Fusion of APEX hyperspectral and LiDAR data for tree species classification

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Motivation

Sustainable forest management

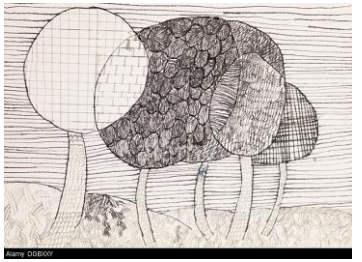
- Ongoing need for accurate fine-scale resource information
- Needed at high spatial resolution over extended areas
- Implies use of automatic mapping methods

Still challenges remain

- Accuracy largely dependent upon structural forest complexity
- Low detection rates/delineation accuracies in closed multi-story forests

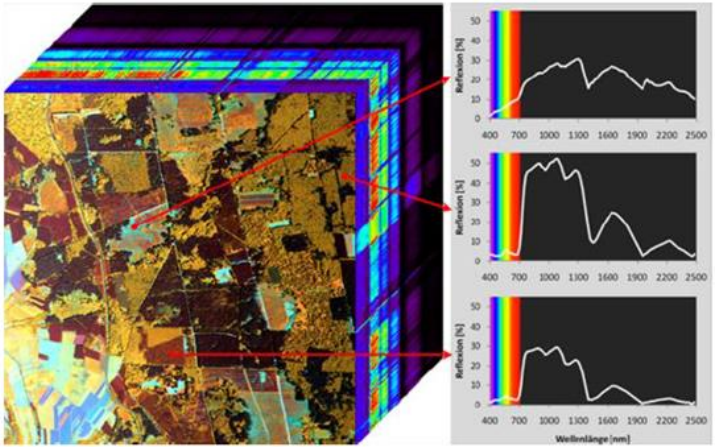
Motivation

Challenge: tree species mapping under complex site conditions



- Complex forest site
  - Unmanaged dense multi-layered forest
  - Overlapping or interlocking crowns
  - High number of different species
  - Occurrence of spectrally similar tree species
  - Non-existence of pre-ordered spatial tree distribution
- Scarce reference data
  - Reference data are very often short in supply
  - Related Hughes phenomenon

Remote sensing in support of forest management



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- ✓ **Tree species mapping, biophysical and chemical properties**
- ❖ **Poor tree delineation, forest structure**

Objective

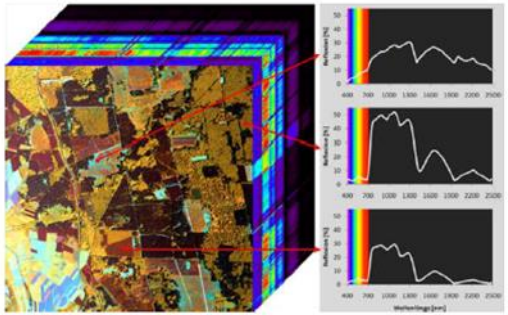
Tree species classification under complex site conditions

1. Capitalize on different information sources
    - HS-derived biophysical information
    - LiDAR-derived information on vertical dimension of forest scene

2. Compare different methods to fuse APEX hyperspectral and LiDAR data

Objective

Fusion of Hyperspectral and Lidar data



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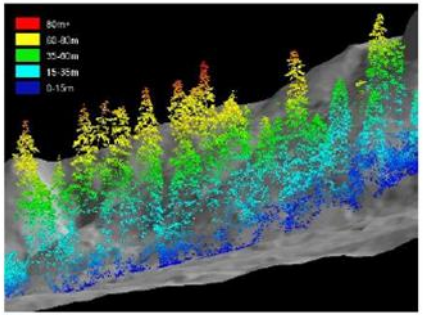
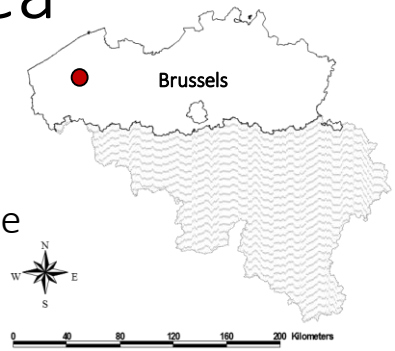


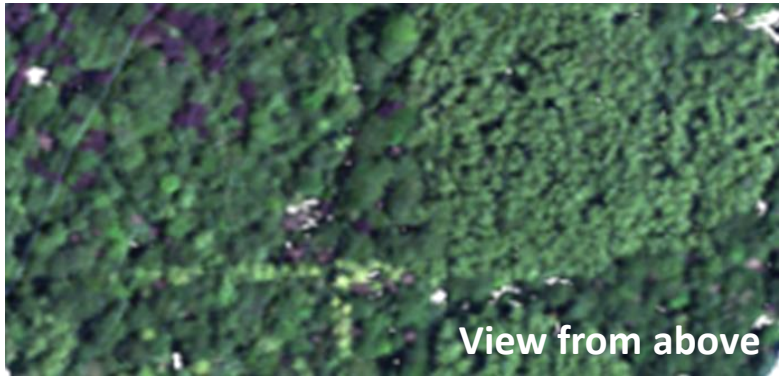
- ✓ Improved hyperspectral pre-processing
- ✓ Improved forest parameter retrieval
- ✓ Improved tree species mapping

Study area and remote sensing data

Study area

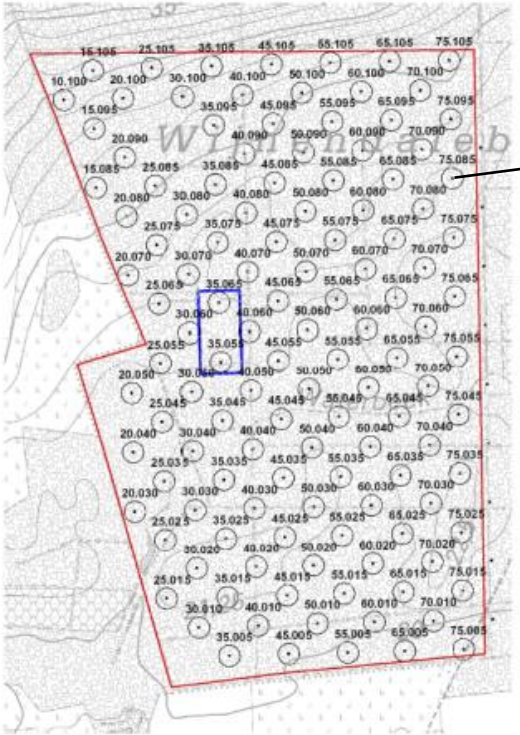
Wijnendale forest
66 ha forest reserve

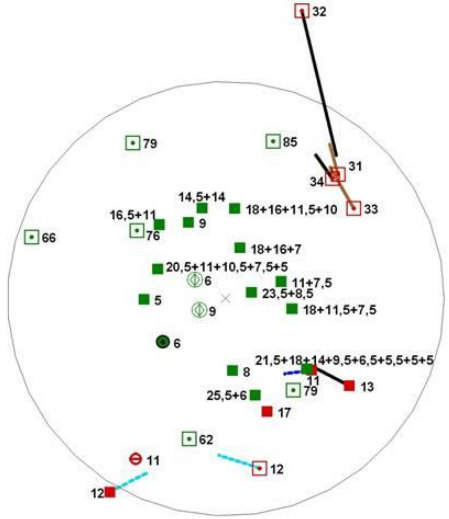




Dominance of common beech, copper beech, pedunculated oak, common ash, European larch, poplar and sweet chestnut

Field survey



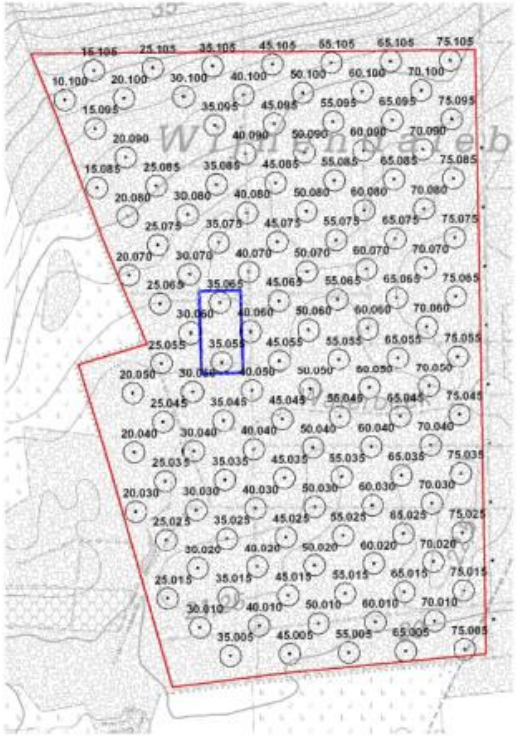


FieldMap technology

121 sample plots (0.1 ha) – 1179 trees

- Tree locations (x,y)
- Species
- DBH (> 5 cm)
- Tree height (upper canopy)

Field survey



Scarce reference data

More rule than exception!

Species	Nof labelled samples
Beech	285
Ash	67
Larch	116
Poplar	284
Copper beech	80
Sweet chestnut	67
Oak	280

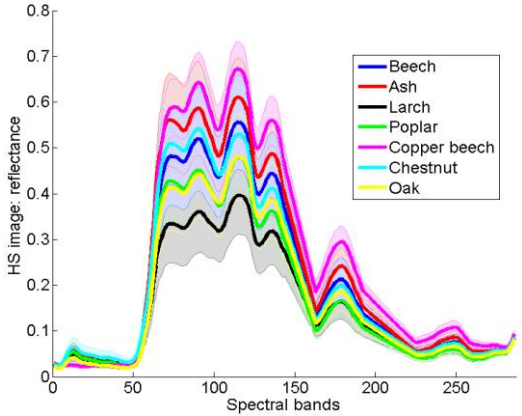
Training set
- 10%

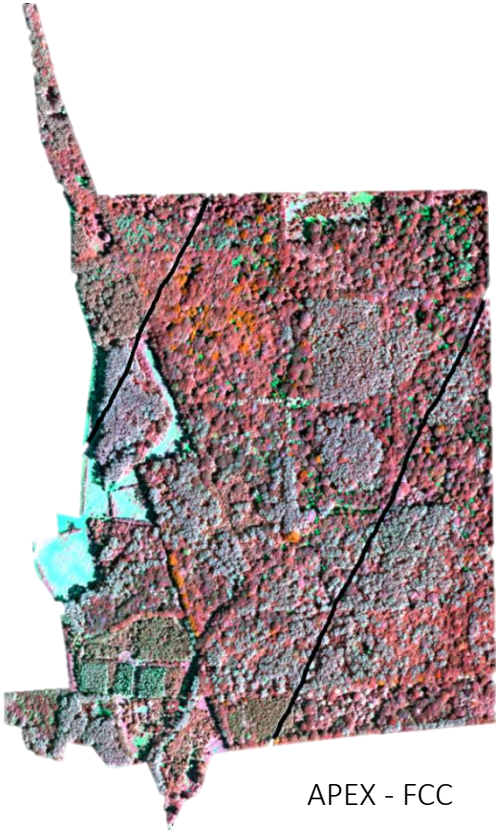
Test set
- 90%

Remote sensing (RS) data

HS APEX data

- 21 June 2010
- 286 bands (400-2500 nm)
- 1.5 m spatial resolution
- MODTRAN4 atmospheric correction





