living planet symposium | BONN 23–27 May 2022

TAKING THE PULSE OF OUR PLANET FROM SPACE

EUMETSAT ECMWF EUSPA

Estimating soil moisture from hyperspectral images using (on-board) machine learning

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KP LABS

May 24, 2022

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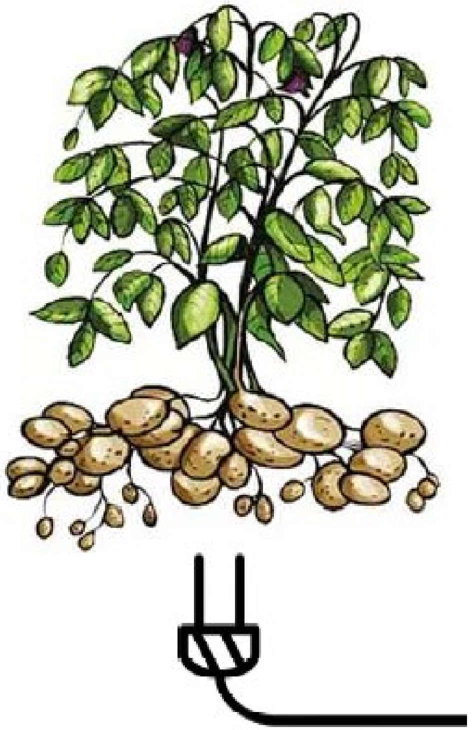

Estimating soil moisture from hyperspectral images

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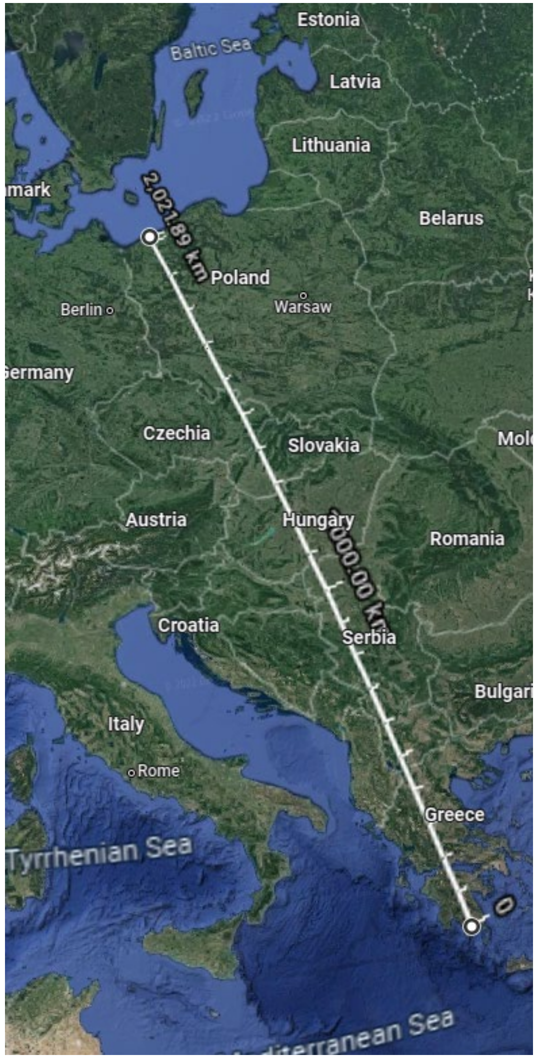
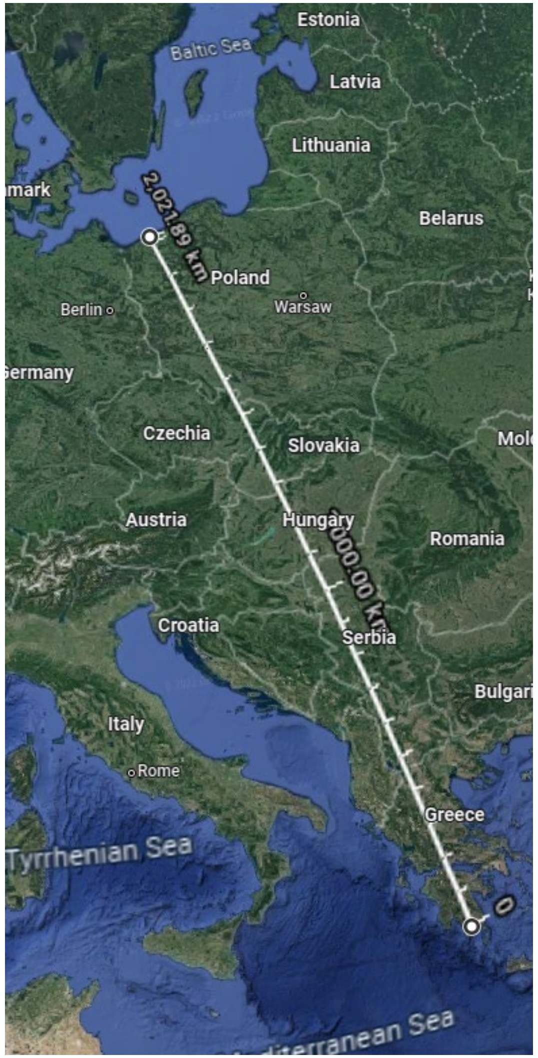


Estimating soil moisture from hyperspectral images



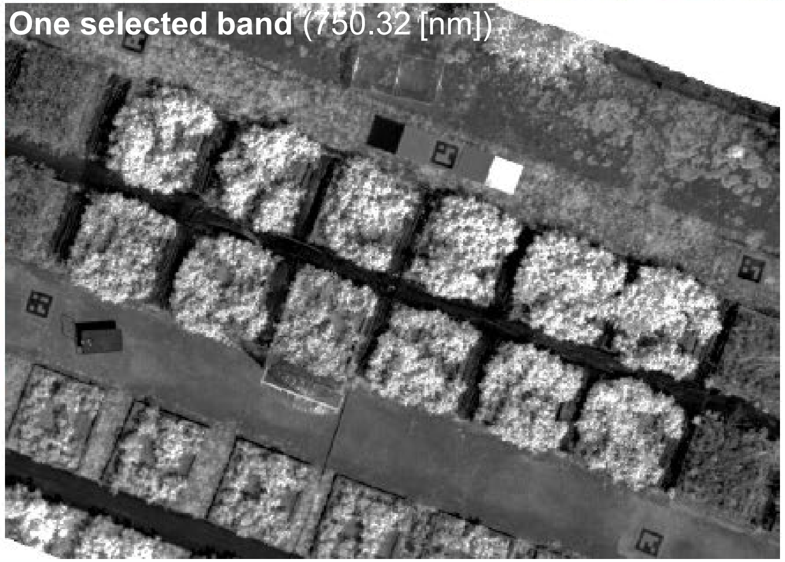
Estimating soil moisture from HSI: data acquisition

More than 3,000 labeled samples (hyperspectral image and in-situ measurements)

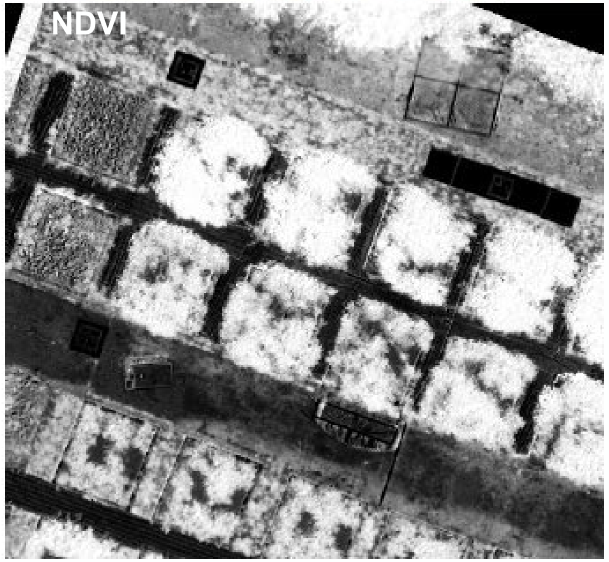
Estimating soil moisture from HSI: data acquisition

