

Delivery of national datasets using Machine Learning and Earth Observation



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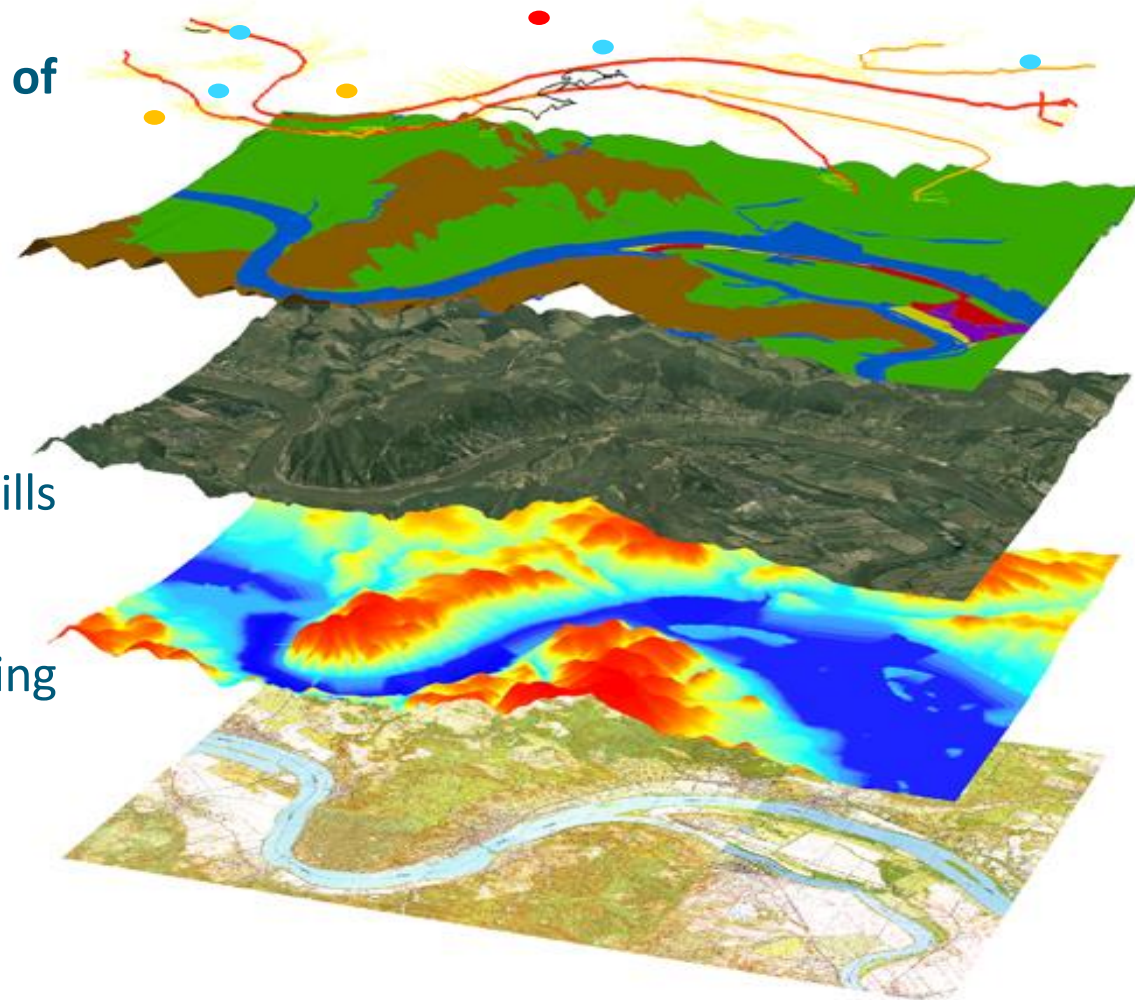