APEX - FCC

RS data

LiDAR Toposys Harrier 56 data

- 4 August 2010
- Full waveform ALS, Point density 13.81 m² - point spacing 0.27 m
- DSM at 0.5 m by selecting max of all pulse returns, next morphological closing filter (circular kernel of 3x3)
- DTM at 0.5 m by removing non-ground features using progressive morphological filter
- DSM and DTM resampled to 1.5 m

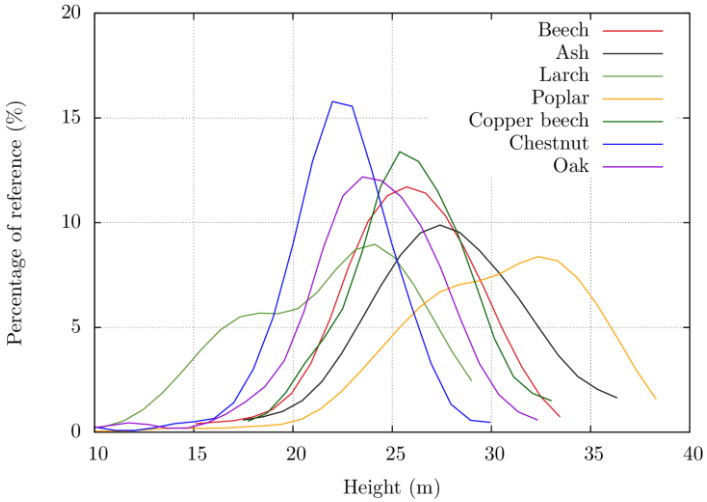
Full wave LiDAR

LiDAR - DSM

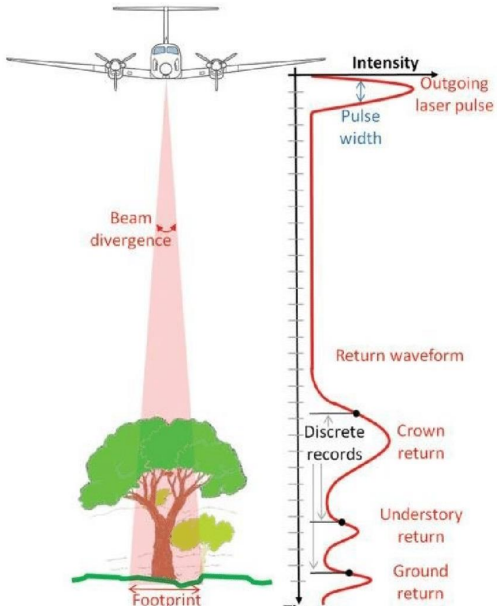
Tree height distribution

LiDAR DSM

Tree height distribution



Full waveform LiDAR data



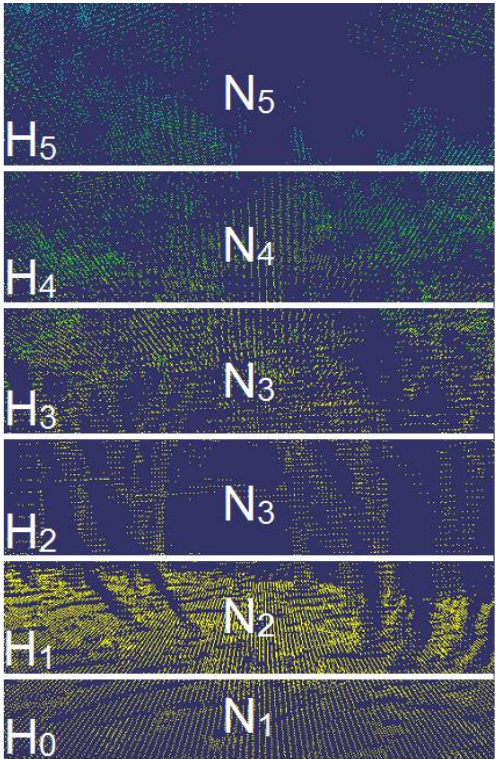
- allow for the registration of the complete wave as the energy pulse interacts with the object.
- capture continuous information from the top of the canopy to the ground.

Improved tree species mapping

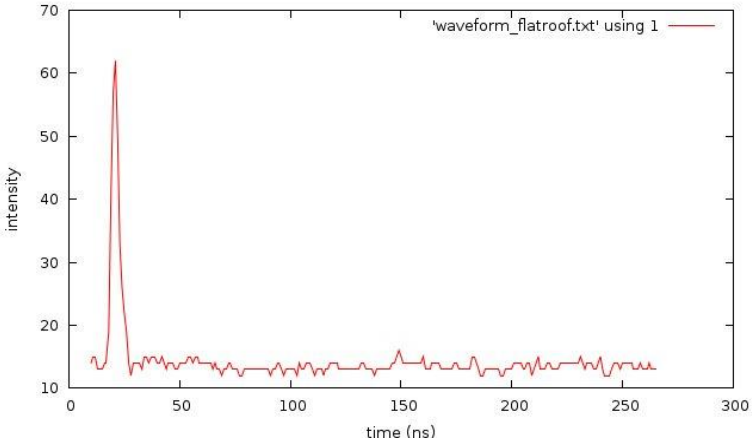
LiDAR-derived Percentile Height (PH) product

- Showing vertical leaf distribution better than DSM
- Height at x % of all vegetation returns (terrain corrected point cloud)
- Multi-band image of 11 PH bands

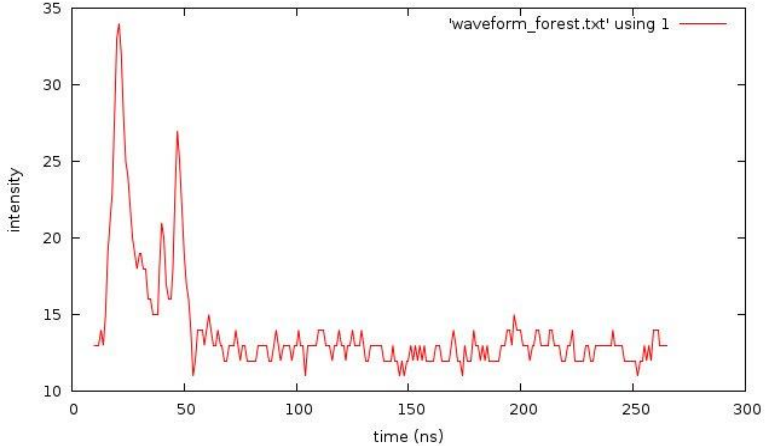
- Similar for density at fixed height intervals (N_1-N_n)



Full waveform LiDAR data



Flat roof top



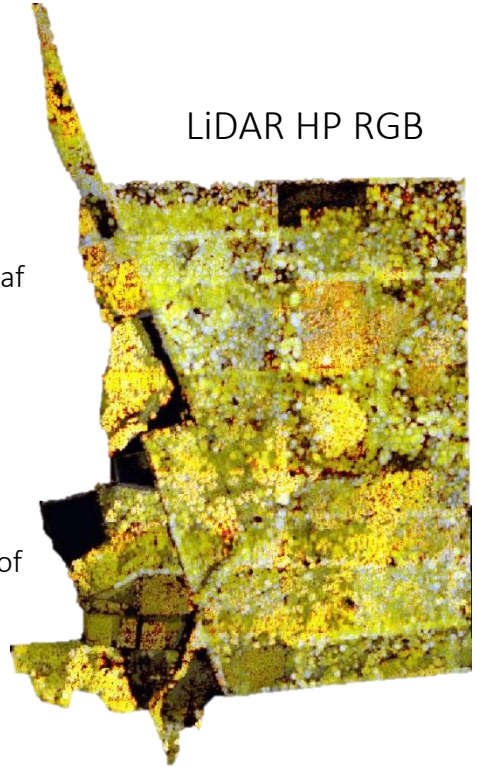
Forest area

Full waveform LiDAR data

LiDAR-derived Percentile Height (PH) product

- Showing vertical leaf distribution better than DSM
- Height at x % of all vegetation returns (terrain corrected point cloud)
- Multi-band image of 11 PH bands

LiDAR HP RGB



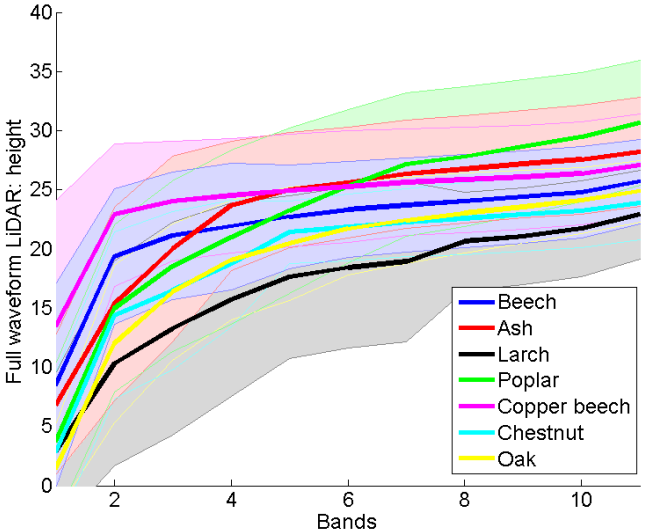
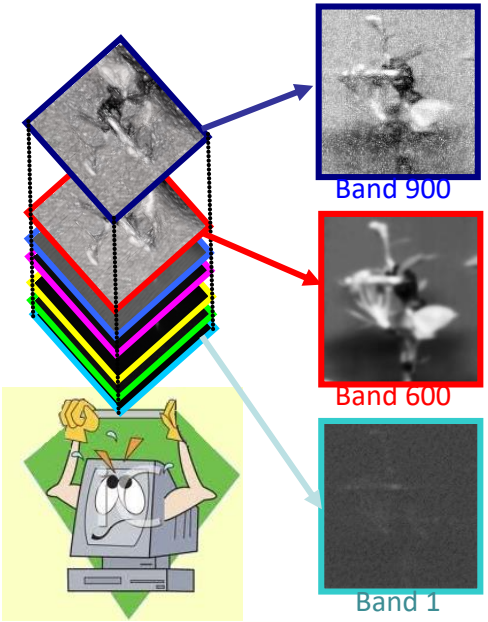


