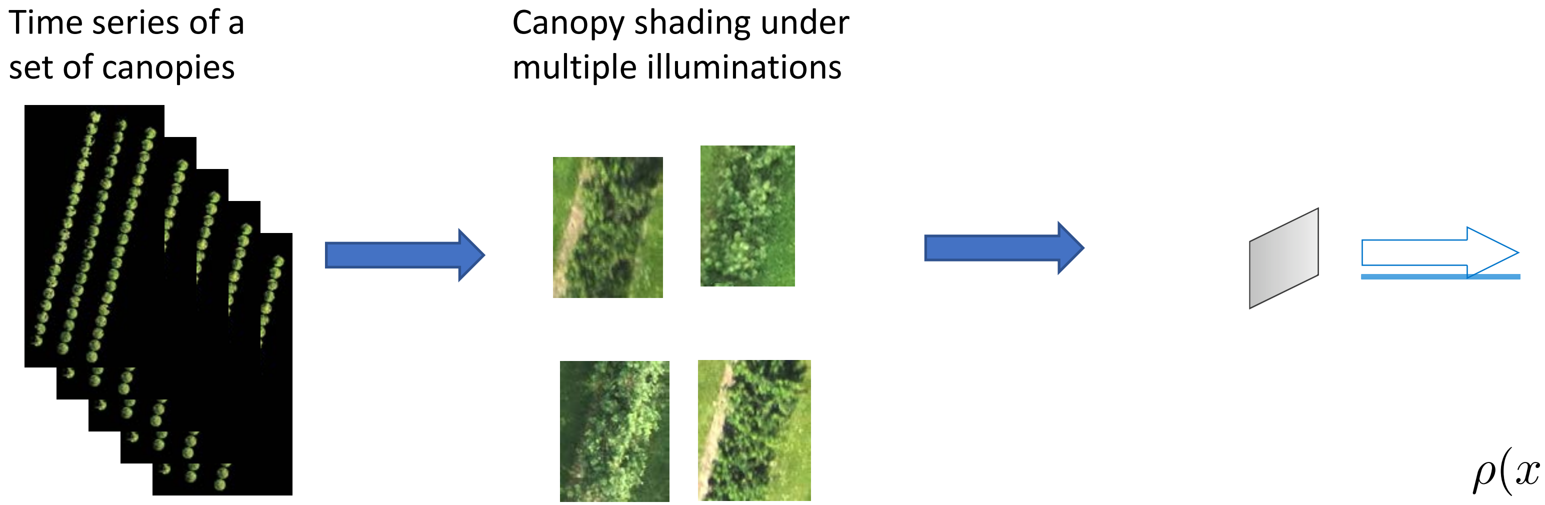
$$\rho(x,t,\lambda) \approx \mathbf{N}(x) \cdot \mathbf{L}\, k(\lambda)$$

Tensor decomposition for canopy shading

- Assumption
  - One endmember per canopy
  - Leaves are under direct sunlight
  - Direct illumination is dominant
  - Snapshot decomposition
  - Multitemporal decomposition: multiple measurements within a day (different sun elevation **L**) are possible



$$\rho(x,t,\lambda) \approx \mathbf{N}(x)\cdot\mathbf{L}\;k(\lambda)$$



$$\rho(x,t,\lambda) \approx \mathbf{N}(x)\cdot\mathbf{L}(t)\;k(\lambda)$$

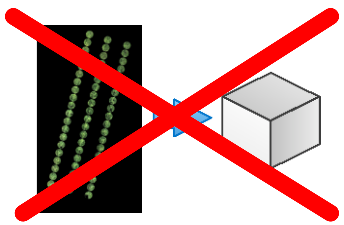
Tensor decomposition

- Tensor per canopy: $\tau_i \in \mathbb{R}^{N_N \times N_L \times N_k} \ (i = 1, \ldots, n)$
- Tensor decomposition
  - Multilinear rank-(Lr,Lr,1) terms, Lr=3
    - Retrieve **N**, **L** and **k**
  - Tensorlab 3.0 (`ll1.m`)
    - http://www.tensorlab.net
- Assumption
  - Canopy regions are given
  - Multiple observation within a day is possible
  - Leaf color within canopy is homogeneous (only endmember)
  - Structure (**N**) and Lambert coefficients (**k**) are stable
  - Most of leaves are under direct sunlight