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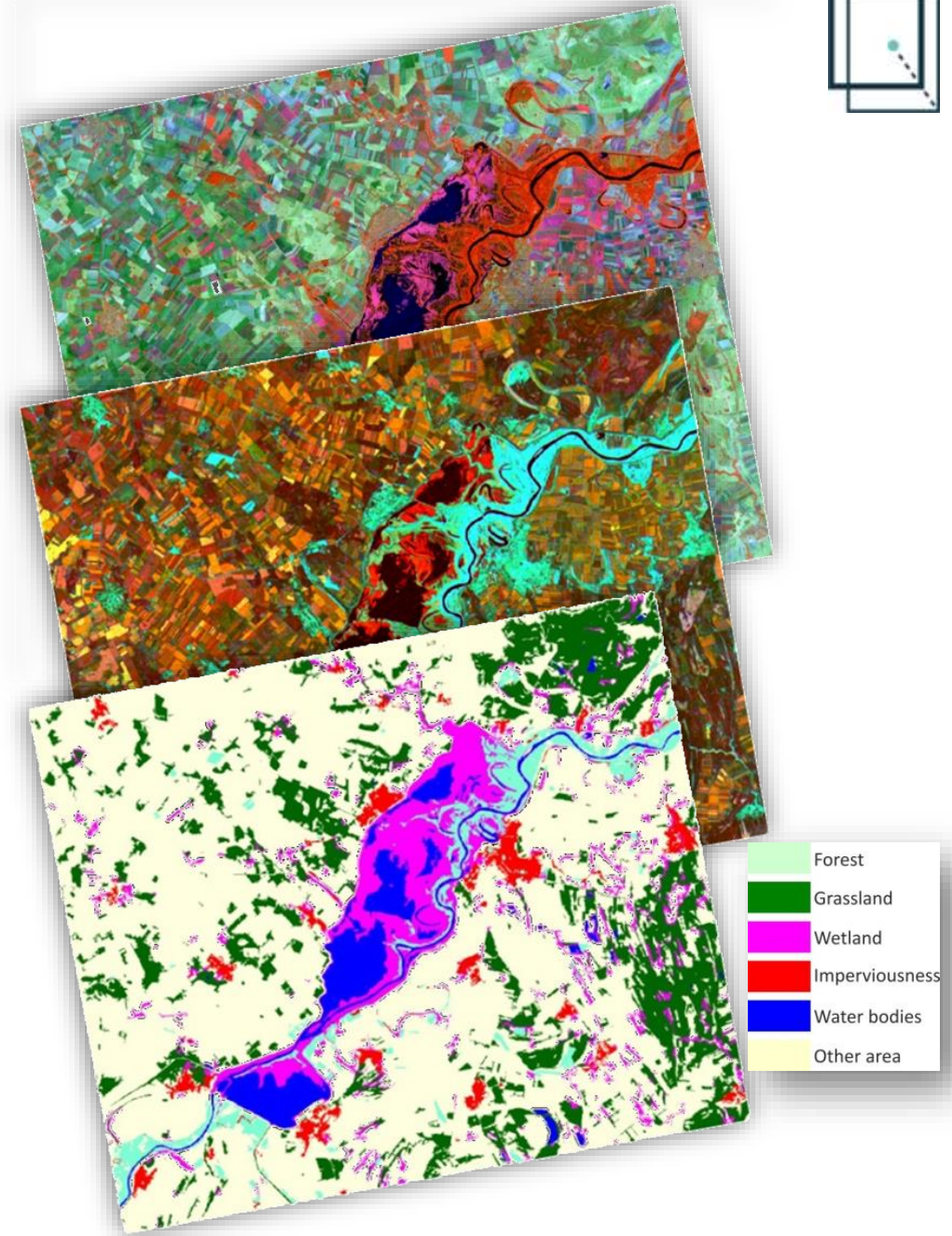
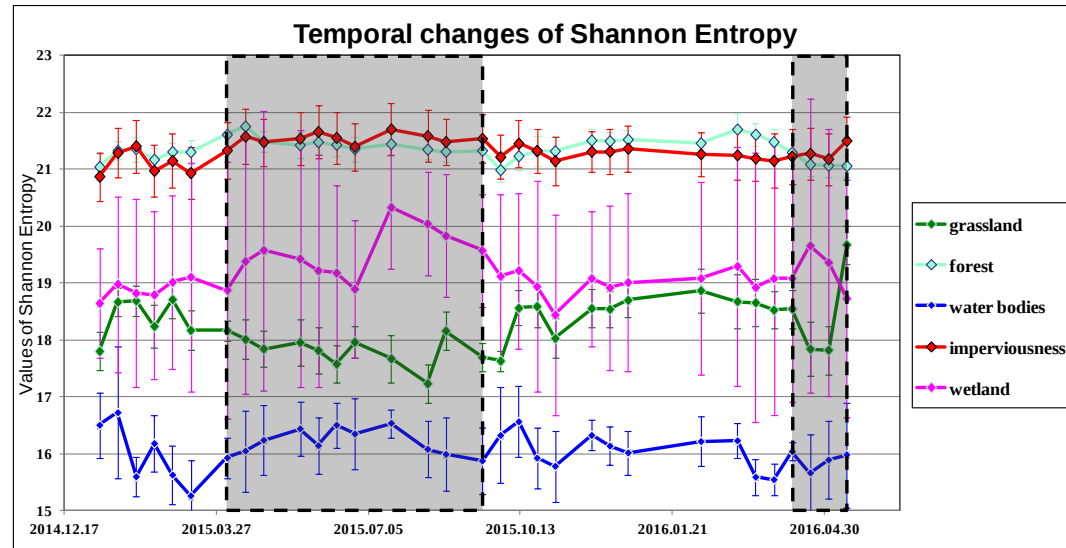
Lechner Knowledge Centre (LTK)