Zebra X1 (Ximea sensor):
150 bands (VIS-NIR: 470-900 [nm])
2.2 cm GSD
24 fields, 5.25 m^2
Two different potato varieties
Two soil profiles (light clay sand, heavy clay sand)
Diverse irrigation scenarios: simulating drought, various irrigation (to keep 100%, 75% or 50% of estimated needs)
Gravimetric in-situ measurements (ratio of the mass of water in soil to its mass after drying up)

RGB (R: 639.49 [nm], G: 551.61 [nm], B: 468.83 [nm])



One selected band (750.32 [nm])



NDVI

Estimating soil moisture from HSI: data acquisition

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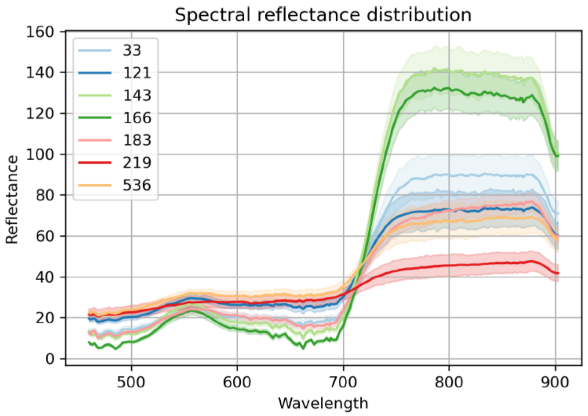
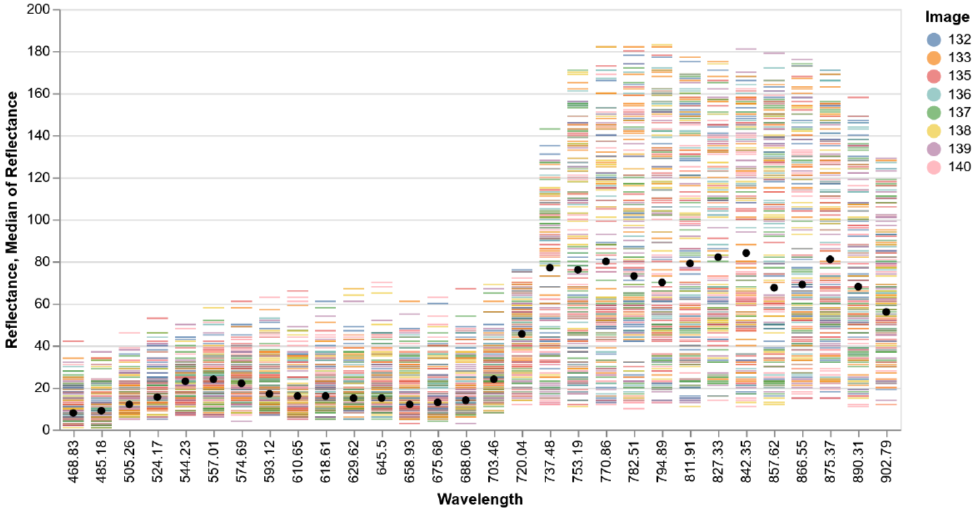


The reflectance distribution for different images:
33: 2020-06-16, moisture: 10.10,
121: 2020-06-09, moisture: 10.93,
143: 2020-07-01, moisture: 10.70,
166: 2020-07-21, moisture: 10.14,
183: 2020-08-13, moisture: 10.15,
219: 2020-06-04, moisture: 10.83,
536: 2020-06-09, moisture: 10.96

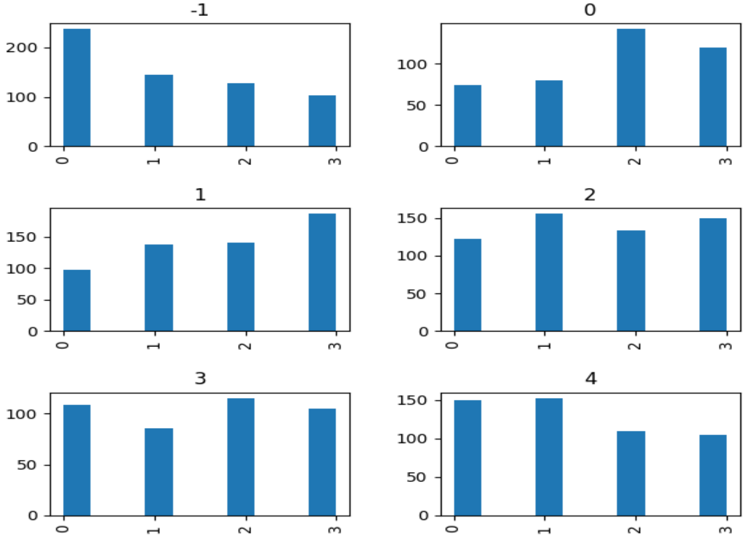


The reflectance distribution for images collected on one day with the same moisture measured (9.4) on the root level on 2020-06-16:
132: 10:21 (time),
133: 10:24,
135: 10:29,
136: 11:42,
137: 11:48,
138: 12:32,
139: 12:35,
140: 13:37.

Estimating soil moisture as classification and regression tasks

More than 3,000 labeled samples (hyperspectral image and in-situ measurements)

	Moisture	
Class	from	to
0	0.21	4.77
1	4.77	8.18
2	8.18	10.70
3	10.70	22.13

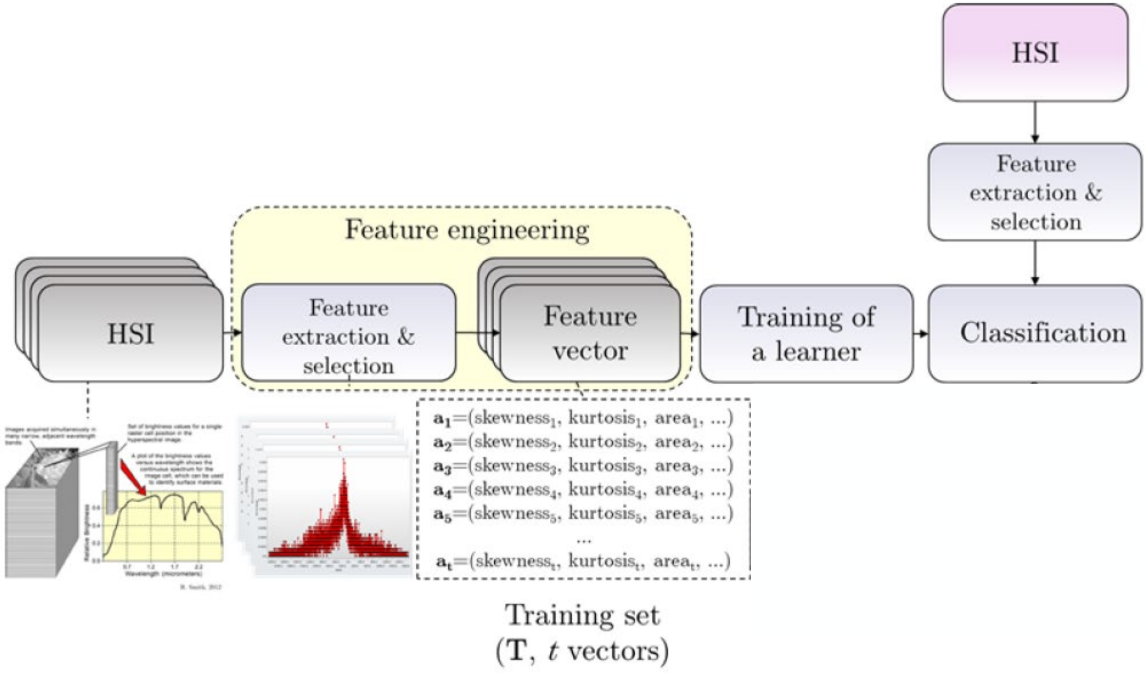


Class distribution in six non-overlapping folds

Fold	Number of samples (in each class)			
	0	1	2	3
-1	237	145	128	102
0	74	80	142	120
1	97	138	141	187
2	122	156	134	150
3	109	86	115	105
4	149	152	109	104