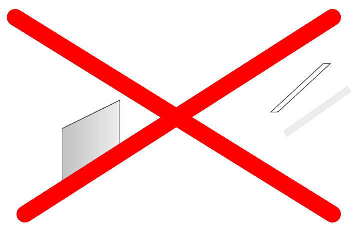
$$\rho(x, t, \lambda) \approx \mathbf{N}(x) \cdot \mathbf{L}(t)\ k(\lambda)$$

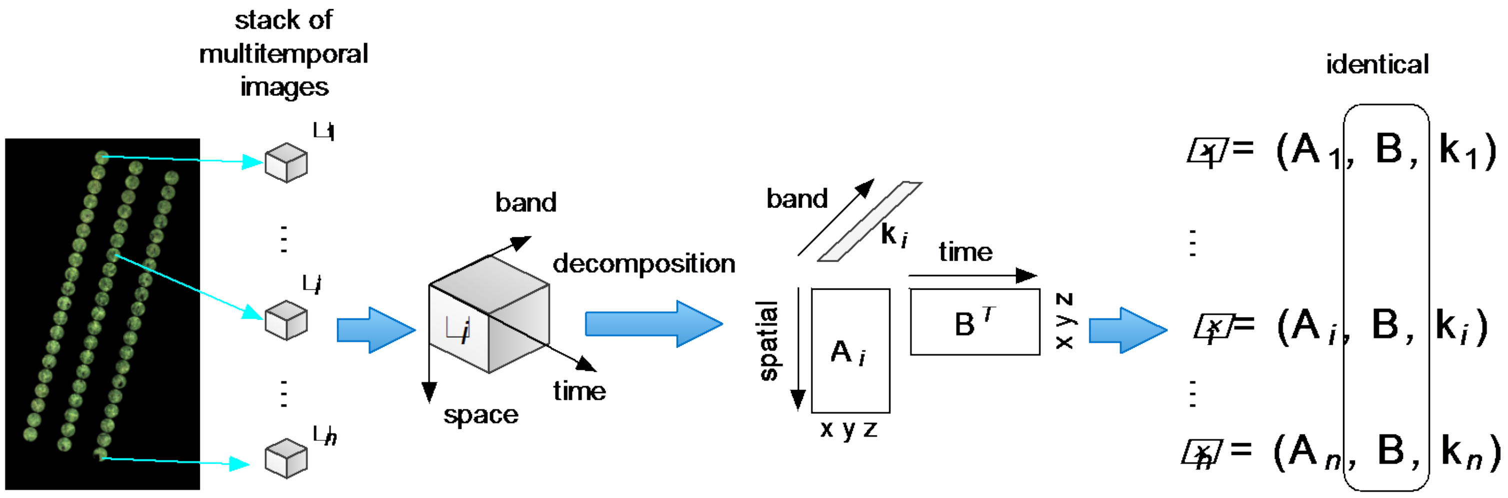
- Constraints
  - **B** is identical (coupling)
  - Lambert coefficients **k** are nonnegative

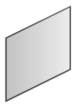
Single Tensor



CP decomposition







gative)