- background institution to the **Prime Minister's Office**
- fulfilling **NMCA roles** since 2019 (integration of FÖMI)
- managing the largest and **most complete collection of spatial data** sets in Hungary
- spatial data related to the **natural environment**
- official records related to the **built environment**
- specific **processing, analysis and IT development** skills and activities in-house
- up-to-date **geospatial solutions** supporting government, authorities and the public
- **sharing and dissemination of knowledge**



Remote Sensing capabilities

- Balanced use of quantitative and visual methods
- Combined use of different data sources
 - RS:
 - airborne/space-borne
 - optical and radar (**fusion**, **polarimetry**)
 - Field surveys
 - Official: LPIS, cadastre, topography
- Processing of big geospatial data (national, EU)



Country-wide mapping of agricultural crops and grasslands based on ML and EO



Motivation



- A huge amount of data available
 - RS/EO: aerial & satellite imagery, ...
 - Thematic: Land Cover, topography, cadastre, ...
- Country-wide, operational tasks
 - Time pressure, only minimal time for R&D
- Limited human resources
- Good IT infrastructure

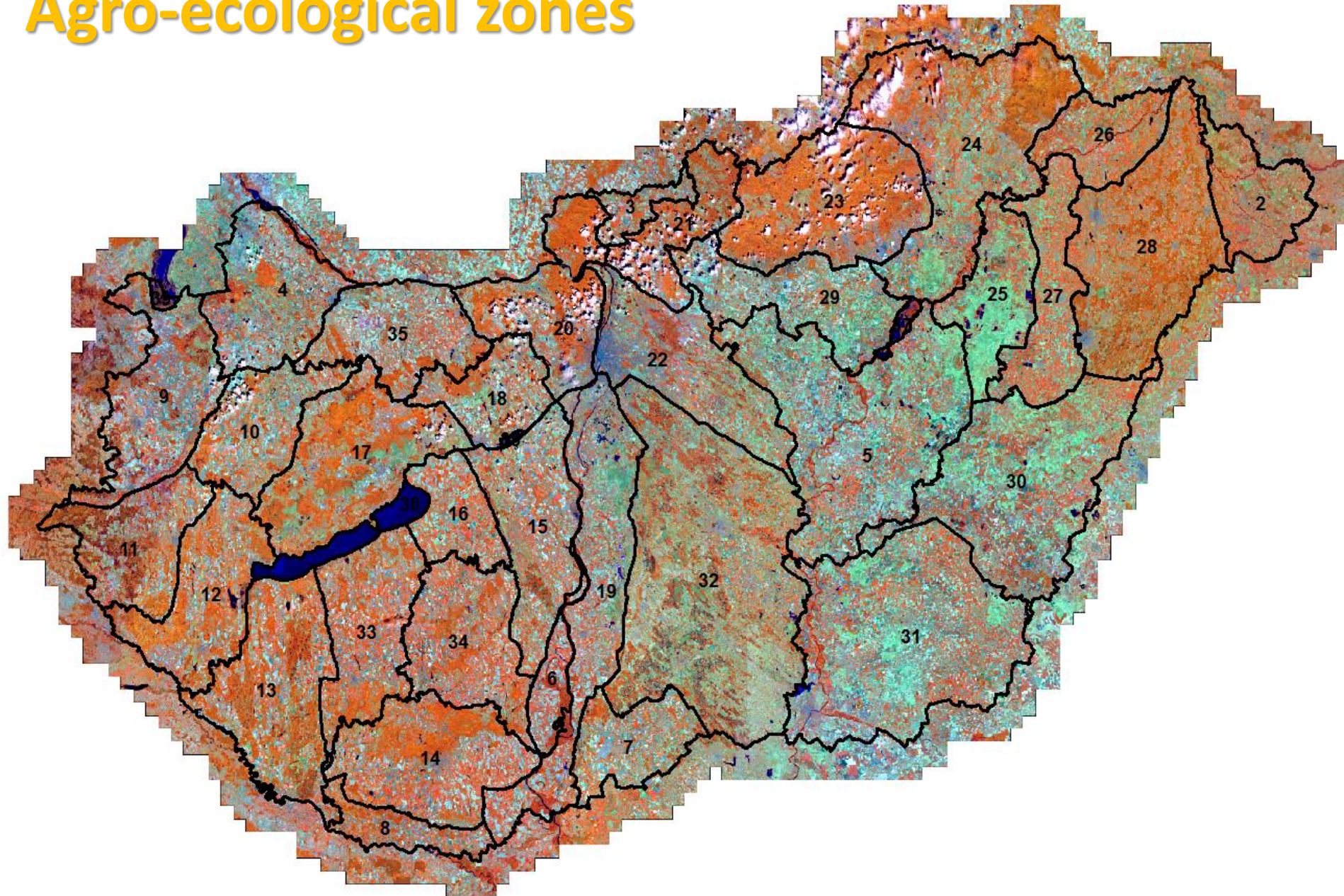


Objective and implementation plan

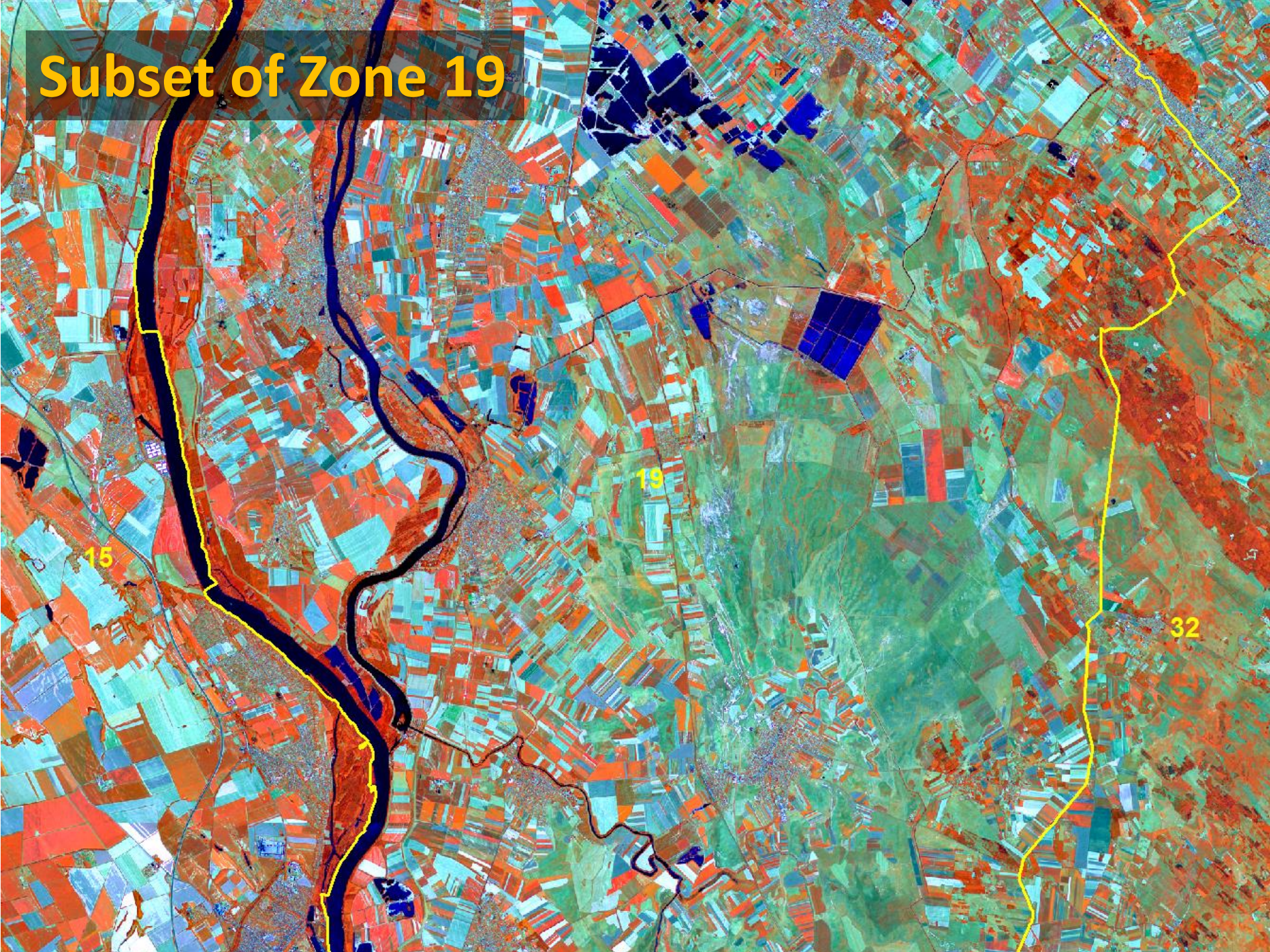
- Objective:
 - Country-wide mapping of grasslands for the control of agricultural subsidies
 - In a couple of weeks
 - With high reliability
 - With up-to-date and repeatable methodology
- Implementation plan:
 - Machine Learning based on time series of optical & radar data (including spectral indices and polarimetry), huge amount of training and test data
 - Based on literature review & expert input: SVM, Random Forest or Deep Learning
- Decision: Random Forest
 - „Ensemble” method based on decision trees
 - Robust, not sensitive to distribution and scale of input variables
 - No preliminary normalization needed
 - Can handle thematic and continuous input variables together
 - Available in numerous open-source projects, easy to automate and run in a distributed environment