Image pre-processing

HS data pre-processing



Existing restoration methods:

$$\hat{u}_i = \arg\min R(TV_i) + \frac{\lambda}{2} \| Hu_i - f_i \|_2^2$$

Regulation: $R(TV_i)$

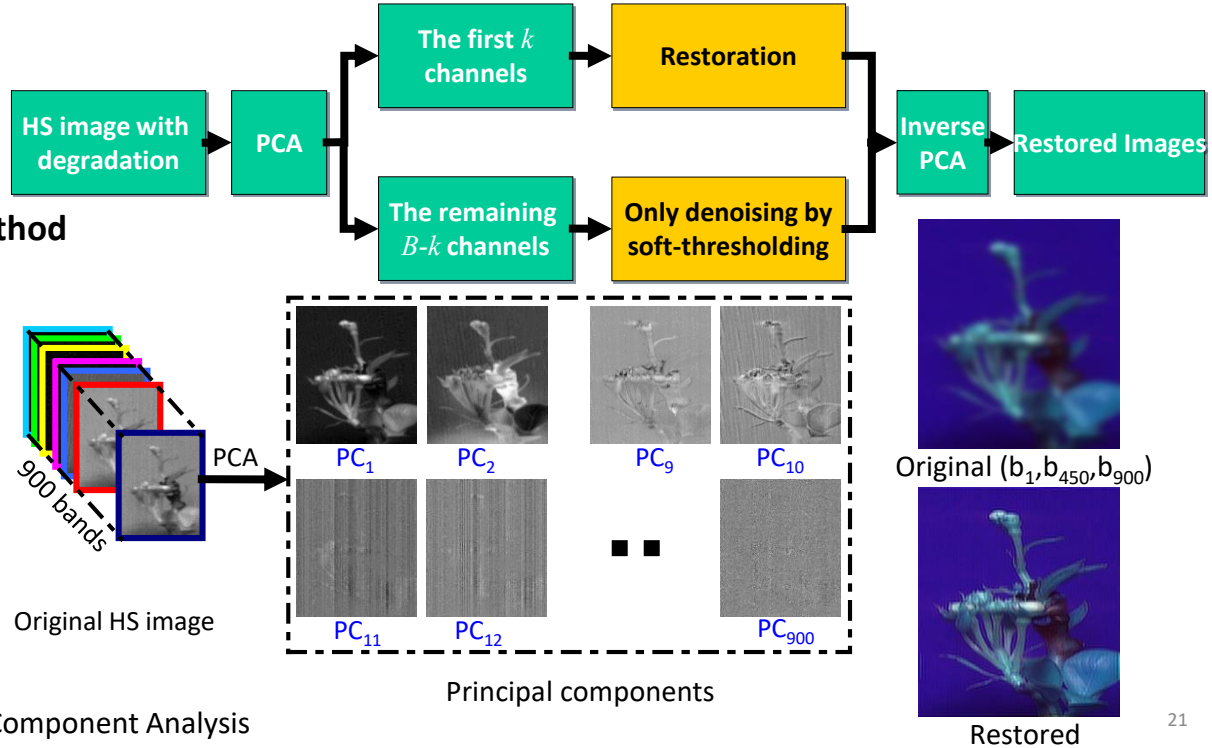
Challenges:

- ✓ High dimensionality
- ✓ Different bands have different noise levels
- ✓ Different bands have different blur levels

High computational complexities and poor performances

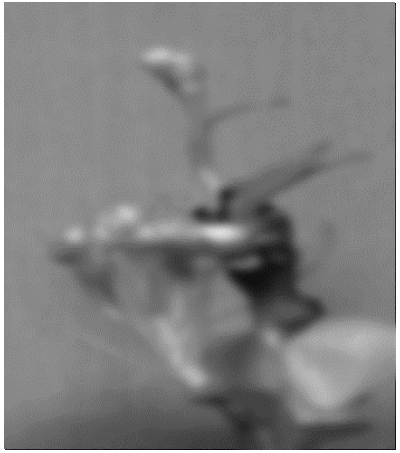
HS data pre-processing

Proposed method for efficient restoration

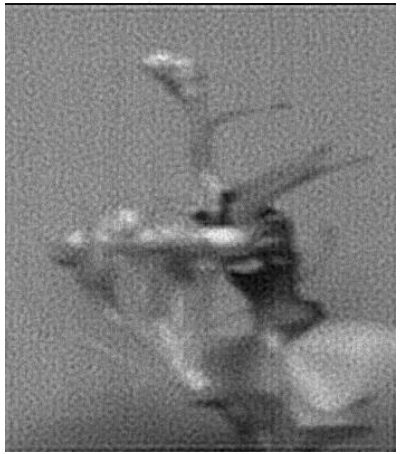


PCA: Principal Component Analysis

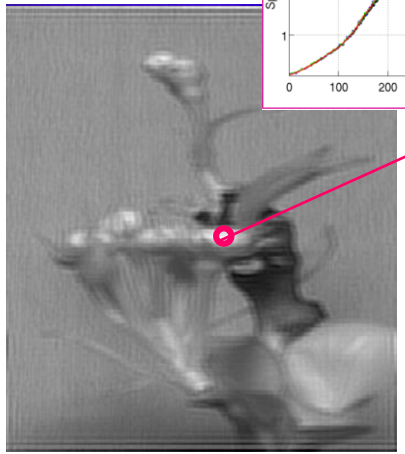
HS data pre-processing

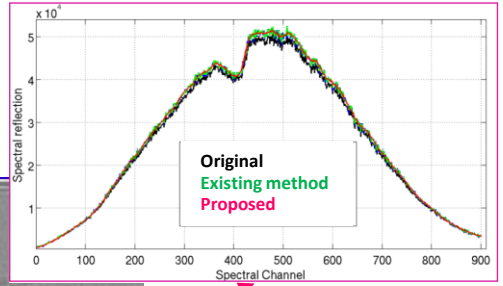


Orig[illegible], b_{900})



Existing method
(Time: **342.4** seconds)



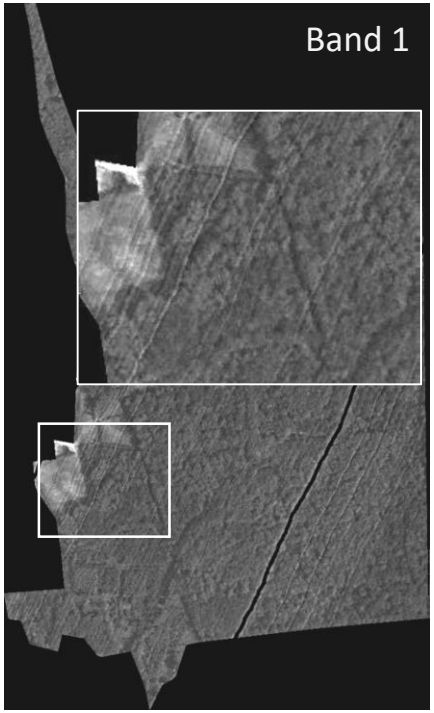


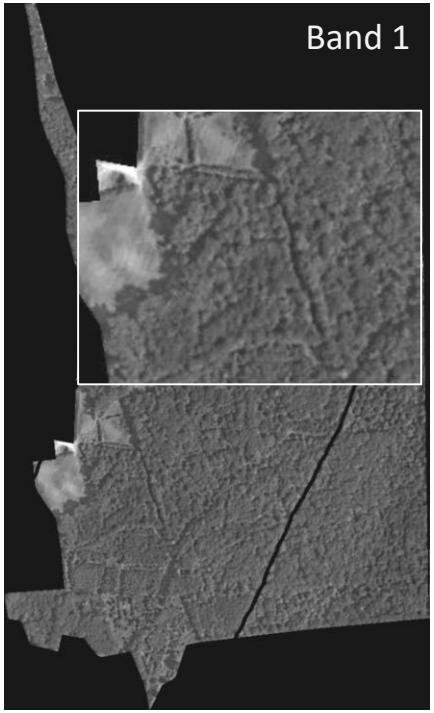
Proposed
(Time: **43.7** seconds)

Image size:
400 x 350 x 900 (spatial x spatial x spectral)