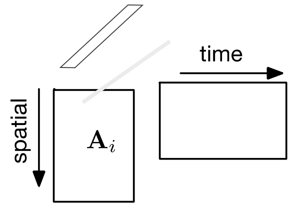
Estimation of canopy structure

- Assumption
  - Most of leaves are under direct illumination
  - Canopy structure can be approximated by hemiellipsoid with parameter c (isotropic along x-, y-axes)

$$\frac{(x-x_c)^2}{R^2}+\frac{(y-y_c)^2}{R^2}+\frac{z^2}{c^2}=1$$

- Estimation of c based on estimated **N** (A_i)
  - Uncertainty in order of elements (x,y,z)

$$\rho(x,t,\lambda)\approx \mathbf{N}(x)\cdot\mathbf{L}(t)\ k(\lambda)$$

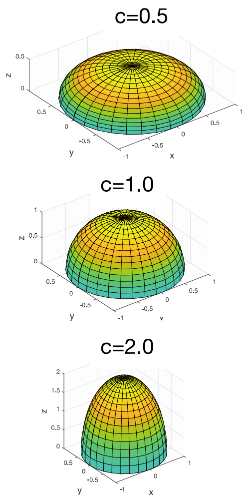


1. Calculate average value per element

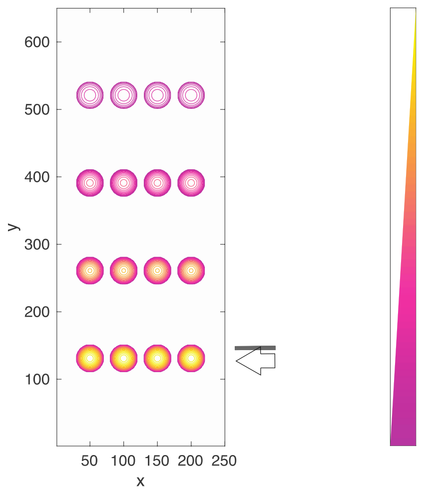
   $\bar{N}_e^i$ Average value of e-th element in A_i
2. Determination of z-element

   $$\hat{z}=\underset{e}{\operatorname{argmax}}\,\bar{N}_e^i$$
3. Use the maximum averaged value as a structural parameter

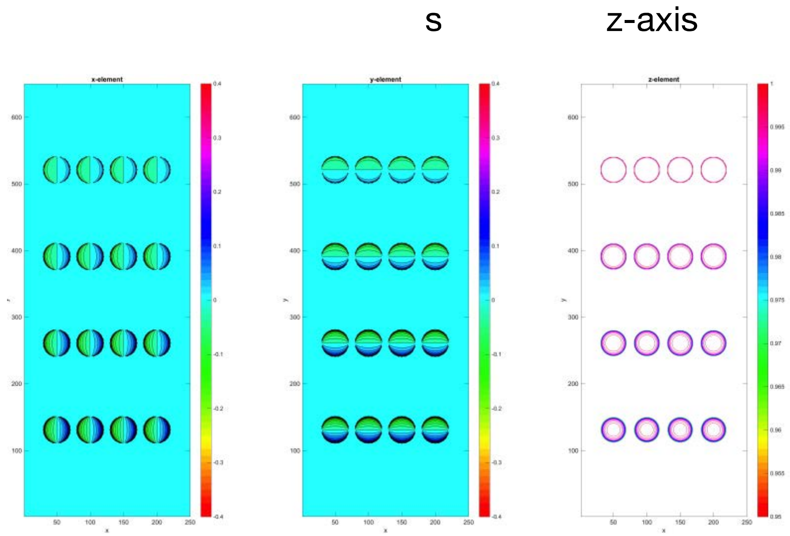
   $\bar{N}_{\hat{z}}^i$



Height contour of hemielllipsoids



Elements of surface normal



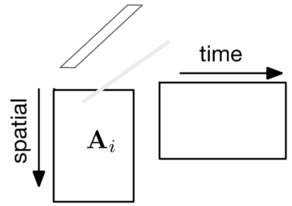
Estimation of canopy structure

- Assumption
  - Most of leaves are under direct illumination
  - Canopy structure can be approximated by hemiellipsoid with parameter c (isotropic along x-, y-axes)

$$\frac{(x-x_c)^2}{R^2} + \frac{(y-y_c)^2}{R^2} + \frac{z^2}{c^2} = 1$$

- Estimation of c based on estimated **N** (A_i)
  - Uncertainty in order of elements (x,y,z)