Agro-ecological zones

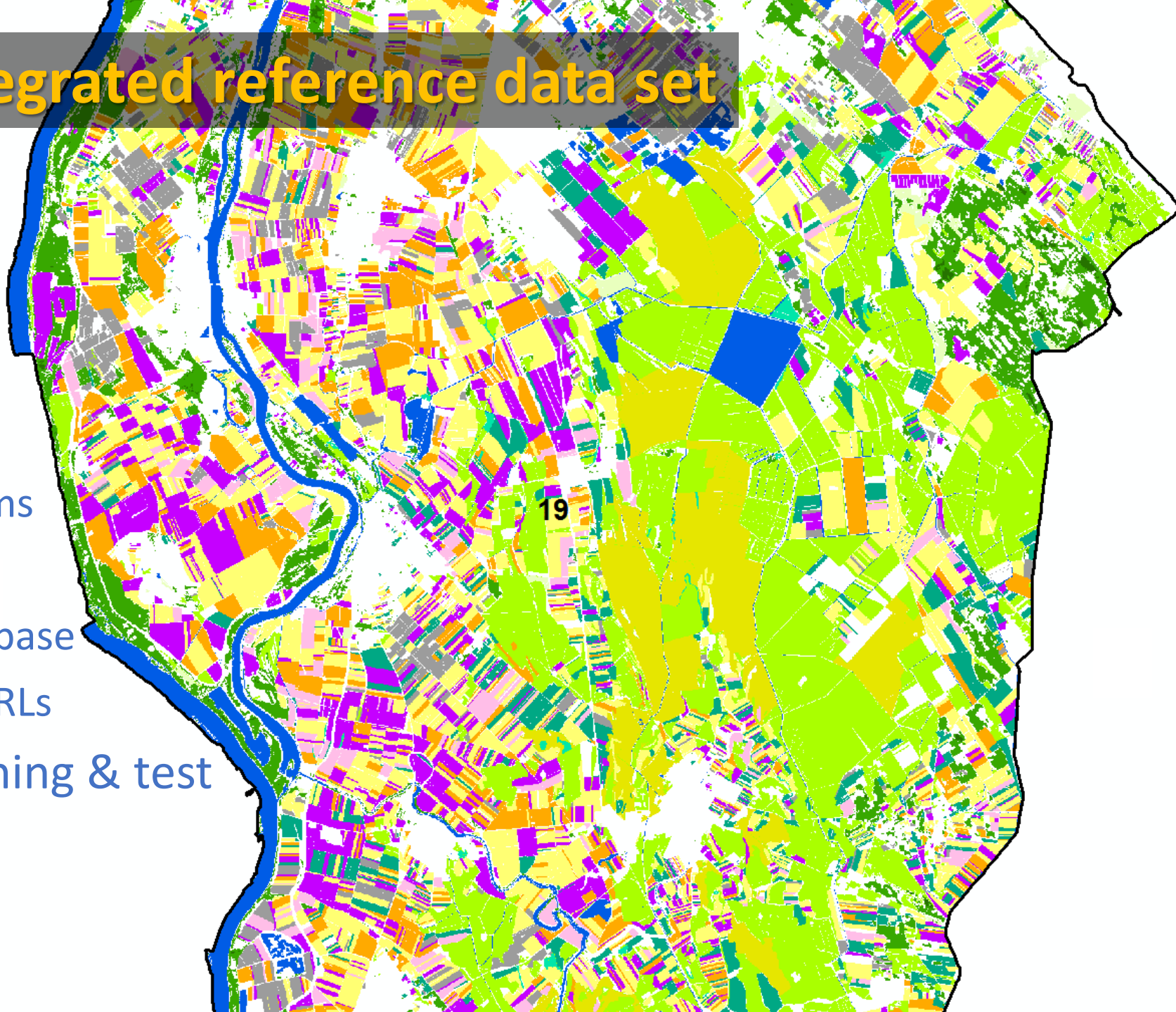


Subset of Zone 19



Integrated reference data set

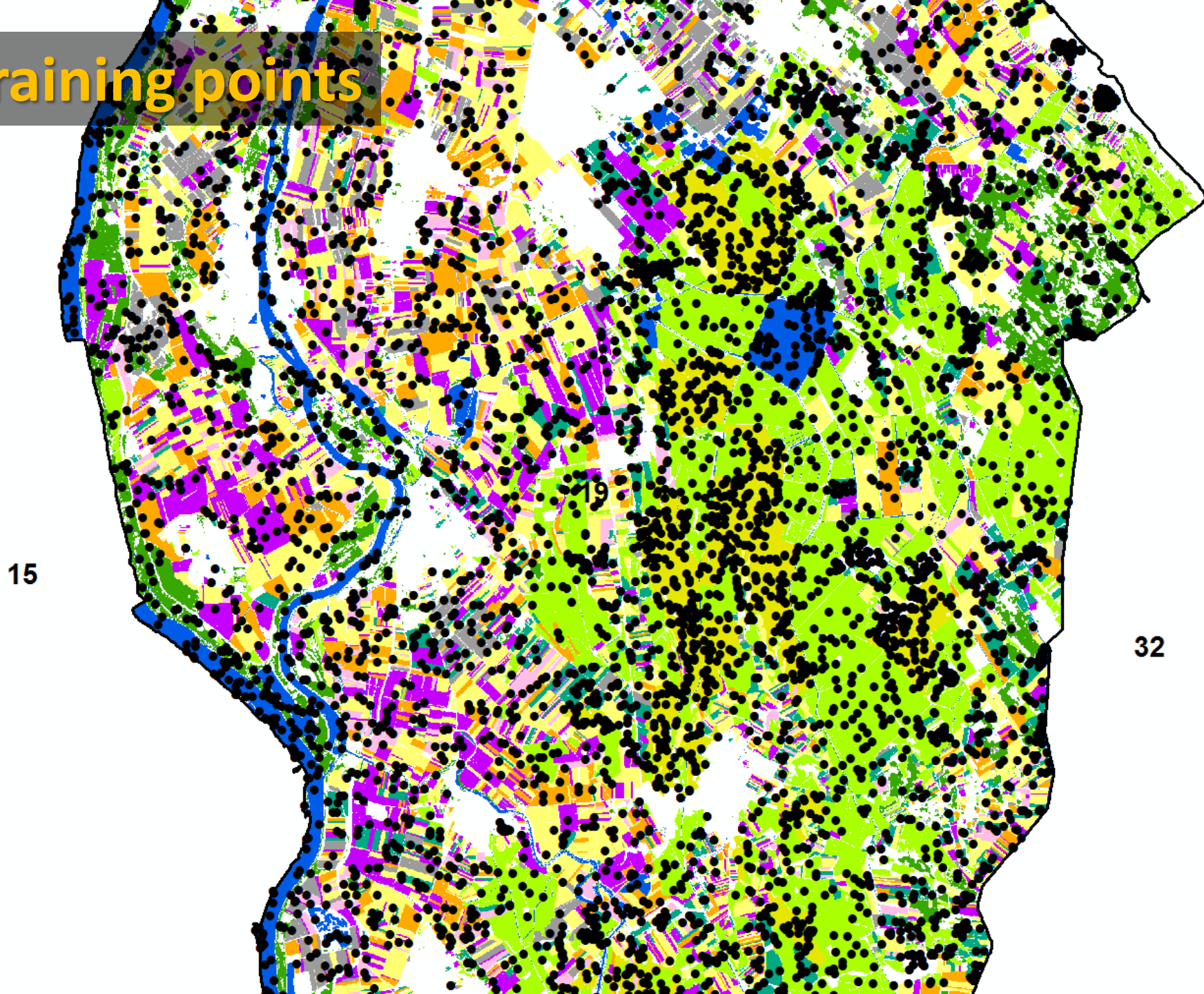
- Sources:
 - LPIS
 - Farmer's claims
 - Topo waters
 - Forestry database
 - Copernicus HRLs
- Divided to training & test



- Kalászos
- Kukorica
- Napraforgó
- Lucerna
- Repce
- Gyep
- Egyéb
- Csúnya gyep
- Vizenyős gyep
- Szikes gyep
- Lombhullató erdő
- Tülevelű erdő
- Víz