HS data pre-processing

Raw

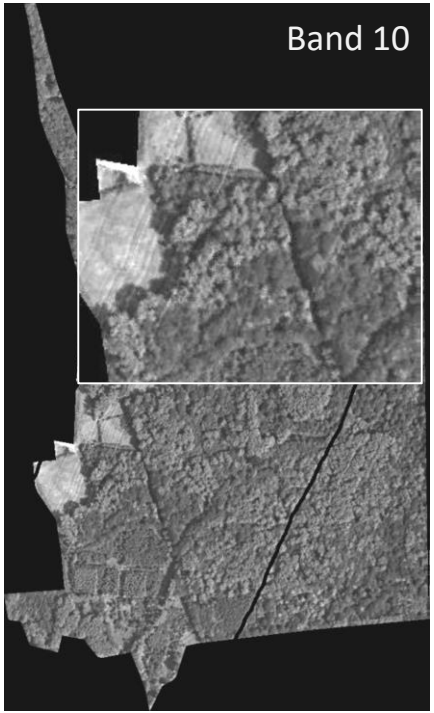


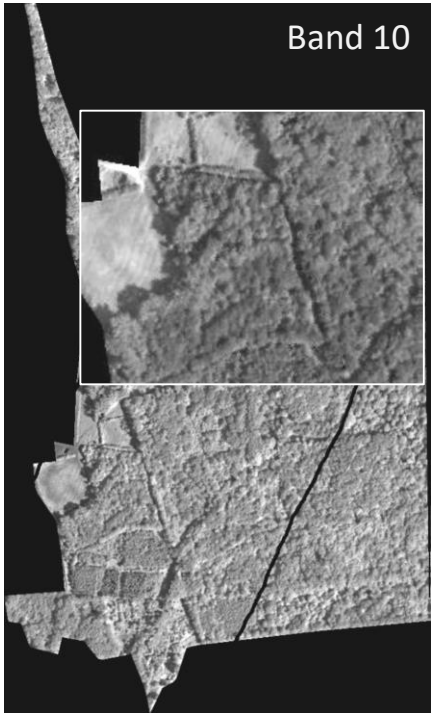


Denoised

HS data pre-processing

Raw

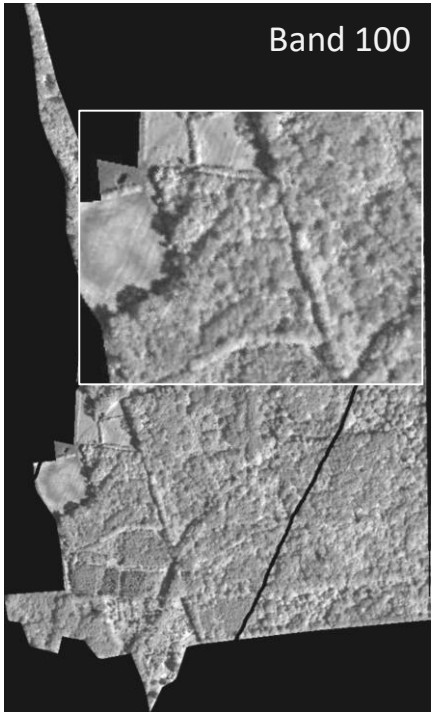


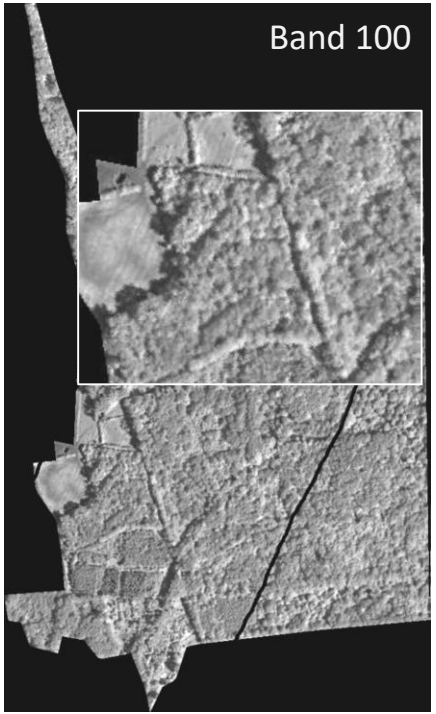


Denoised

HS data pre-processing

Raw

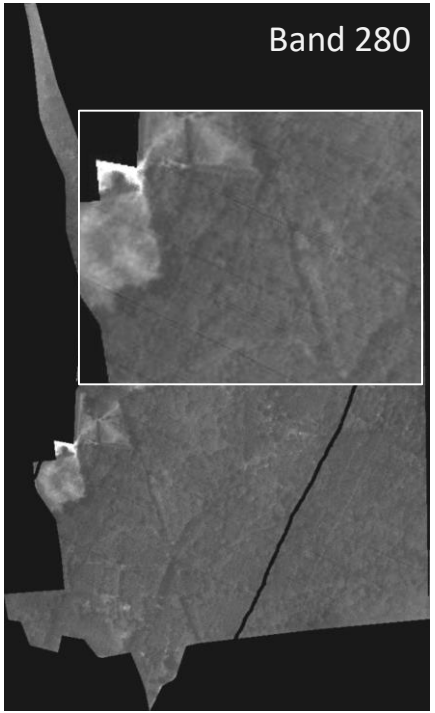


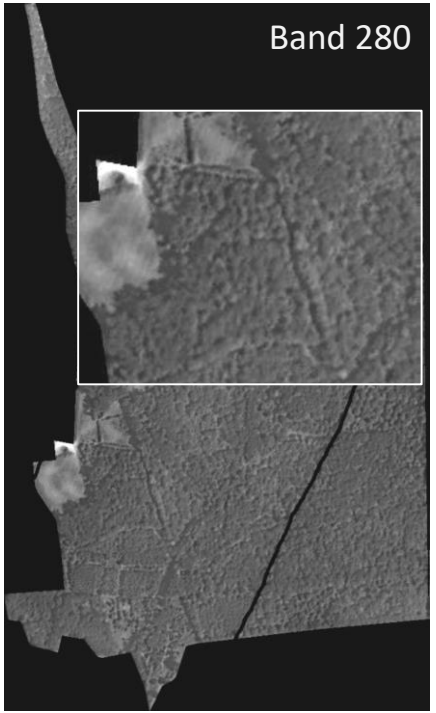


Denoised

HS data pre-processing

Raw





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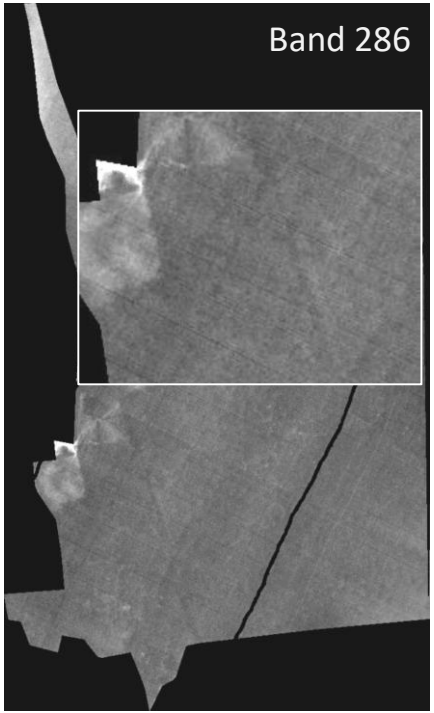
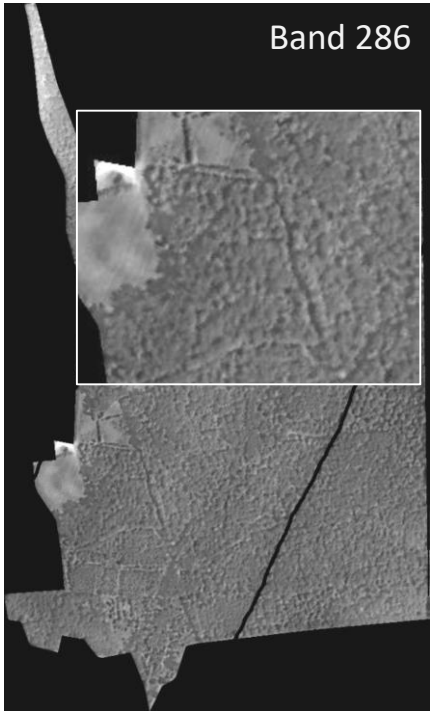
HS data pre-processing

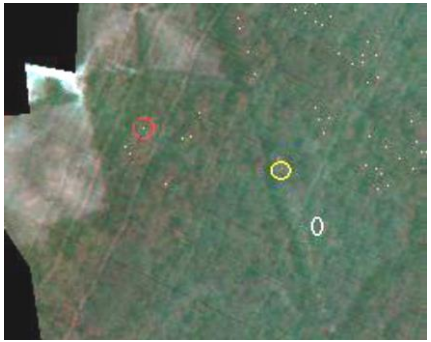
Raw

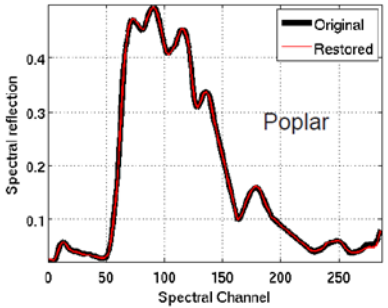


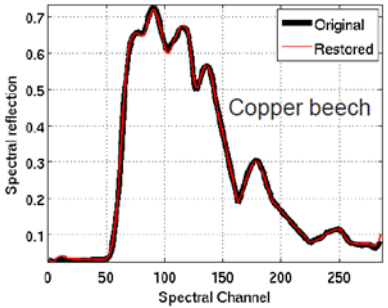


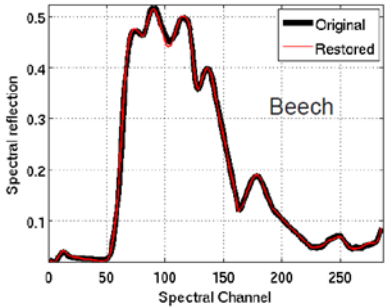
Denoised

HS data pre-processing





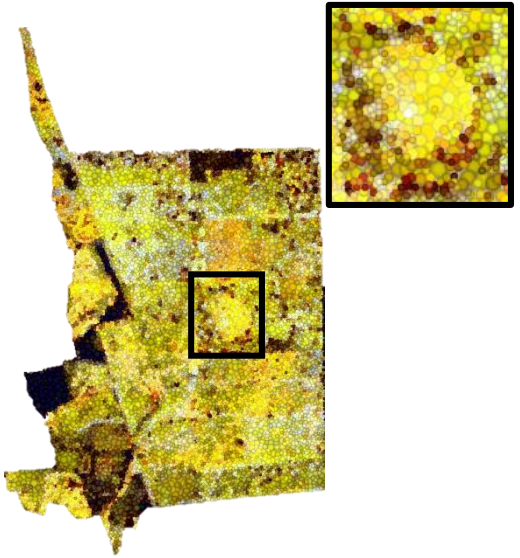




Fusion methods

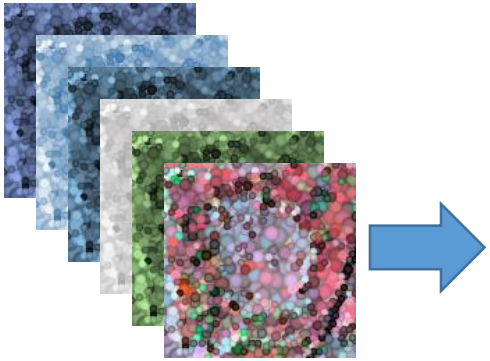
Object-based fusion

Feature fusion of HS and LiDAR HP data



Segmentation on LiDAR

Extract object-based features on HS image

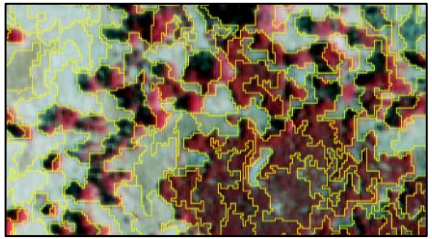


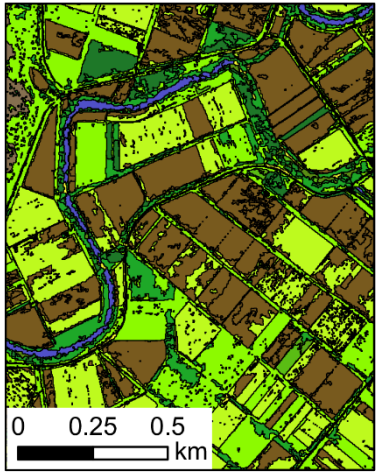
Extracted features

Object-based fusion

Work well for high resolution data

- Segment data and use pixel mean within objects
- Can use other statistics (e.g., standard deviation)
- Allows using contextual information (e.g., close to water)



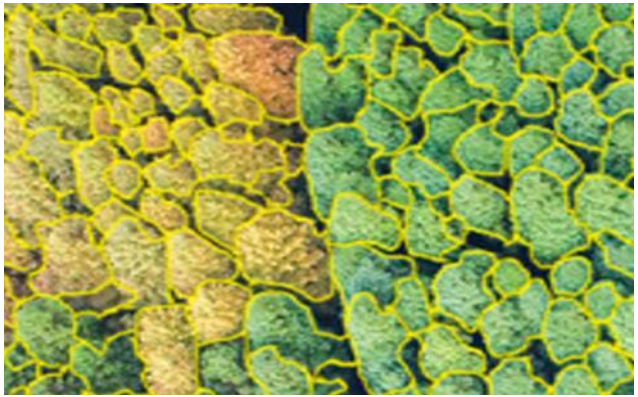


Available in a couple of packages

- eCognition
- **RSGISLib (open source)**

Clewley, D.; Bunting, P.; Shepherd, J.; Gillingham, S.; Flood, N.; Dymond, J.; Lucas, R.; Armston, J.; Moghaddam, M. A Python-Based Open Source System for Geographic Object-Based Image Analysis (GEOBIA) Utilizing Raster Attribute Tables. Remote Sensing 2014, 6, 6111-6135. (open access).