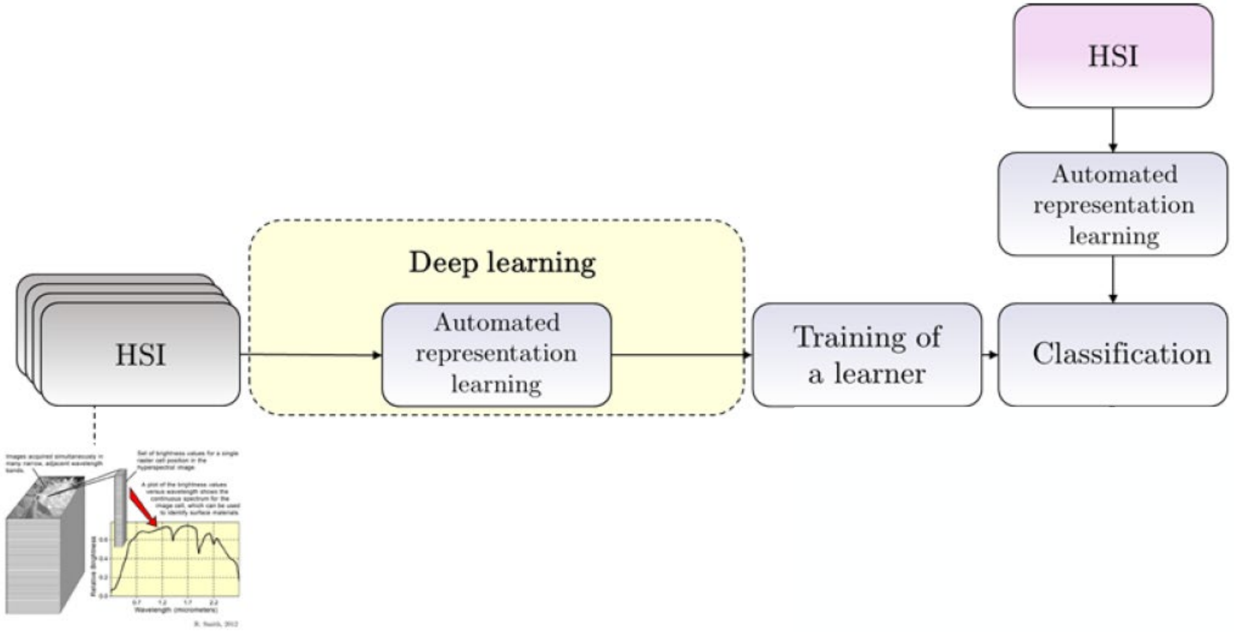
Estimating soil moisture using classical machine learning

More than 3,000 labeled samples (hyperspectral image and in-situ measurements)

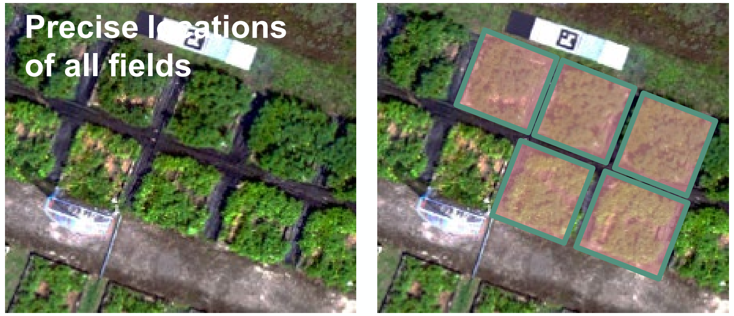


Estimating soil moisture using deep machine learning

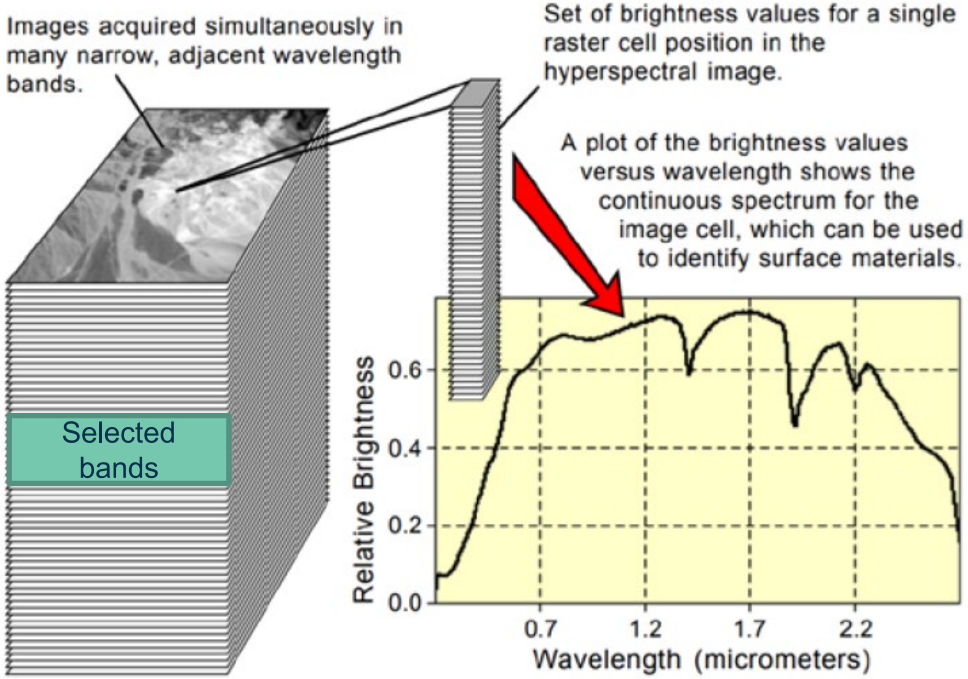
More than 3,000 labeled samples (hyperspectral image and in-situ measurements)