$$\rho(x,t,\lambda) \approx \mathbf{N}(x) \cdot \mathbf{L}(t)\ k(\lambda)$$



1. Calculate average value per element

   $\bar{N}_e^i$ Average value of e-th element in A_i

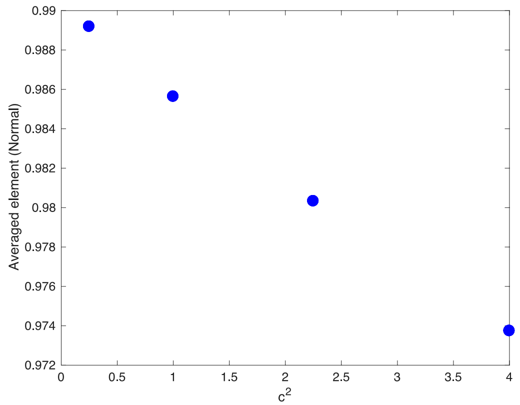
2. Determination of z-element

   $$\hat{z} = \underset{e}{\operatorname{argmax}}\ \bar{N}_e^i$$

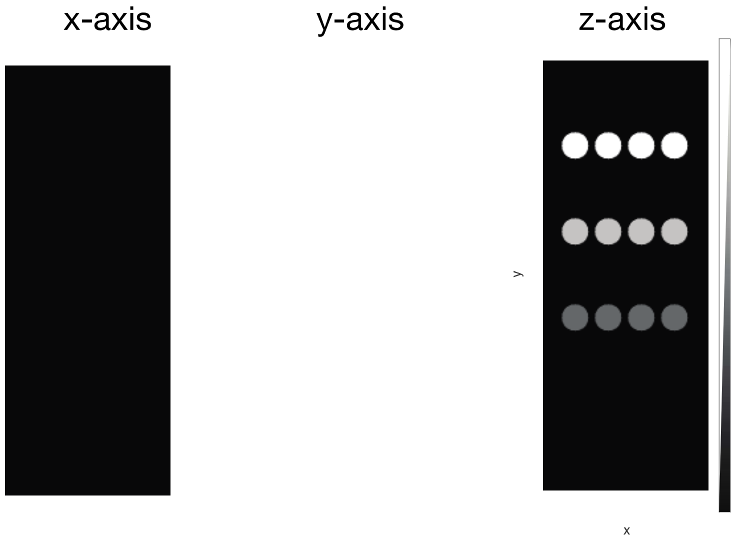
3. Use the maximum averaged value as a structural parameter

   $\bar{N}_{\hat{z}}^i$

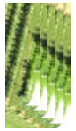
Relationship between c and averaged values