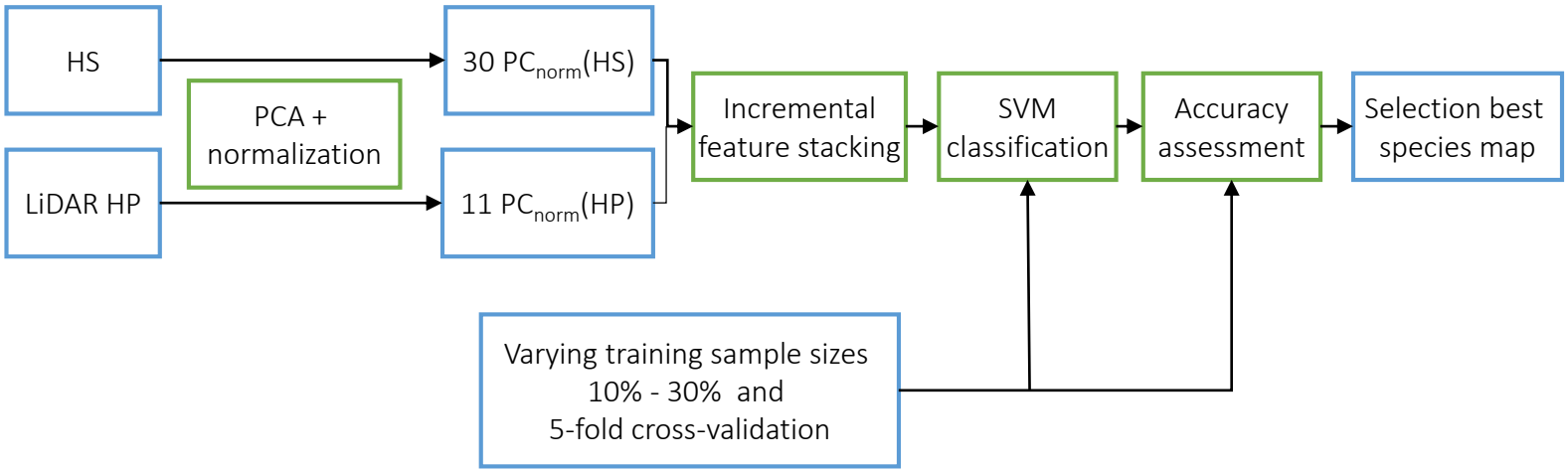
Object-based fusion



Challenges on image segmentation especially for complexity forest

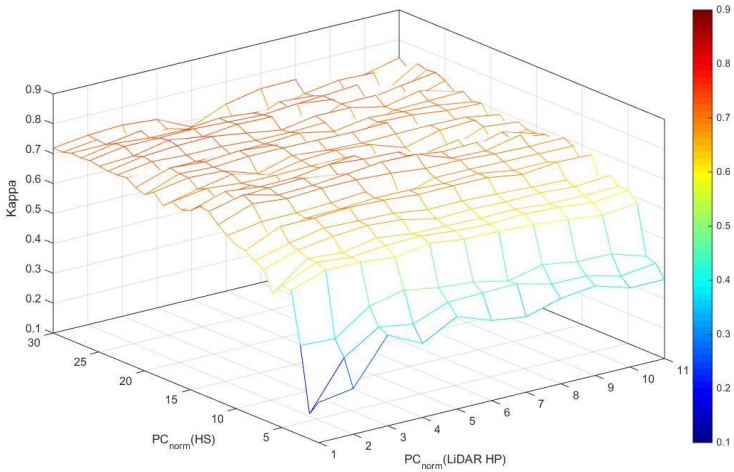
PCA feature fusion

Feature fusion of HS and LiDAR HP data

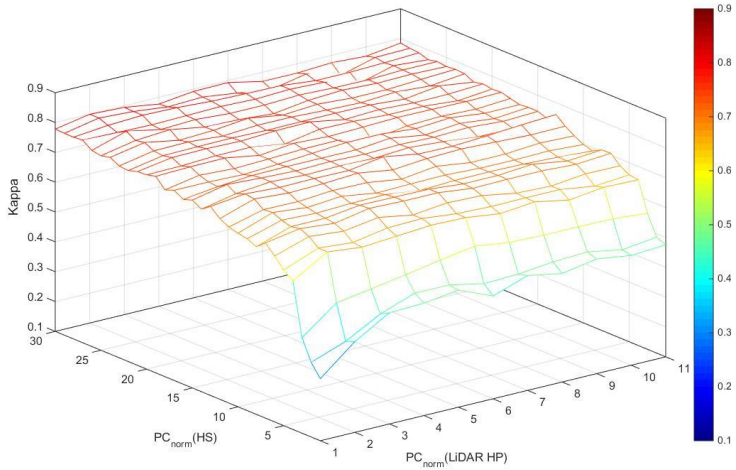


PCA feature fusion

Sample size - 10%

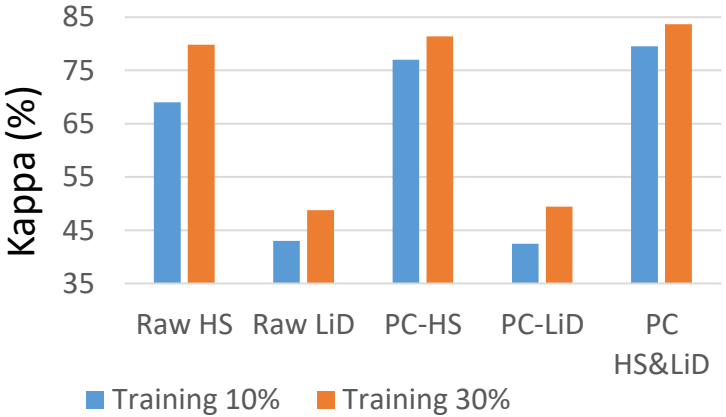


Sample size - 30%



PCA feature fusion

- Single data source
  - HS: Kappa 69-77%
  - LiDAR HP: Kappa 43-48% → importance of canopy structure
- Transformation to PCA domain → Kappa increase
  - HS: sign. Kappa increase for 5%
  - LiDAR HP: non-sign. Kappa increase
- Fusion in PCA domain
  - Sign. increased Kappa all training sizes
  - Effect largest for small training sets



PCA feature fusion

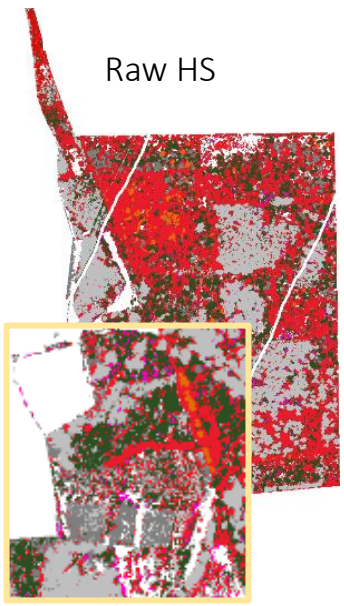
Fusion in PCA domain:

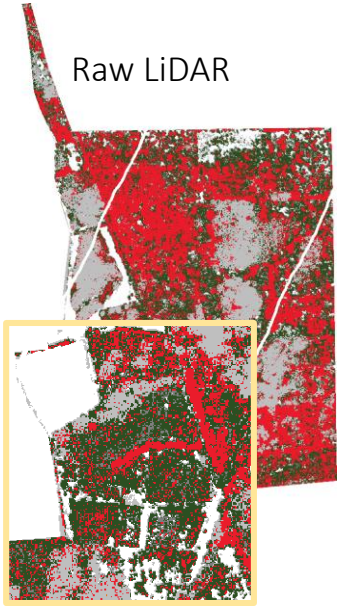
Improved the performances of HS and Fusion

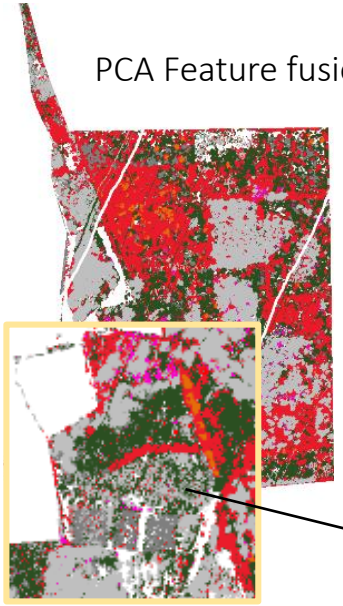
	Raw HS	Raw LiD	PC-HS	PC-LiD	PC HS&LiD
Raw HS		11.96	-6.04	11.39	-8.09
Raw LiD	-11.96		-15.62	-0.74	-17.58
PC-HS	6.04	15.62		15.12	-2.94
PC-LiD	-11.39	0.74	-15.12		-17.16
PC HS&LiD	8.09	17.58	2.94	17.16	
Raw HS		13.84	-1.63	13.83	-2.99
Raw LiD	-13.84		-14.86	-0.27	-16.29
PC-HS	1.63	14.86		14.77	-2.18
PC-LiD	-13.83	0.27	-14.77		-16.04
PC HS&LiD	2.99	16.29	2.18	16.04	

Z-scores comparing Kappa coefficients of best mapping results for varying training set sizes

PCA feature fusion







- Background
- Beech
- Ash
- Larch
- Poplar
- Copper beech
- Chestnut
- Oak

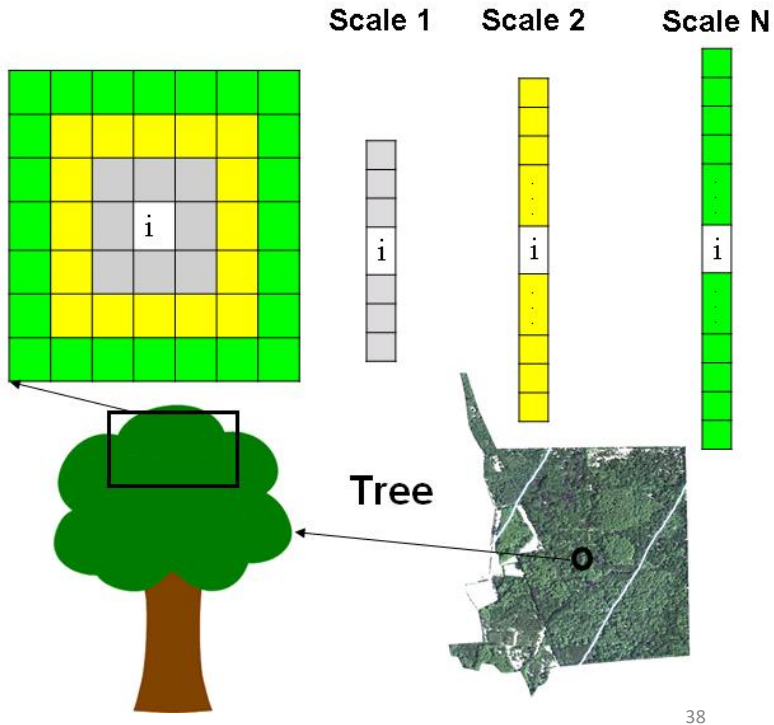
30% training set size

Few beech trees mixed with poplar

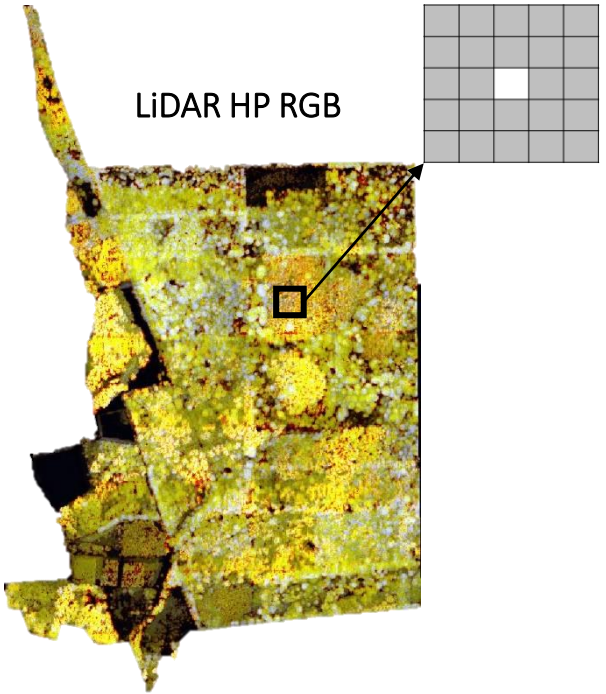
Including spatial information

- The scale size is denoted by the size of sliding widow.
- Each tree species has their own diameter, which can be indicated by the scale size.
- PCA Dimension reduction for hyperspectral image.