Estimating soil moisture: dimensionality reduction



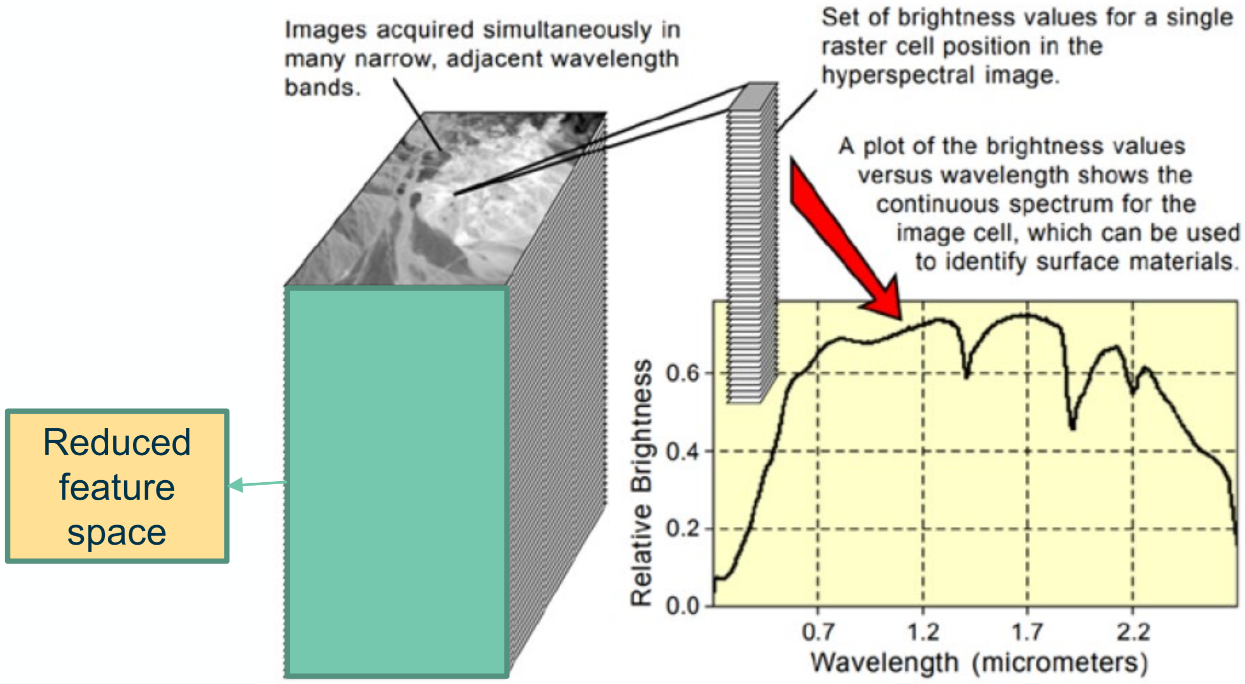
More than 3,000 labeled samples (hyperspectral image and in-situ measurements)



R. Smith, 2012

Estimating soil moisture: dimensionality reduction

More than 3,000 labeled samples (hyperspectral image and in-situ measurements)



R. Smith, 2012

Estimating soil moisture: dimensionality reduction

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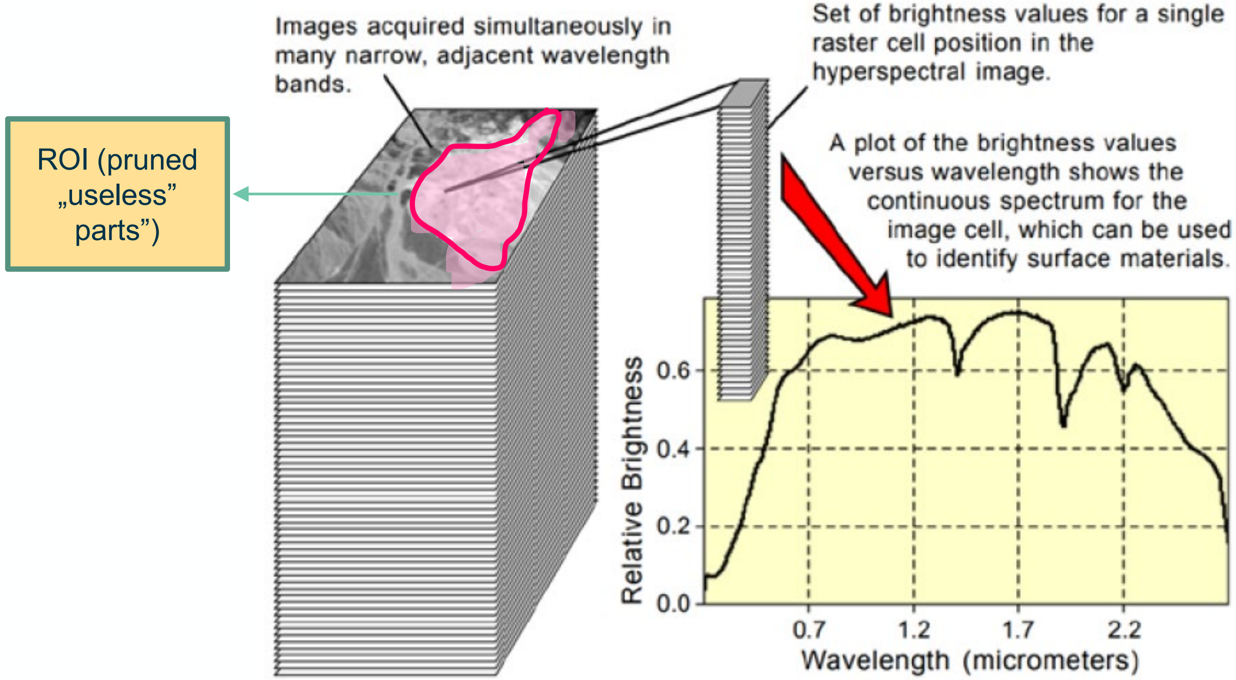

R. Smith, 2012

Estimating soil moisture: the results (classification: TOP 5)

	Fold 0			Fold 1			Fold 2			Fold 3			Fold 4			Fold -1		
Type of model	**Acc**	**Pre**	**F1**	**Acc**	**Pre**	**F1**	**Acc**	**Pre**	**F1**	**Acc**	**Pre**	**F1**	**Acc**	**Pre**	**F1**	**Acc**	**Pre**	**F1**
1D-CNN (NDVI)	0.601	0.594	0.590	0.508	0.503	0.500	0.582	0.594	0.587	0.553	0.565	0.551	**0.654**	**0.653**	**0.654**	**0.631**	**0.621**	**0.624**
Random forest (S-MSI), statistical (mean, std, median), histogram features	0.632	**0.624**	0.615	**0.591**	**0.596**	**0.580**	**0.626**	**0.645**	**0.630**	0.578	**0.602**	0.567	0.611	0.623	0.622	0.482	0.509	0.490
Random forest (S-MSI), statistical (mean), histogram features	**0.637**	0.622	**0.620**	0.572	0.569	0.561	0.623	0.641	0.625	**0.581**	0.596	**0.575**	0.605	0.612	0.615	0.475	0.487	0.479
Random forest, statistical (median)	0.587	0.561	0.563	0.551	0.545	0.541	0.559	0.578	0.559	0.564	0.564	0.546	0.623	0.618	0.624	0.479	0.486	0.478
Random forest (S-MSI), statistical (mean)	0.625	0.607	0.610	0.561	0.565	0.553	0.617	0.637	0.620	0.561	0.574	0.559	0.617	0.628	0.626	0.475	0.481	0.473

Estimating soil moisture: the results (classification: TOP 5)

	Fold 0			Fold 1			Fold 2			Fold 3			Fold 4			Fold -1		
Type of model	Acc	Pre	F1	Acc	Pre	F1	Acc	Pre	F1	Acc	Pre	F1	Acc	Pre	F1	Acc	Pre	F1
1D-CNN (NDVI)	0.601	0.594	0.590	0.508	0.503	0.500	0.582	0.594	0.587	0.553	0.565	0.551	**0.654**	**0.653**	**0.654**	**0.631**	**0.621**	**0.624**
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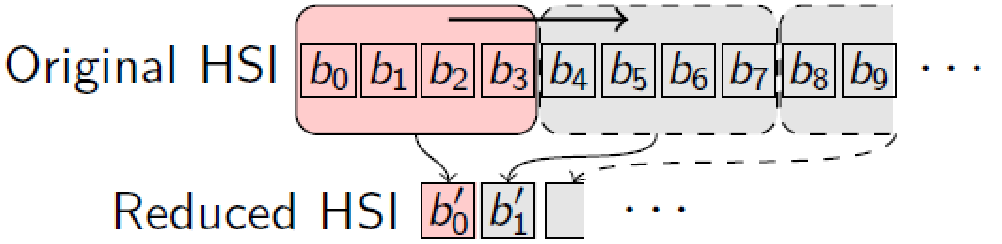