Averaged normal element per canopy



Flow of canopy-scale parameter estimation



Stack of multitemporal images

Extraction of ROIs

Generation of Tensors

Tensor decomposition

- identical **L**
- non-negative **k**>0

$_1\ \mathbf{A}_2$

$\mathbf{B}\ \ \mathbf{B}$

$\mathbf{k}_1\ \ \mathbf{k}_2$

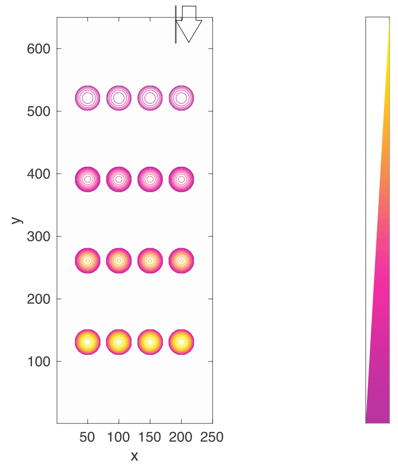
Estimation of **N**, **L** and **k**

Simulation

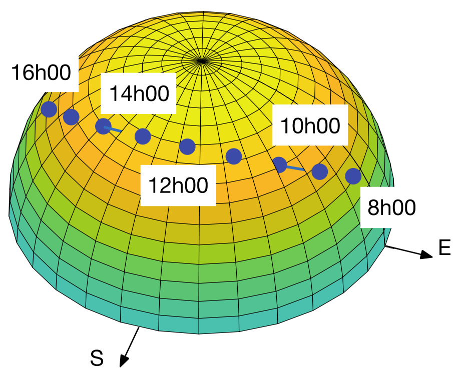
- Simulated data
  - Daily change in solar elevation
  - 4 types of hemiellipsoid: **A**
  - 9 illumination conditions: **B**
  - 4 endmembers (5 bands): **k**
  - Specular reflection included

Original

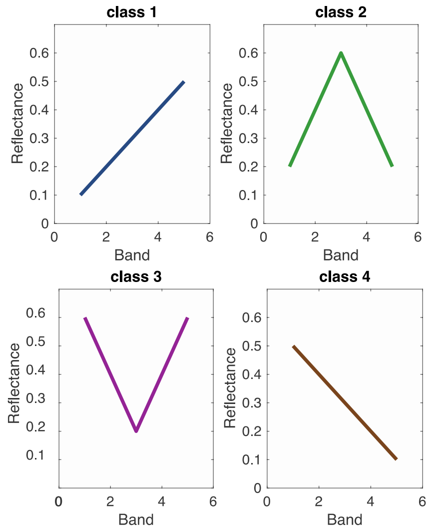
Type of hemiellipsoid (**A**)



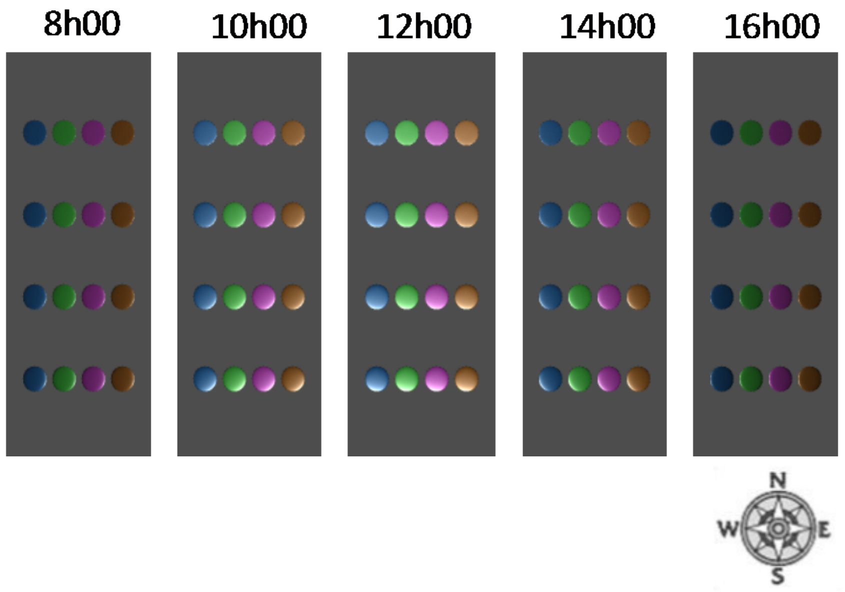
Illumination conditions (**B**)