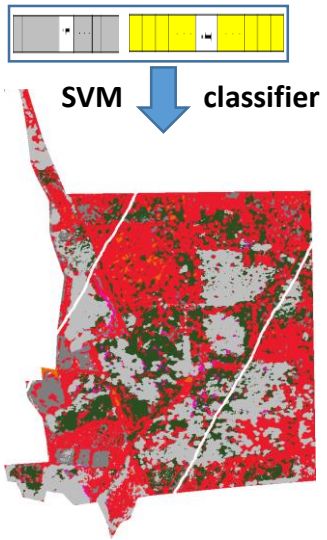
Multi-scale features

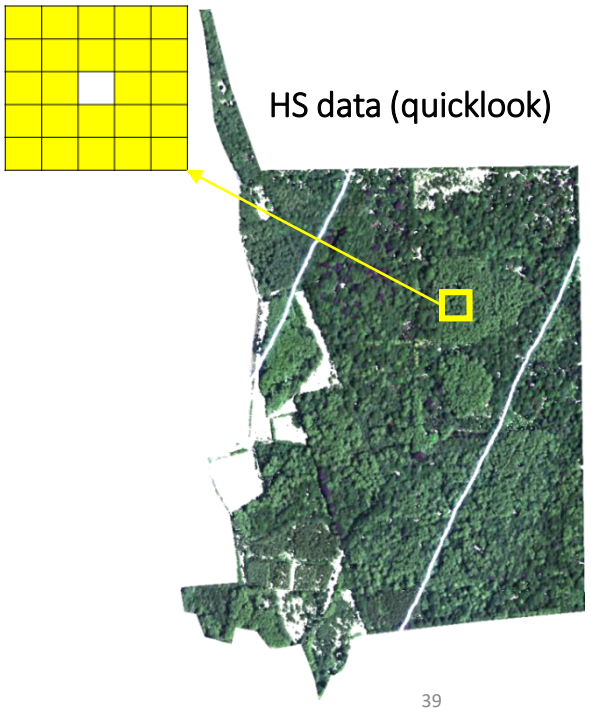


SVM fusion (including spatial info.)

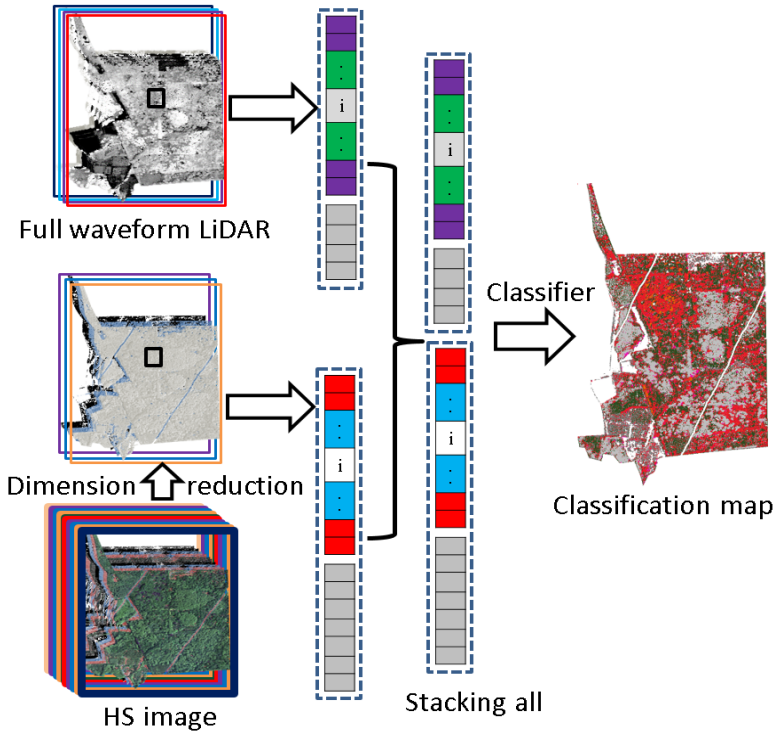


+





SVM fusion (including spatial info.)



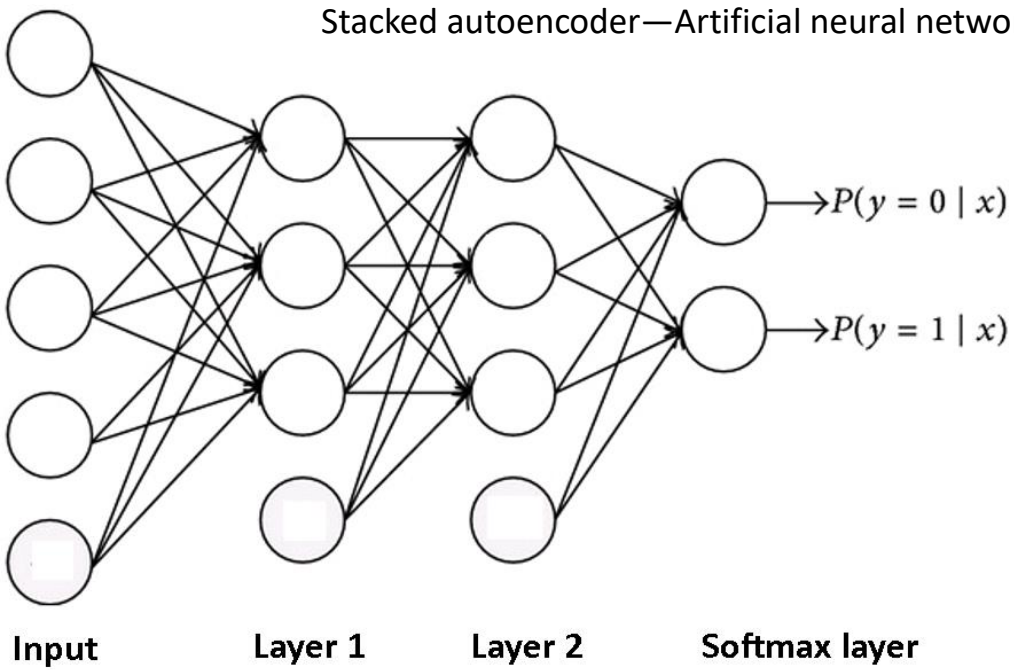
✓Simple and easy

× Increase the dimension

× Complementary information not well exploited

Deep Learning fusion

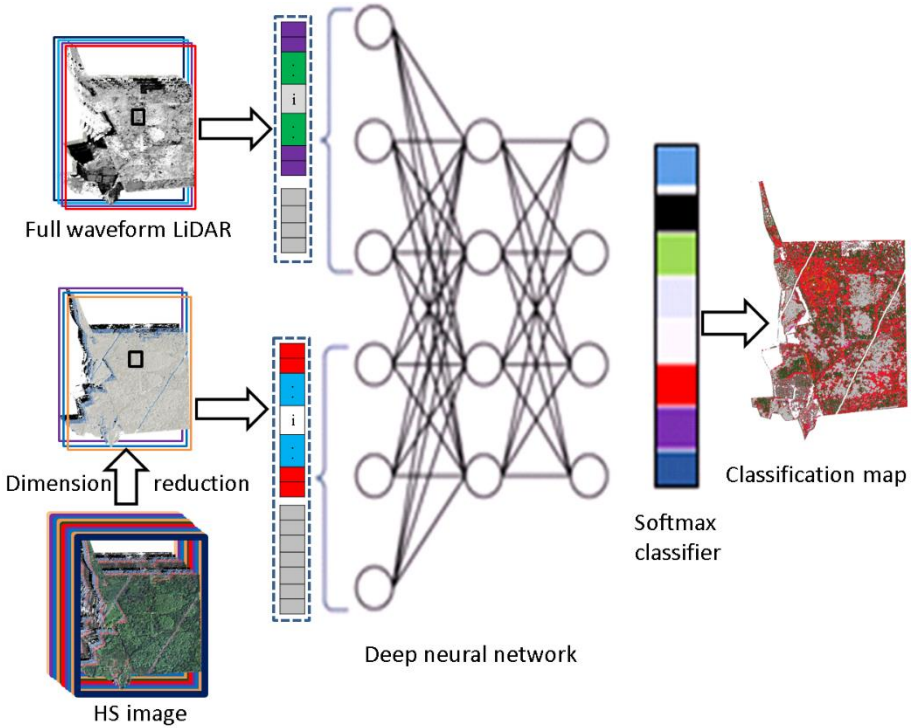
Stacked autoencoder—Artificial neural network



Goal:

Learn a representation of a set of data

Deep Learning fusion



- ☑ Reduce the dimension
- ☑ Learn joint feature representation

Experimental results (SVM Fusion)

- HS data performs better at scale 5x5, while LiDAR at 7x7.
- Better fusion performances at scale 5x5