J. Nalepa, M. Myller, M. Kawulok: Transfer Learning for Segmenting Dimensionally Reduced Hyperspectral Images. IEEE Geosci. Remote. Sens. Lett. 17(7): 1228-1232 (2020)

Estimating soil moisture: the results (regression: TOP 5)

	Fold 0			Fold 1			Fold 2			Fold 3			Fold 4			Fold -1		
Type of model	**MAE**	**MSE**	**R^2**	**MAE**	**MSE**	**R^2**	**MAE**	**MSE**	**R^2**	**MAE**	**MSE**	**R^2**	**MAE**	**MSE**	**R^2**	**MAE**	**MSE**	**R^2**
Random forest (S-MSI), statistical (mean, std, median), histogram features	2.078	7.524	0.476	**2.072**	9.230	0.365	1.828	9.574	0.490	2.329	10.940	0.482	1.680	**5.127**	**0.673**	**2.411**	**10.270**	**0.428**
Random forest (S-MSI), statistical (mean), histogram features	2.062	8.154	0.433	2.127	**8.839**	**0.392**	1.830	9.357	0.501	2.390	11.800	0.441	**1.669**	5.239	0.665	2.599	11.350	0.368
Random forest (S-MSI), statistical (mean, std, median)	1.890	6.824	0.525	2.323	10.270	0.294	1.866	9.844	0.476	**2.237**	**10.240**	**0.515**	1.715	5.314	0.661	2.586	11.520	0.358
Random forest statistical (mean, std, median), histogram features	**1.833**	**6.666**	**0.536**	2.198	10.000	0.312	**1.726**	**9.116**	**0.514**	2.367	10.920	0.482	1.799	5.941	0.621	2.614	11.560	0.356
Random forest (S-MSI), statistical (mean), histogram features	2.158	9.146	0.364	2.22	9.505	0.347	1.904	10.410	0.446	2.487	12.890	0.389	1.762	5.696	0.636	2.692	12.020	0.330

Estimating soil moisture: the results (regression: TOP 5)

	Fold 0			Fold 1			Fold 2			Fold 3			Fold 4			Fold -1		
Type of model	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2
Random forest (S-MSI), statistical (mean, std, median), histogram features	2.078	7.524	0.476	**2.072**	9.230	0.365	1.828	9.574	0.490	2.329	10.940	0.482	1.680	**5.127**	**0.673**	**2.411**	**10.270**	**0.428**
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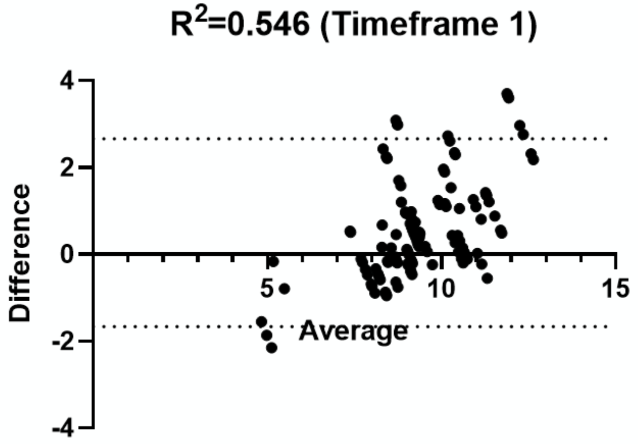

Estimating soil moisture: the results (regression: TOP 5)

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Type of model	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2
Random forest (S-MSI), statistical (mean, std, median), histogram features	2.078	7.524	0.476	**2.072**	9.230	0.365	1.828	9.574	0.490	2.329	10.940	0.482	1.680	**5.127**	**0.673**	**2.411**	**10.270**	**0.428**
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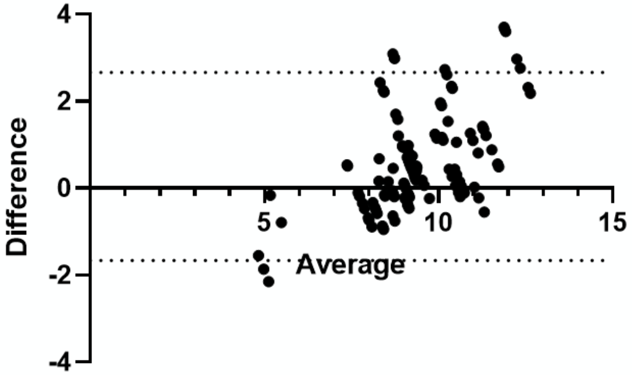
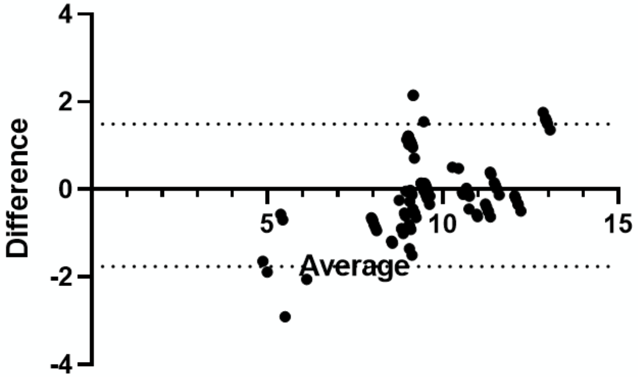
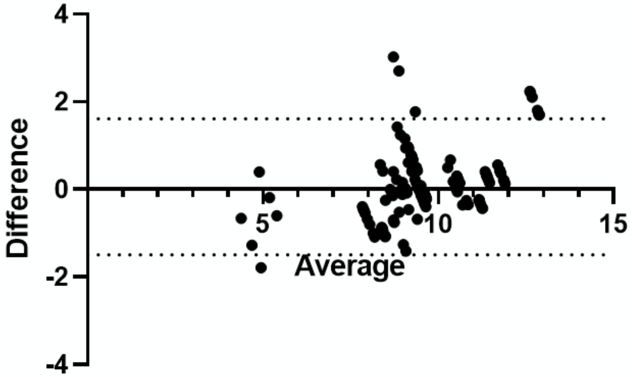
R^2=0.546 (Timeframe 1)



R^2=0.783 (Timeframe 1)

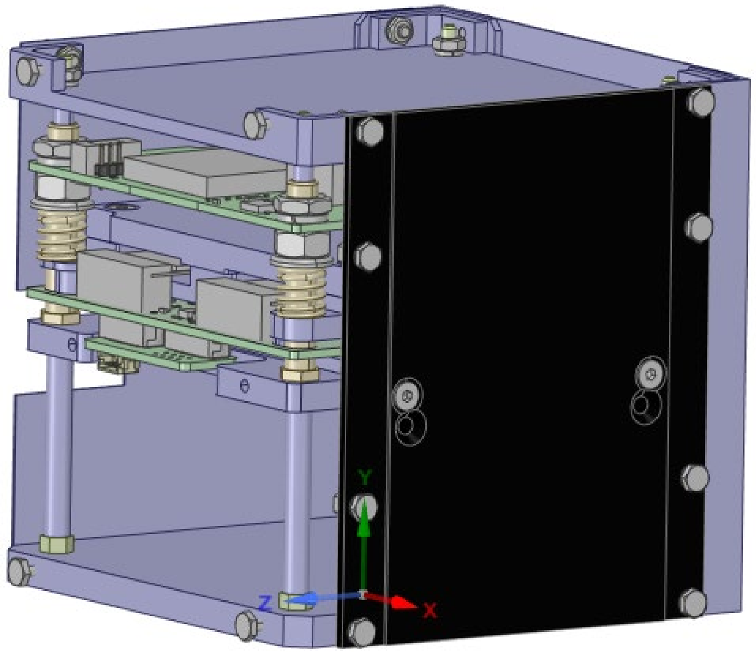


R^2=0.807 (Timeframe 1)