endmembers



Generated images

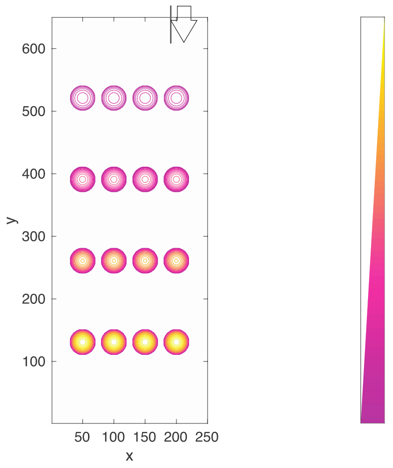


Simulation

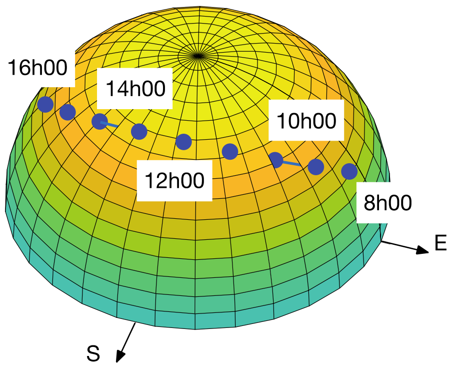
- Simulated data
  - Daily change in solar elevation
  - 4 types of hemiellipsoid: **A**
  - 9 illumination conditions: **B**
  - 4 endmembers (5 bands): **k**
  - Specular reflection included
- Tensor decomposition
  - Multilinear rank-(3,3,1) terms
  - **B** (illmination matrix) is identical (coupling)
  - Lambert coefficients **k** are nonnegative

Original

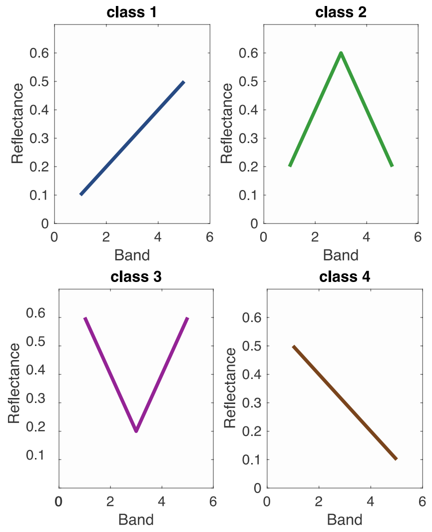
Type of hemiellipsoid (**A**)



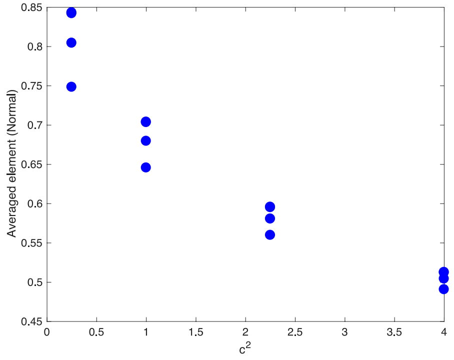
Illumination conditions (**B**)



endmembers



Relationship between c and $\bar{N}^{i}_{\hat{z}}$

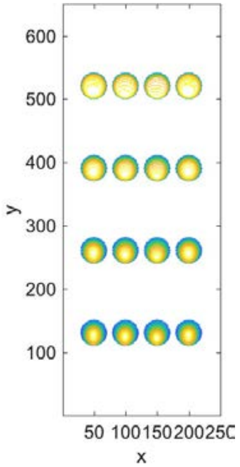


average of SAM (rad)

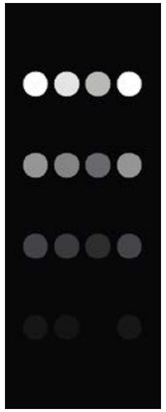
Endmember 1	0.1721
Endmember 2	0.1367
Endmember 3	0.0994
Endmember 4	0.1721

Estimation

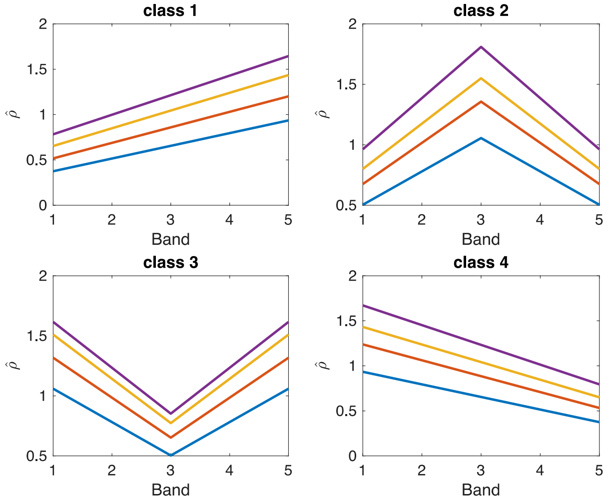
Distribution of z elements (N)