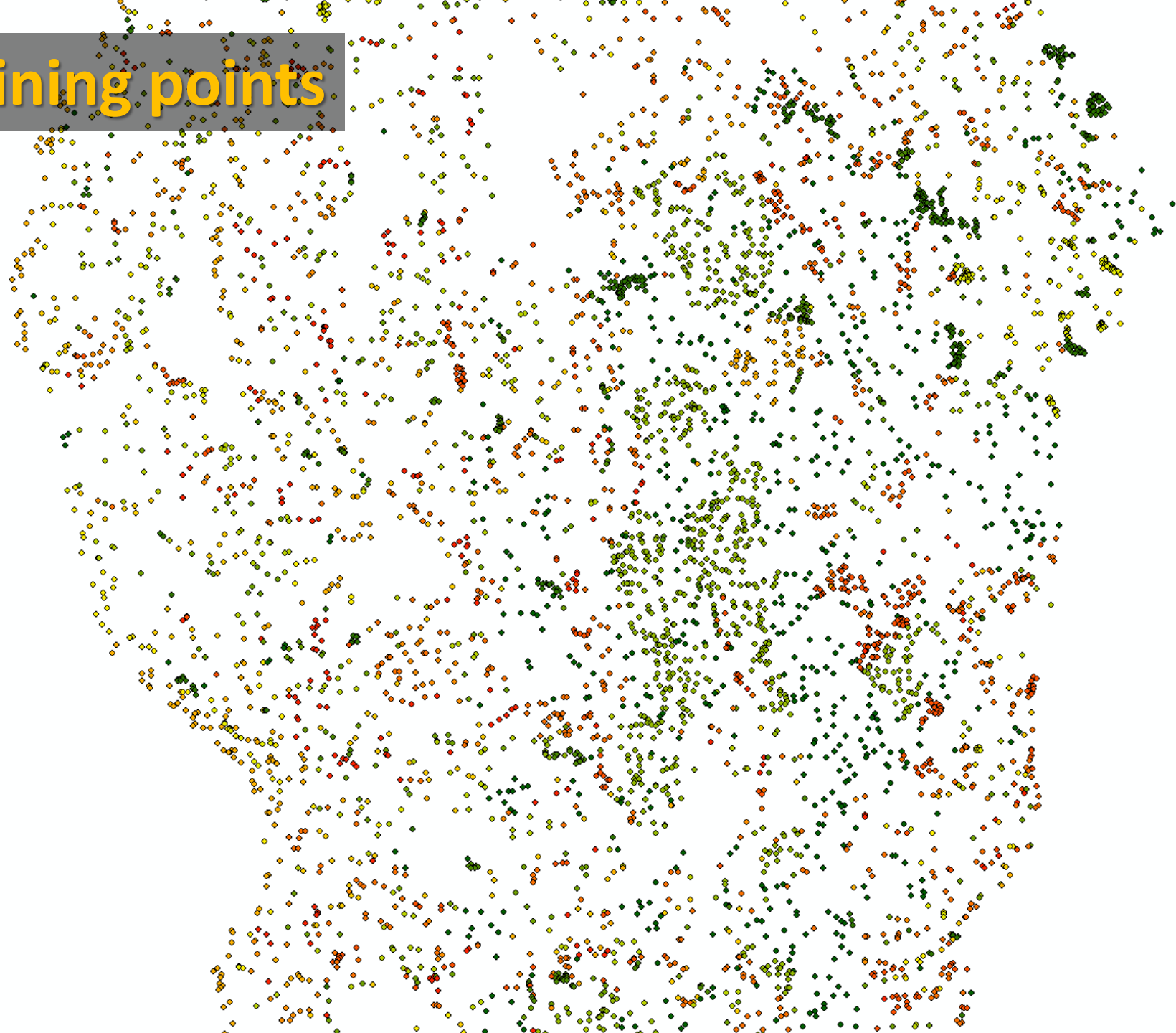
Training points



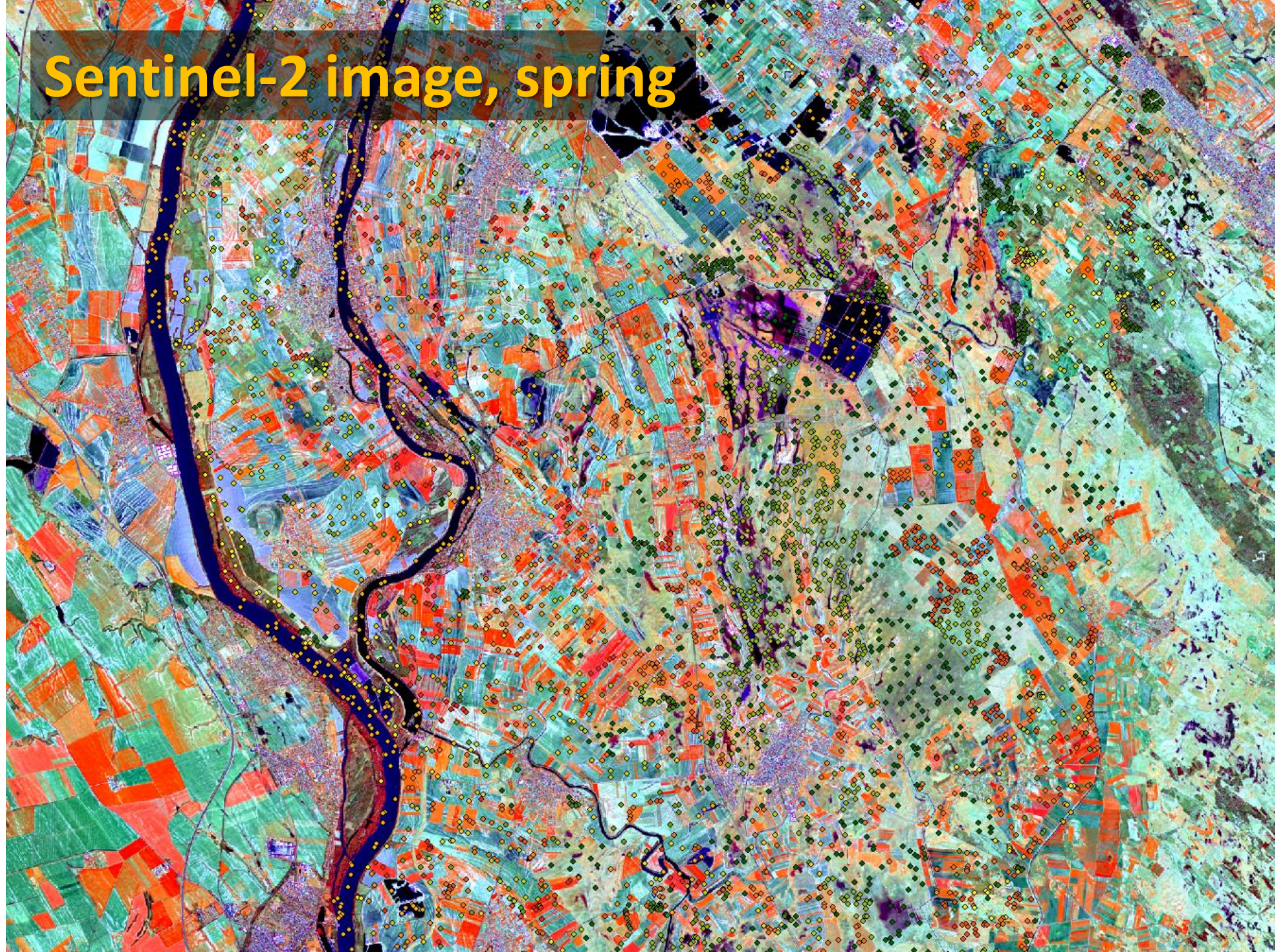
- Kalászos