Specializing classifiers (**left**: single CNN operating on 4x4 patches for a field, and averaging the predictions, **right**: ensemble of heterogeneous models)

Toward on-board processing: data-level digital twin



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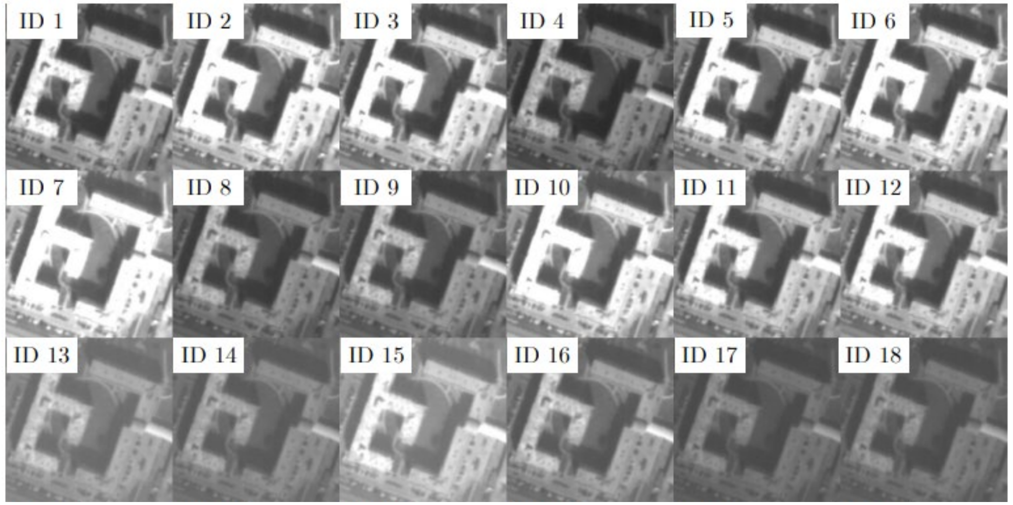

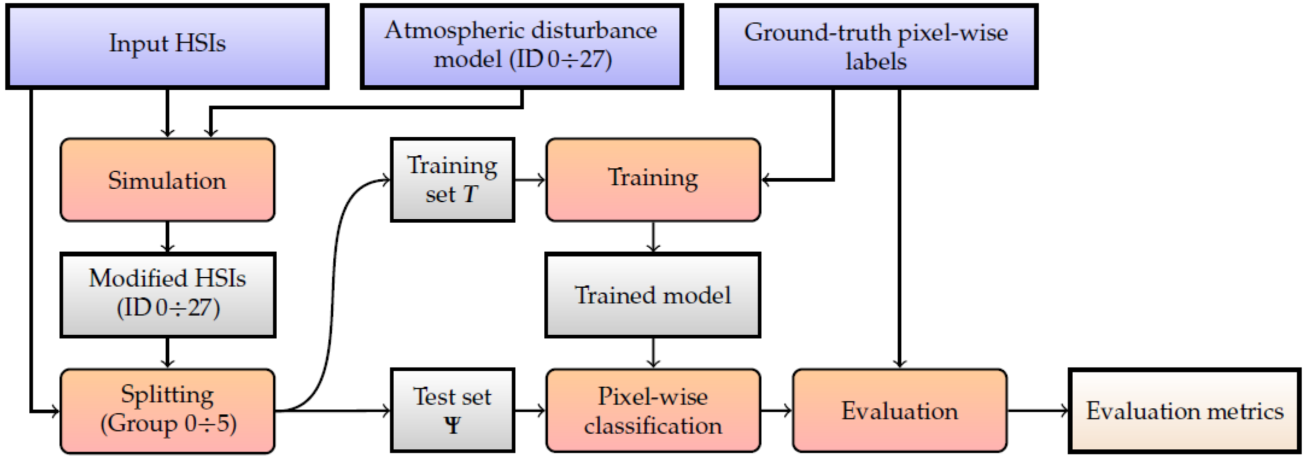

J. Nalepa et al.: Towards on-board hyperspectral satellite segmentation, Remote Sensing 2021, 13(8), 1532 (https://www.mdpi.com/2072-4292/13/8/1532)

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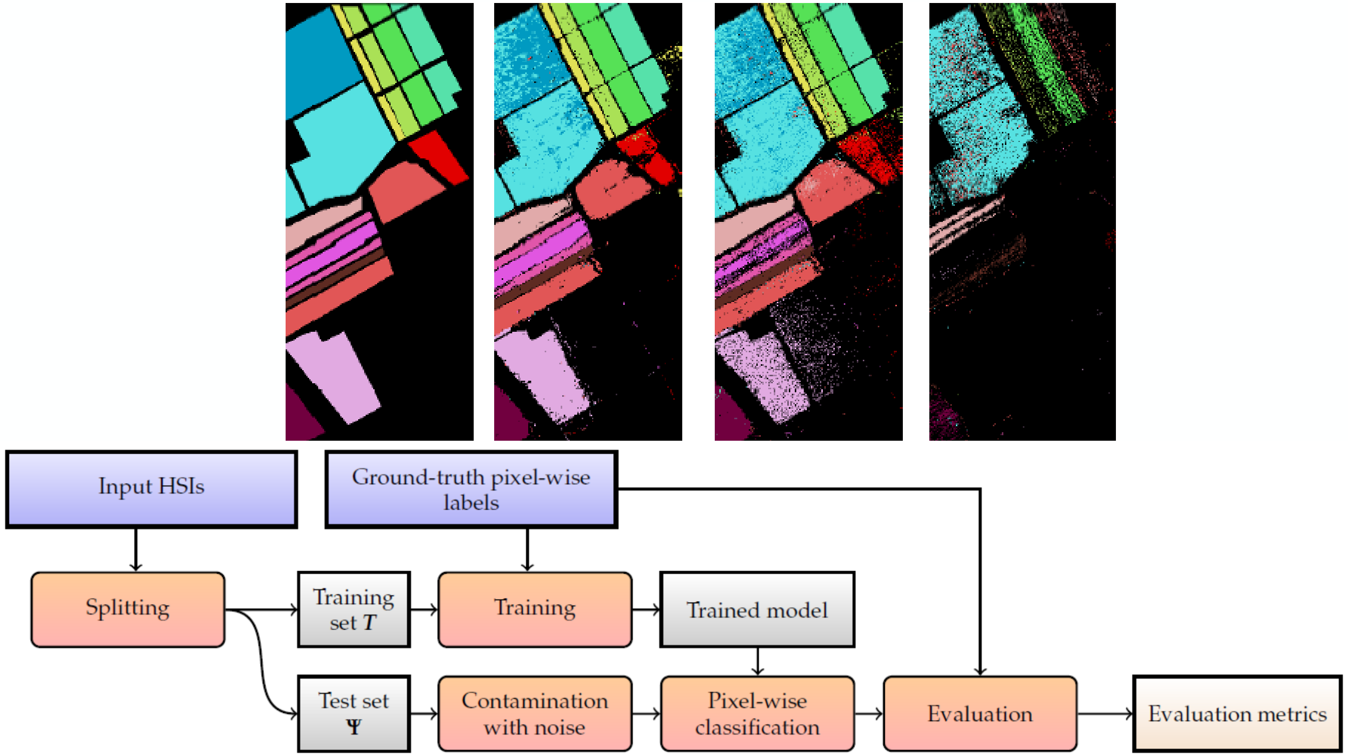