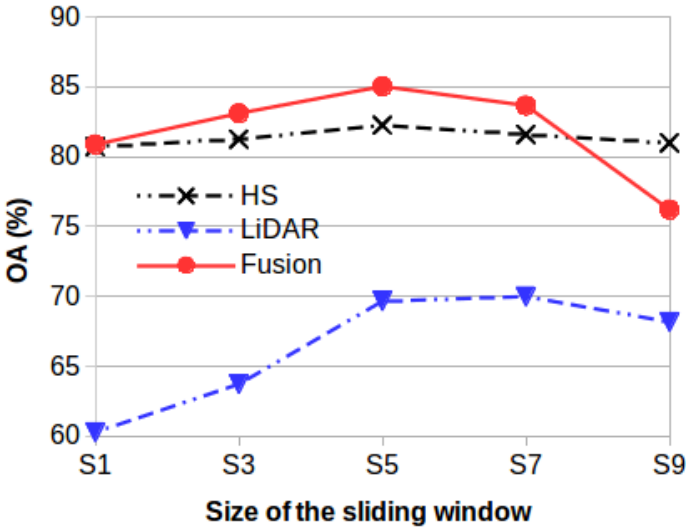
	Raw HS	Raw LiD	S-HS	S-LiD	SVM Fusion
S_{1x1}	80,69	60,28	80,71	60,28	80,87
S_{3x3}	80,69	60,28	81,25	63,72	83,1
S_{5x5}	80,69	60,28	82,24	69,66	85,03
S_{7x7}	80,69	60,28	81,58	69,99	83,66
S_{9x9}	80,69	60,28	80,98	68,17	76,21

Deep learning fusion results

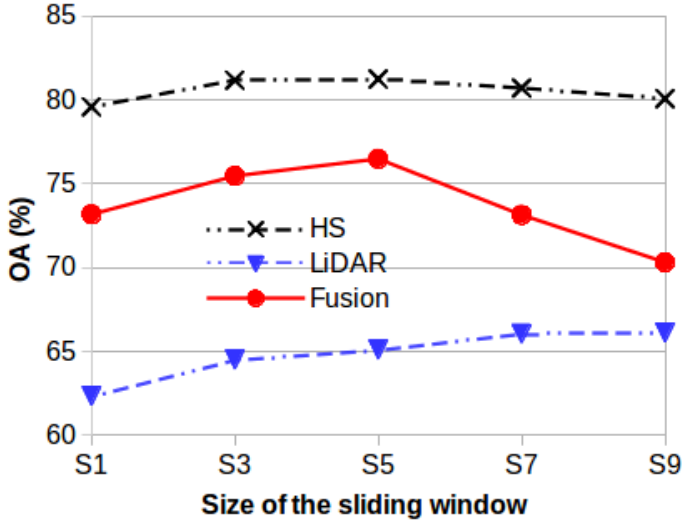
- HS data performs better at scale 5x5, while LiDAR at 9x9.
- Better fusion performances at scale 5x5

	Raw HS	Raw LiD	S-HS	S-LiD	Deep Fusion
S_{1x1}	79,38	62,34	79,58	62,34	73,17
S_{3x3}	79,38	62,34	81,17	64,51	75,46
S_{5x5}	79,38	62,34	81,24	65,1	76,48
S_{7x7}	79,38	62,34	80,7	66,07	73,14
S_{9x9}	79,38	62,34	80,07	66,12	70,31

Comparisons



SVM fusion



Deep learning fusion

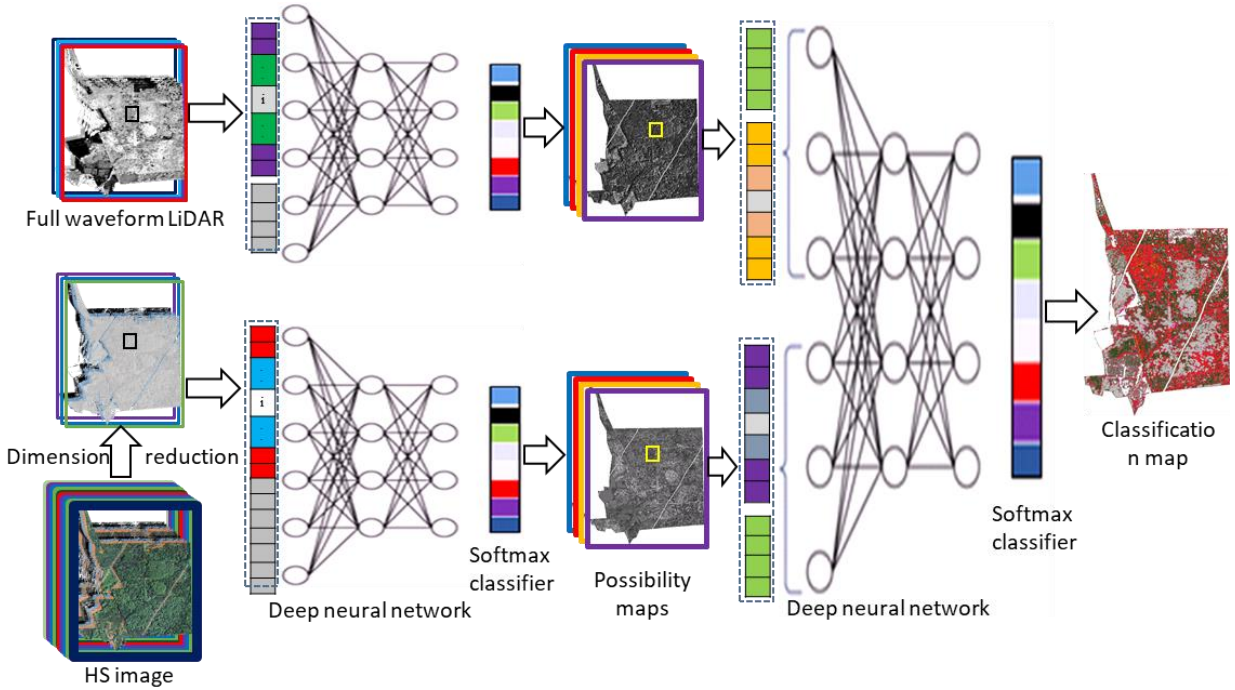
Comparisons

Class	SVM			Deep learning		
	HS data	LiDAR	Fusion	HS data	LiDAR	Fusion
Beech	80.55	83.04	88.53	73.82	68.58	77.31
Ash	52.24	22.39	70.15	68.66	29.85	55.22
Larch	83.62	26.72	86.21	87.93	36.21	53.45
Popolar	93.99	66.35	96.63	93.51	79.33	90.38
Copper Beech	100.0	3.57	85.00	90.00	31.25	87.50
Chestnut	47.76	2.99	32.84	53.73	20.90	50.75
Oak	69.97	70.63	78.88	69.31	65.36	72.31
OA	80.69	60.28	85.03	79.38	62.34	76.48

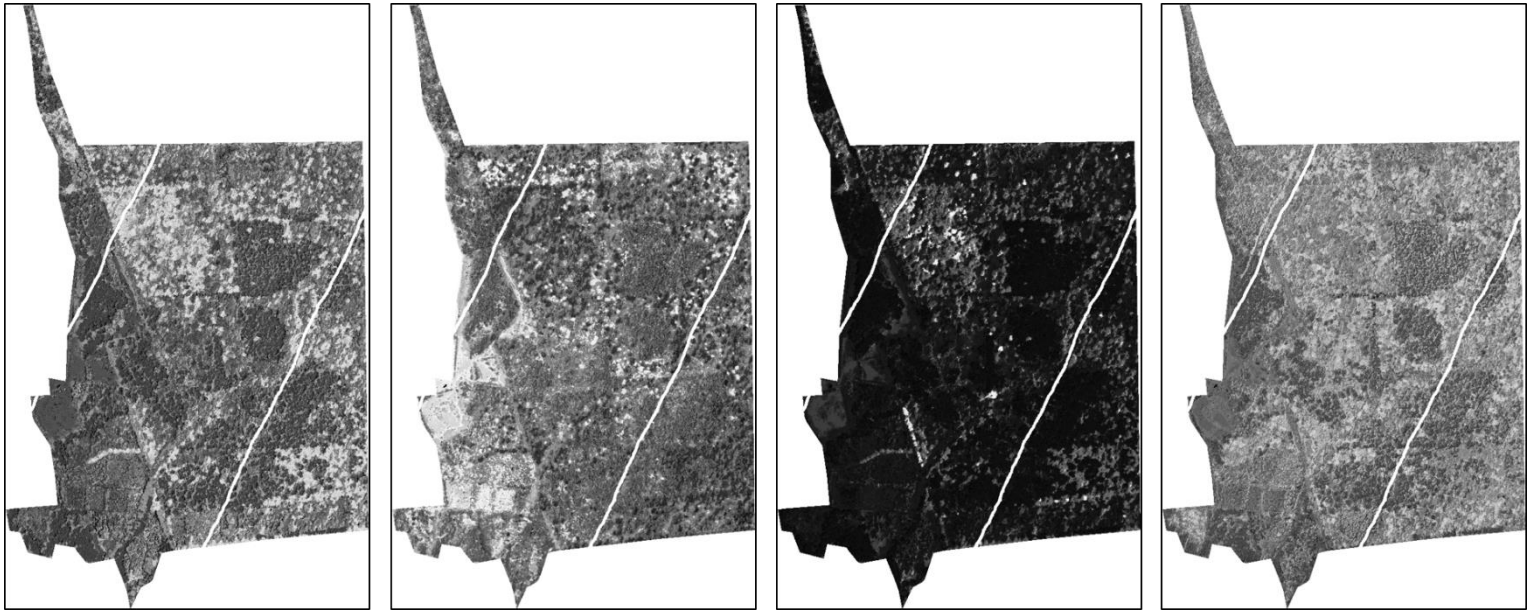
Decision-level data fusion

W. Liao, F. Coillie, L. Gao, L. Li, B. Zhang, J. Chanussot, "Deep Learning for Fusion of APEX Hyperspectral and Full-Waveform LiDAR Remote Sensing Data for Tree Species Mapping", IEEE Access, vol. 6, pp. 68716 - 68729, 2018.