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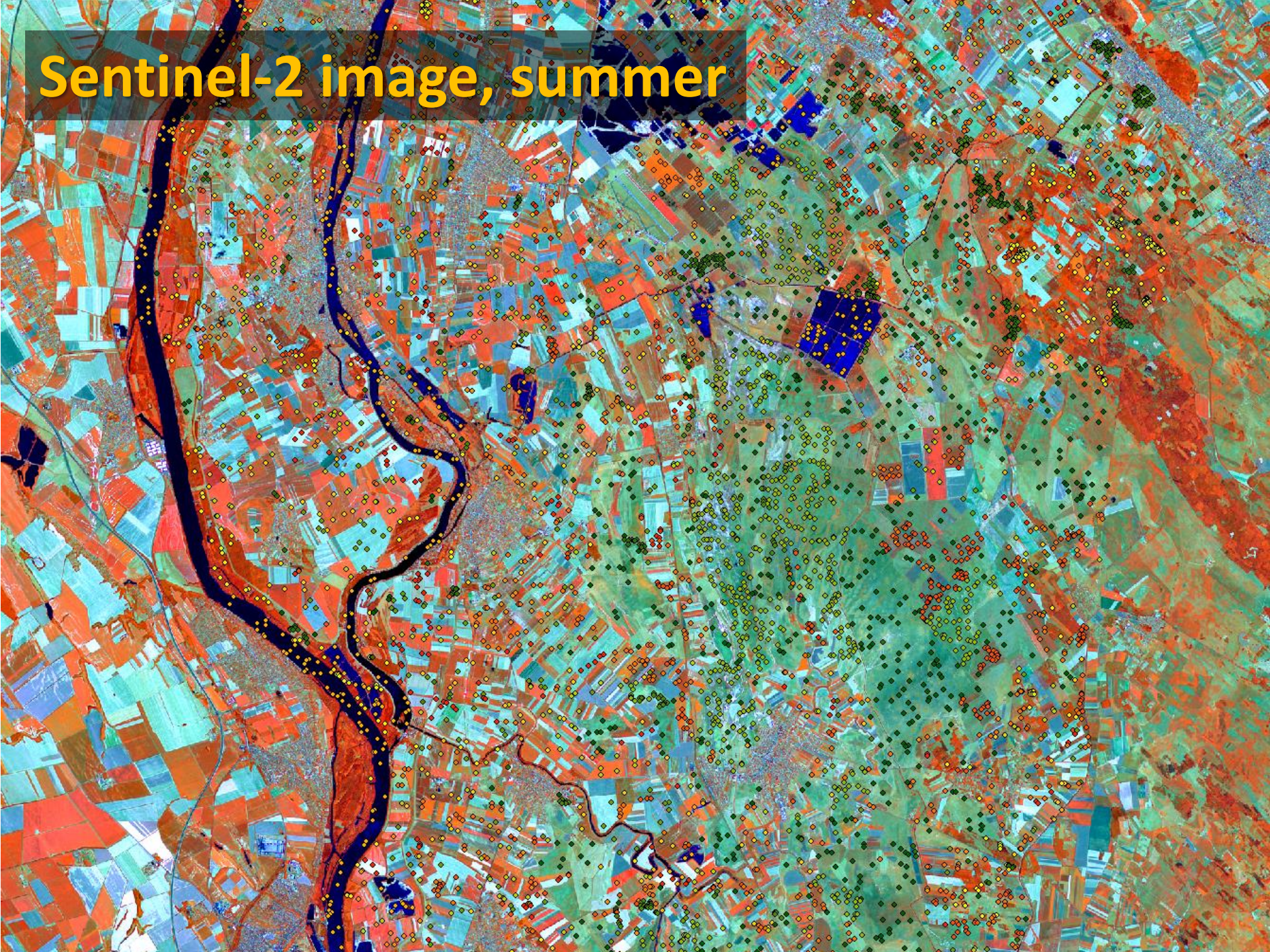
Training points