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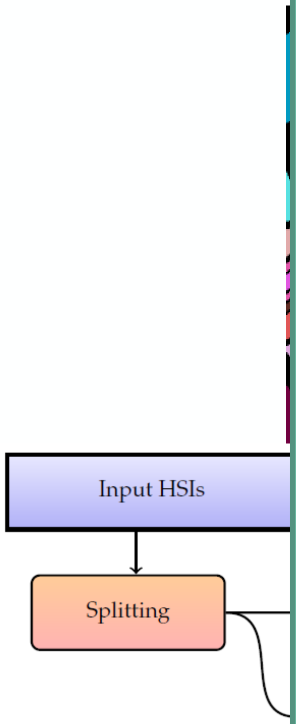
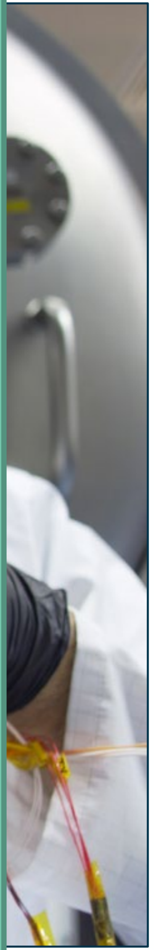
Toward on-board processing: data-level digital twin

Example: Differences between metrics for uncontaminated and noisy HSI in hyperspectral classification (average over four benchmarks, Indian Pines, Salinas Valley, Pavia University and Houston)

1D CNN															
	Gaussian					Impulsive					Poisson				
$\eta_P \rightarrow$	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5
OA	0.87	1.74	2.61	3.50	4.35	5.15	10.28	15.41	20.62	25.76	4.16	8.33	12.51	16.61	20.83
BA	0.98	1.92	2.77	3.76	4.67	4.91	9.72	14.68	19.47	24.36	3.99	8.04	12.13	16.07	20.12
κ	1.12	2.23	3.34	4.48	5.58	6.03	11.95	17.87	23.66	29.46	4.97	9.94	14.91	19.76	24.74
OA′	−0.35	0.54	1.43	2.34	3.22	4.16	9.56	15.00	20.43	25.83	3.14	7.54	11.96	16.28	20.74
BA′	−0.60	0.53	1.54	2.73	3.81	4.15	9.97	15.91	21.71	27.63	2.96	7.76	12.62	17.29	22.10
κ'	−0.71	0.44	1.59	2.77	3.92	4.92	11.51	18.03	24.52	30.88	3.51	8.87	14.22	19.44	24.79
2.5D CNN															
	Gaussian					Impulsive					Poisson				
$\eta_P \rightarrow$	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5
OA	0.08	0.09	0.09	0.10	0.12	4.53	8.97	13.43	17.90	22.32	1.58	3.09	4.57	6.09	7.59
BA	0.13	0.15	0.15	0.16	0.20	4.05	7.98	11.87	15.78	19.68	1.61	3.08	4.54	6.01	7.50
κ	0.10	0.12	0.13	0.14	0.17	5.03	9.88	14.69	19.43	24.15	2.04	4.01	5.98	7.99	10.00
OA′	0.08	0.09	0.09	0.11	0.12	4.83	9.55	14.32	19.07	23.84	1.62	3.17	4.70	6.26	7.80
BA′	0.16	0.18	0.18	0.20	0.23	4.88	9.61	14.25	18.94	23.69	1.93	3.70	5.46	7.23	9.02
κ'	0.10	0.12	0.13	0.15	0.17	5.87	11.57	17.17	22.68	28.13	2.11	4.15	6.18	8.26	10.35
3D CNN															
	Gaussian					Impulsive					Poisson				
$\eta_P \rightarrow$	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5
OA	0.07	0.12	0.18	0.24	0.30	3.90	7.74	11.61	15.46	19.33	3.07	6.11	9.17	12.22	15.22
BA	−0.04	0.02	0.09	0.15	0.21	4.16	8.43	12.65	16.92	21.19	3.21	6.54	9.85	13.17	16.45
κ	0.03	0.10	0.17	0.25	0.32	5.00	10.01	15.04	20.07	25.22	3.82	7.66	11.55	15.43	19.29
OA′	0.07	0.13	0.19	0.25	0.74	4.06	8.09	12.12	16.14	20.18	3.25	6.47	9.71	12.94	16.12
BA′	−0.05	0.03	0.10	0.16	−0.19	4.96	10.06	15.06	20.16	25.26	3.78	7.70	11.60	15.50	19.37
κ'	0.04	0.11	0.19	0.27	0.34	5.51	11.06	16.61	22.06	27.67	4.14	8.28	12.46	16.62	20.76