Distribution of $\bar{N}^{i}_{\hat{z}}$

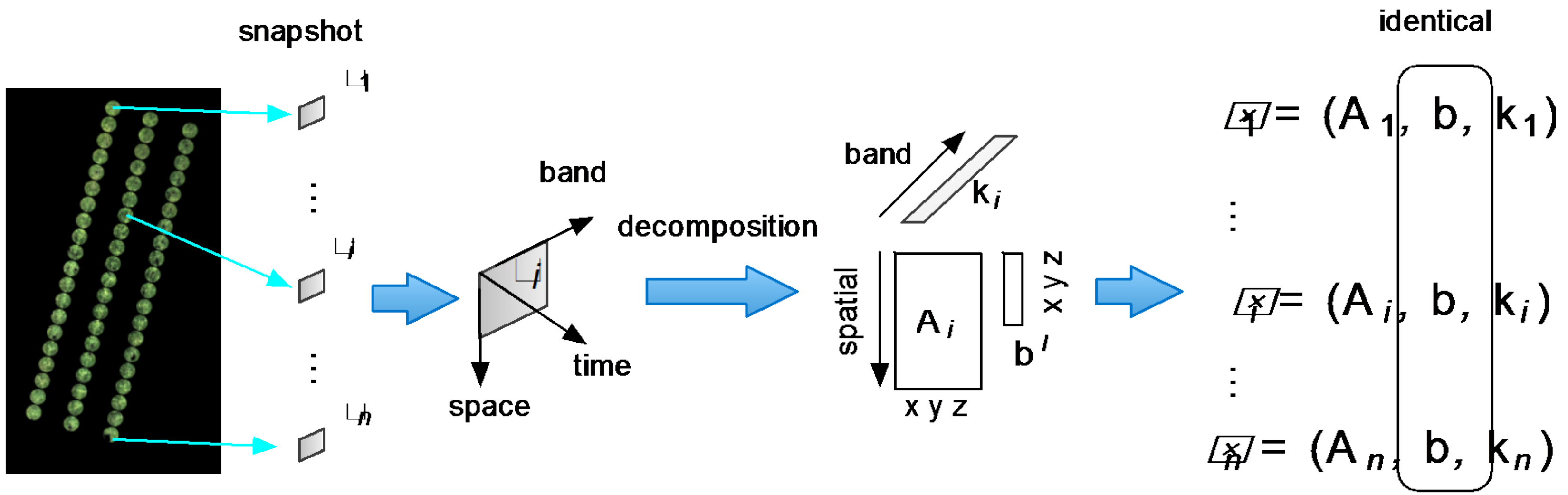


Estimated Lambert coefficients



Tensor decomposition of multispectral data

- Restrictions
  - No multiple observations within a day (snapshot)
  - Pixel-to-pixel registration between different days is not possible
- Snapshot decomposition
  - **b** is identical (coupling)
  - Lambert coefficients **k** are nonnegative