Decision level-fusion by deep learning

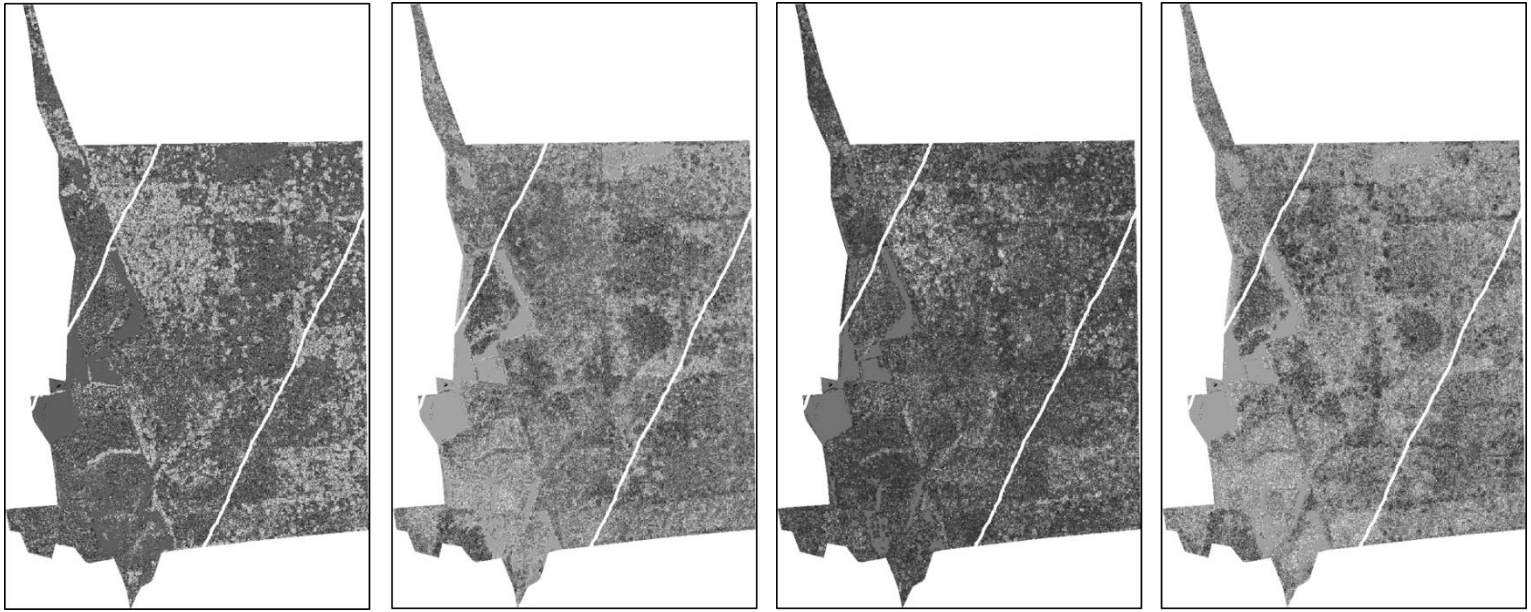


Decision level-fusion by deep learning



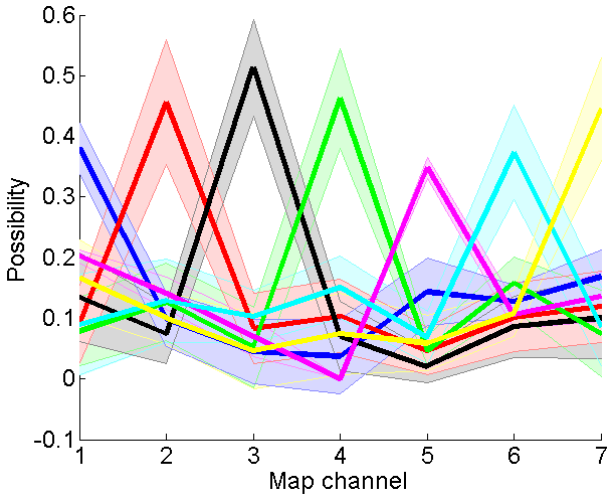
Possibility maps of HS image, possibility channel 1, 3, 5 and 7

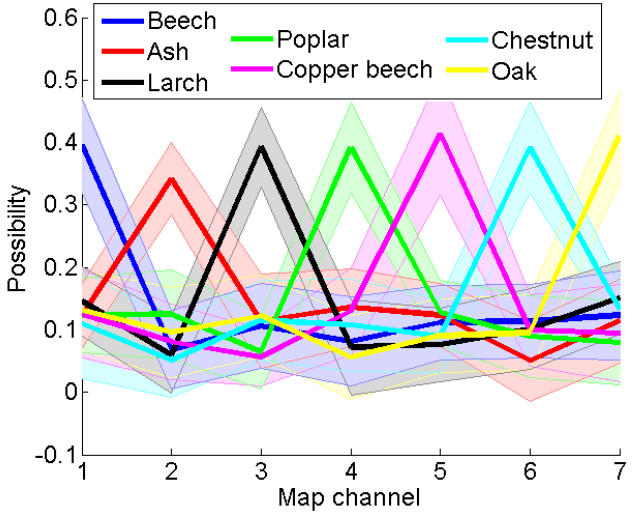
Decision level-fusion by deep learning



Possibility maps of LiDAR data, possibility channel 1, 3, 5 and 7

Decision level-fusion by deep learning





Possibility maps: Mean possibility profile (solid line) and standard deviation (error bar) with shaded area of (Left) HS image; (Right) full-waveform LiDAR image.

Decision level-fusion by deep learning

Classification accuracy (%) using single data source

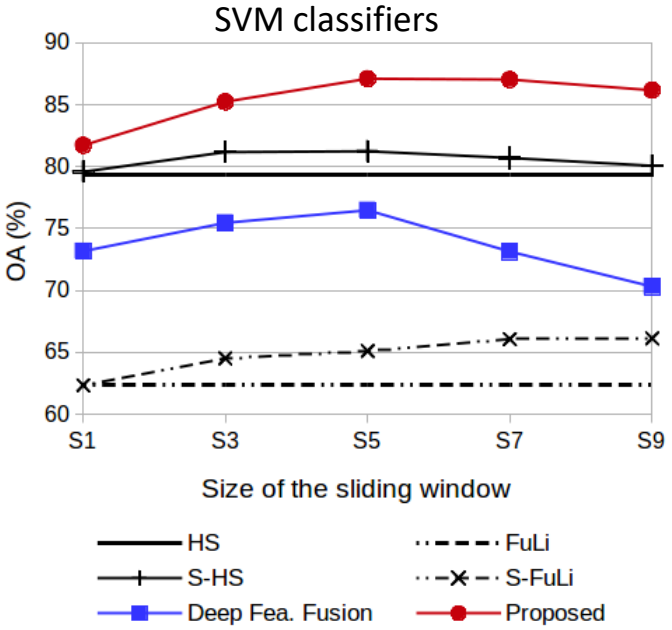
	SVM						Deep Learning					
Class	HS	DSM	FuLi	S-HS	S-DSM	S-FuLi	HS	DSM	FuLi	S-HS	S-DSM	S-FuLi
1	80.55	79.05	83.04	83.79	78.05	**85.79**	73.82	53.87	68.58	79.55	53.37	76.06
2	52.24	0.0	22.39	61.19	4.48	16.42	**68.66**	4.48	29.85	**68.66**	26.87	23.88
3	83.62	0.0	26.72	80.17	21.55	42.24	**87.93**	25.0	36.21	84.48	42.24	37.07
4	93.99	64.42	66.35	**96.15**	67.79	85.34	93.51	60.58	79.33	92.31	66.35	82.69
5	**100.0**	0.0	3.57	85.00	5.0	20.0	90.0	6.25	31.25	93.75	28.75	37.50
6	47.76	0.0	2.99	37.31	1.49	13.43	**53.73**	4.48	20.9	35.82	23.88	29.85
7	69.97	0.0	70.63	75.58	24.75	74.59	69.31	36.3	65.35	**76.57**	43.56	61.39
OA	80.69	40.34	60.28	**82.21**	48.48	69.66	79.38	42.62	62.34	81.24	50.21	65.10
AA	75.45	20.50	39.41	74.17	29.02	48.26	**76.71**	27.28	47.35	75.88	40.72	19.78
κ	75.12	17.2	47.61	**76.89**	30.02	59.81	73.65	23.59	51.28	75.97	36.38	54.48

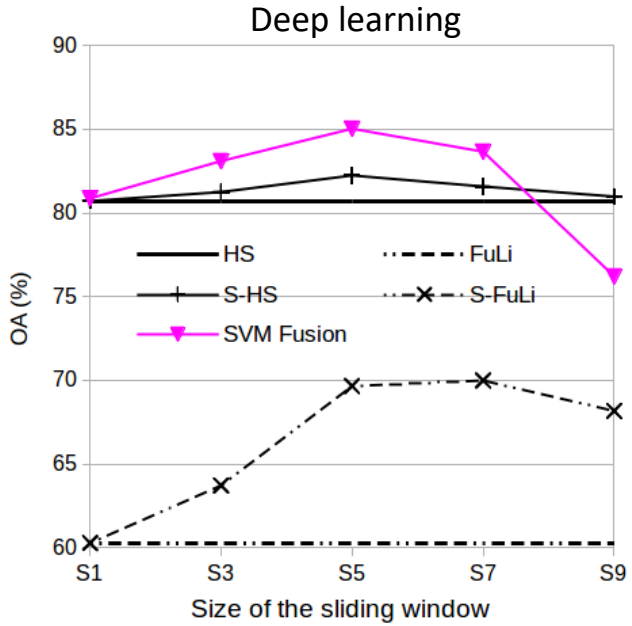
Decision level-fusion by deep learning

Classification accuracy (%) by fusing HS and LiDAR data

Class	Fusion of DSM and HS data			Fusion of full-waveform LiDAR and HS data		
	SVM Fusion	Deep Fea. Fusion	Proposed	SVM Fusion	Deep Fea. Fusion	Proposed
1	79.30	68.33	83.04	**88.53**	77.31	84.54
2	**76.12**	55.22	74.63	70.15	55.22	71.64
3	85.34	72.41	**87.07**	86.21	53.45	**87.07**
4	**96.63**	88.22	95.67	**96.63**	90.38	93.27
5	93.75	87.50	86.25	85.00	87.50	**95.00**
6	38.81	47.76	49.25	32.84	50.75	**64.18**
7	73.60	72.94	79.21	78.88	72.31	**88.45**
OA	82.34	74.83	84.41	85.03	76.48	**87.10**
AA	77.65	70.34	79.30	76.89	69.60	**83.45**
κ	77.22	67.84	79.93	80.59	69.77	**83.51**

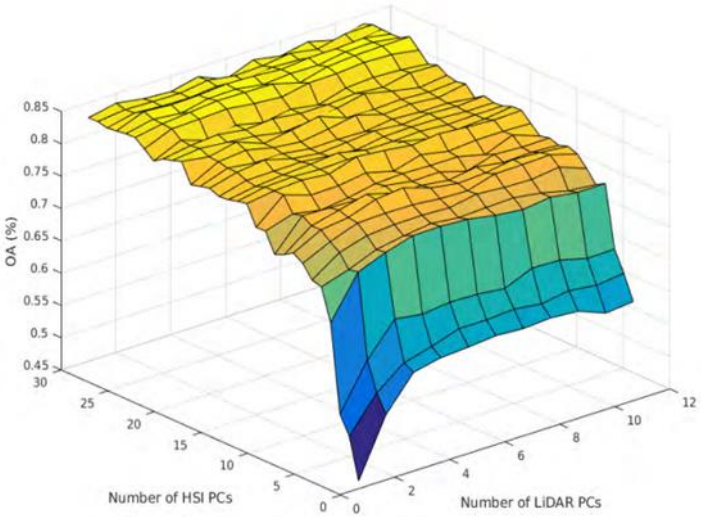
Decision level-fusion by deep learning





Classification accuracy as a function of the sliding window size. S3 denotes the size of sliding window is 3x3.

Decision level-fusion by deep learning



Surface of the OA as a function of the number of the principal components (PCs) for both hyperspectral and LiDAR data

Conclusion

- Fusion of APEX HS and full waveform LiDAR data
- Comparisons on different fusion methods for tree species classification
- Get better performances when fusion HS and LiDAR data at right scale
- SVM fusion performs better than current deep learning fusion

Future work

- Application to more forest reserves (initial testing promising)
- Fusion of extremely high-resolution images from UAV

THANK YOU!

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