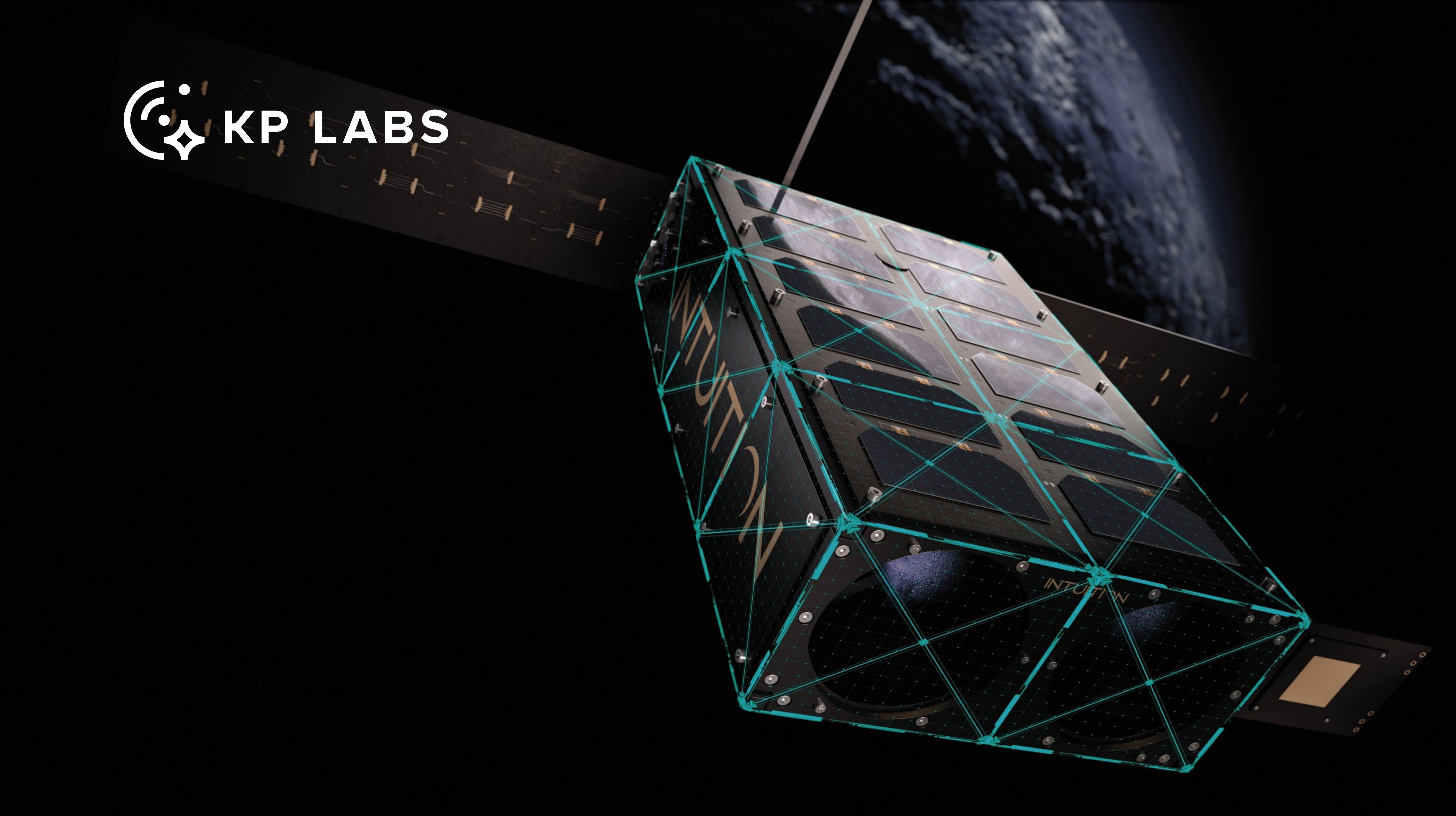




J. Nalepa et al.: Tow
2021, 13(8), 1532 (h


#HYPERVIEW
19
K
Potassium
39.098
pH
12
Mg
Magnesium
24.305
15
P
Phosphorus
30.974
KP LABS
Mission Complete


OPEN
3dB
-25 20 10 7 5 3 1 0 +1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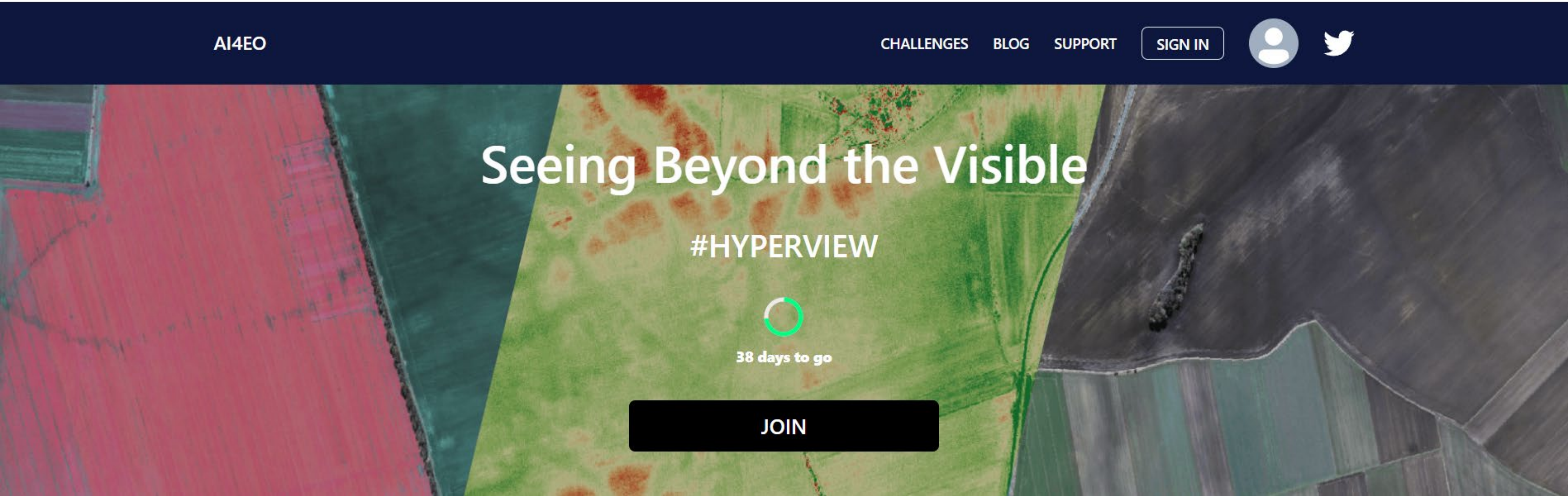
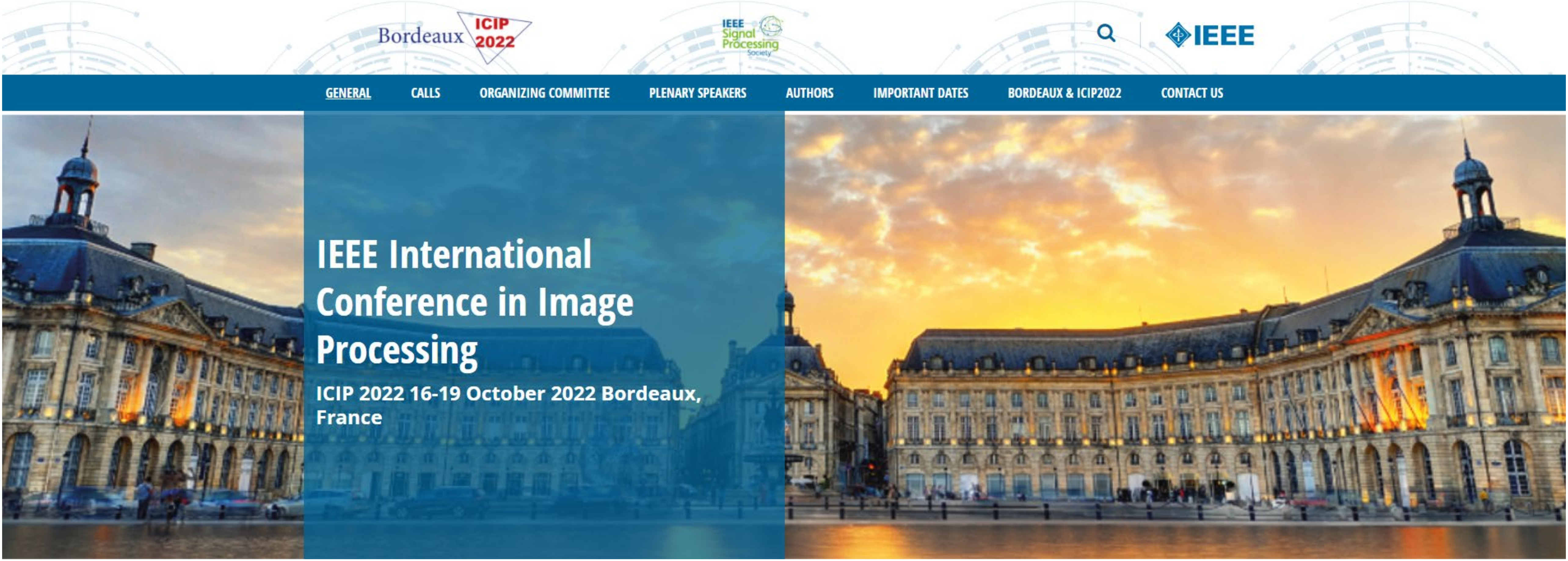
Estimating soil moisture from HSI: data acquisition

https://platform.ai4eo.eu/seeing-beyond-the-visible



Estimating soil moisture from HSI: data acquisition



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TAKING THE PULSE OF OUR PLANET FROM SPACE

EUMETSAT ECMWF EUSPA

Estimating soil moisture from hyperspectral images using (on-board) machine learning

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May 24, 2022