Results and Discussion

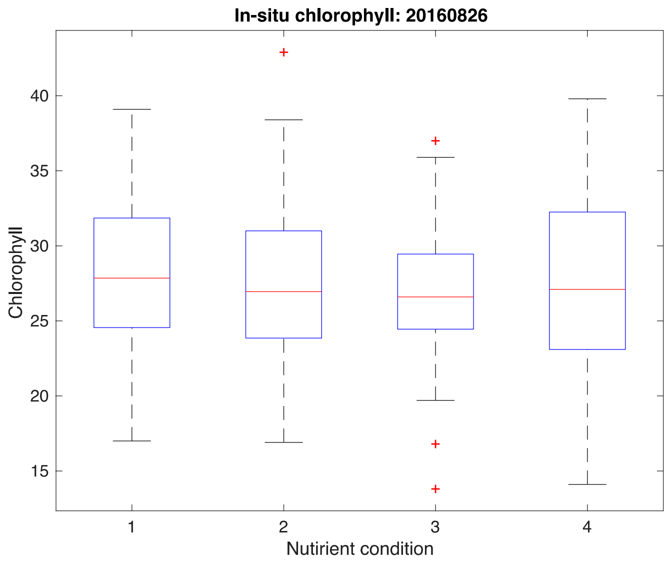
(yellow)	over 0.6
(red)	over 0.5

Classification (overall accuracy, Multispec data)

	Mean value	Variance	Skewness	Kurtosis	k
11/05/2017	0.62972	0.31361	0.52028	0.26083	0.364
01/07/2015	0.54139	0.37333	0.27639	0.25528	0.326
13/08/2015	0.52639	0.31806	0.35056	0.31444	0.301
09/09/2015	0.42111	0.36278	0.36333	0.29639	0.436

- Classification (nutrient treatments) accuracy
  - estimated Lambert coefficients < original averaged reflectance
- There is not significant difference in in-situ chlorophyll contents among different nutrient treatments

Chlorophyll measurement by Chlorophyll content meter CCM-200 plus (20 leaves per tree)



Mineral contents (50 leaves, middle trees of each plots, 3 tree per treatment)

May, 2015

Treatment	mg/100 g fresh weight				
	N	P	K	Ca	Mg
Treatment 1	3.2	0.27	1.45	1.1	0.36
Treatment 2	2.9	0.25	1.40	1.0	0.35
Treatment 3	3.0	0.28	1.57	1.1	0.37
Treatment 4	3.0	0.27	1.44	1.2	0.38
Target values	2.9- 3.7	0.2-0.5	1.5-2.5	0.9-2.0	0.25-0.5

Harvest, 2015

Treatment	mg/100 g fresh weight				
	N	P	K	Ca	Mg
Treatment 1	1.9	0.11	0.52	2.48	0.46
Treatment 2	1.9	0.13	0.61	2.37	0.46
Treatment 3	1.9	0.12	0.56	2.17	0.44
Treatment 4	1.9	0.12	0.57	2.29	0.46
Target values	2.0-2.5	> 0.14	> 0.90	> 1.50	> 0.23

Color	Treatment
(green)	$CaNO_3$ (artificial)
(yellow)	Slurry (organic)
(orange)	Digestant (organic)
(blue)	Liquid N (artificial)

Results and Discussion (cont.)

- Yield estimation
  - No correlation between yields and leaf color
    - Hyperspecral observation in 2017
  - Some correlation between yields and structure parameter
    - Not sufficient for reliable estimation
    - Lack of temporal analysis
    - Higher spatial resolution images (e.g., RGB, RE)
- Schedule
  - Multitemporal data analysis for real data
  - Hyperspectral analysis
  - Fusion of multimodal data (RGB, RE, Multispectral, HS)
  - Multitemporal observation within a day

Regression (yield, number of pears per tree)

	Mean value	k	k + $\bar{N}_{\hat{z}}^{i}$	$\bar{N}_{\hat{z}}^{i}$
11/05/2015	-0.12104	0.172	0.126	0.377
01/07/2015	0.051739	0.031	0.147	0.267
13/08/2015	0.33369	0.017	0.356	0.311
09/09/2015	-0.15193	-0.104	0.322	0.424

Regression (yield, weight of pears per tree)

	Mean value	k	k + $\bar{N}_{\hat{z}}^{i}$	$\bar{N}_{\hat{z}}^{i}$
11/05/2015	-0.36464	-0.029	-0.004	0.306
01/07/2015	0.060387	0.086	0.198	0.332
13/08/2015	0.16699	0.117	0.312	0.294
09/09/2015	0.078858	0.051	0.229	0.331

	over 0.4
	over 0.35