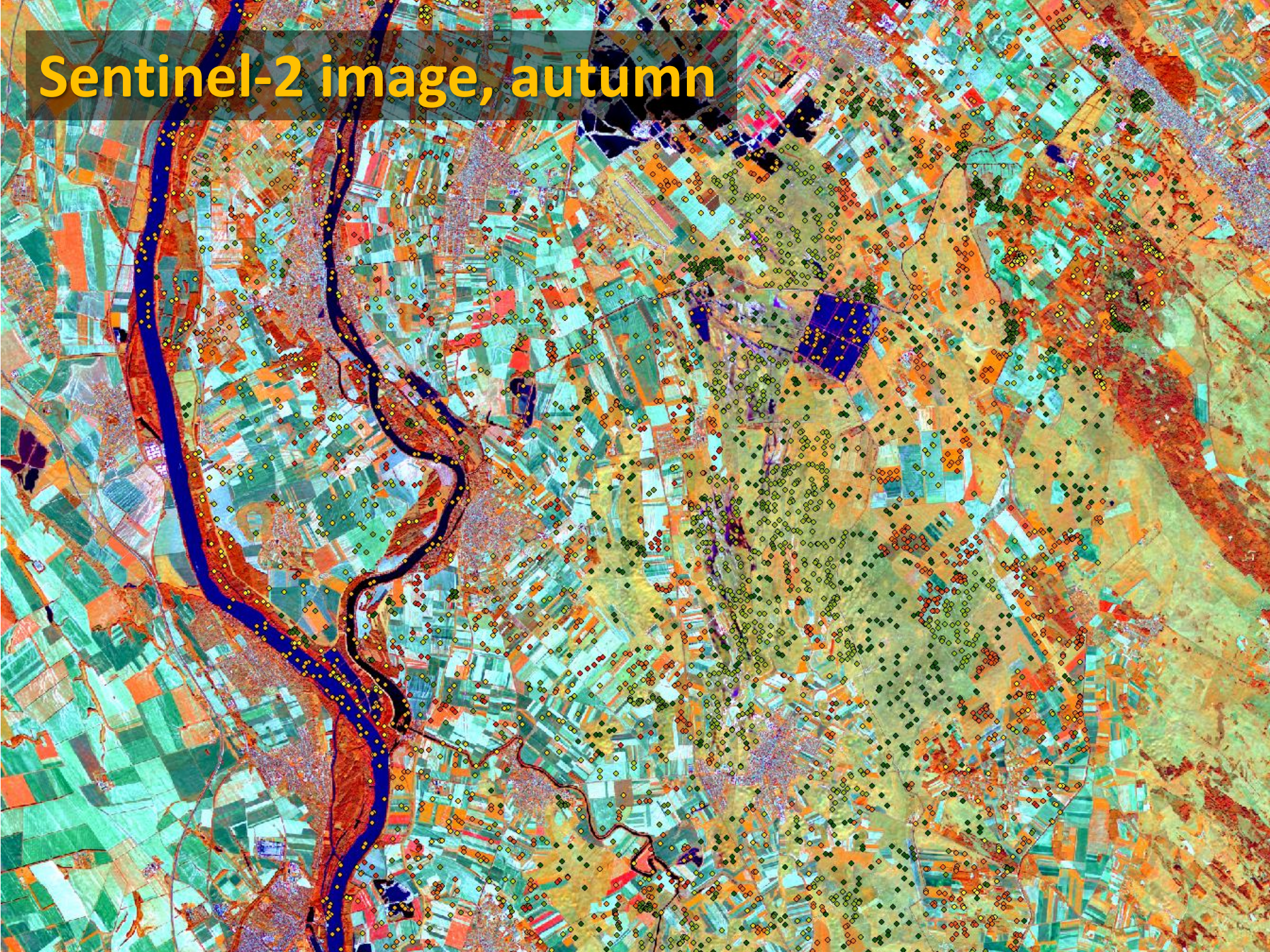
Sentinel-2 image, spring



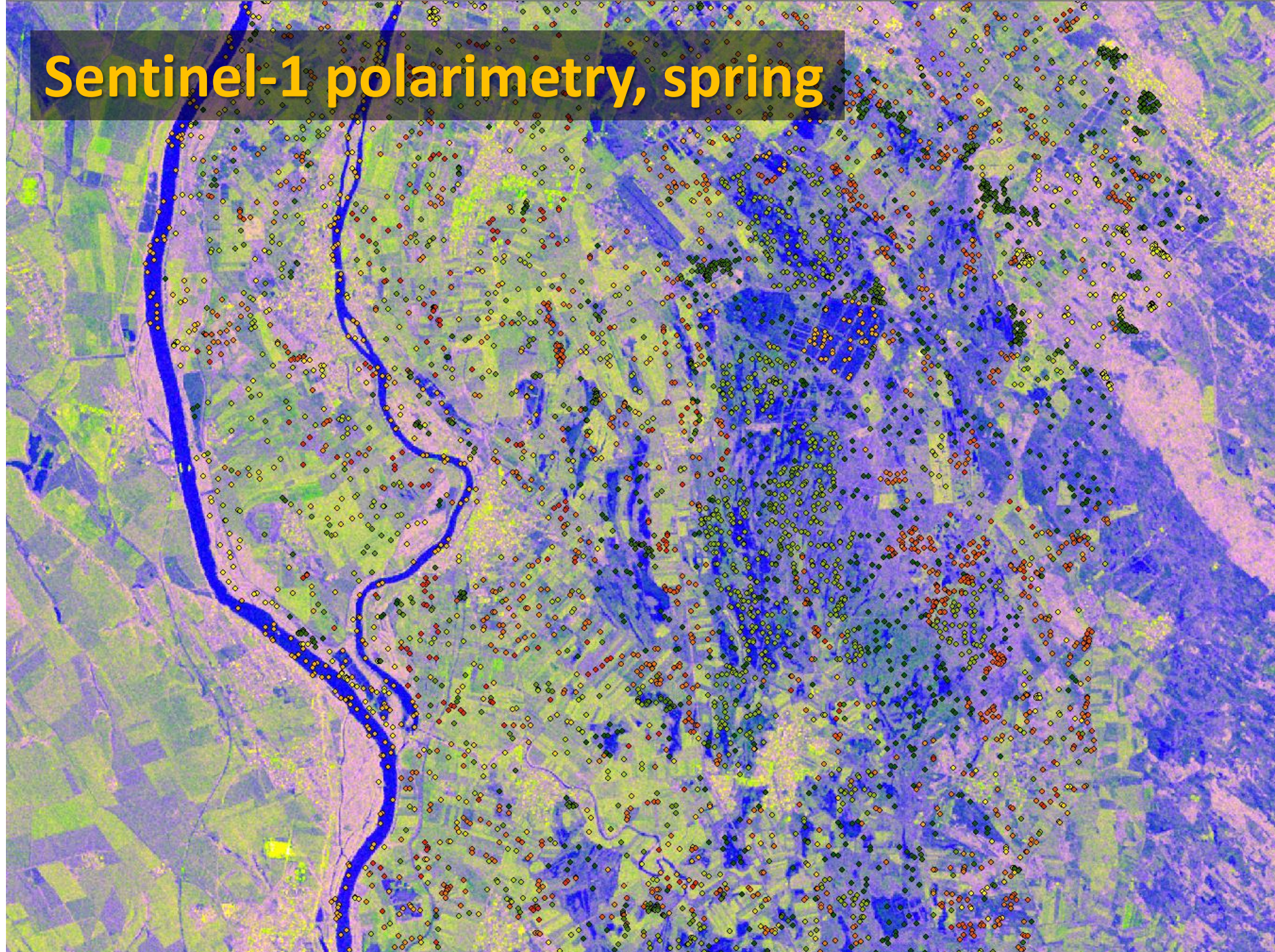
Sentinel-2 image, summer



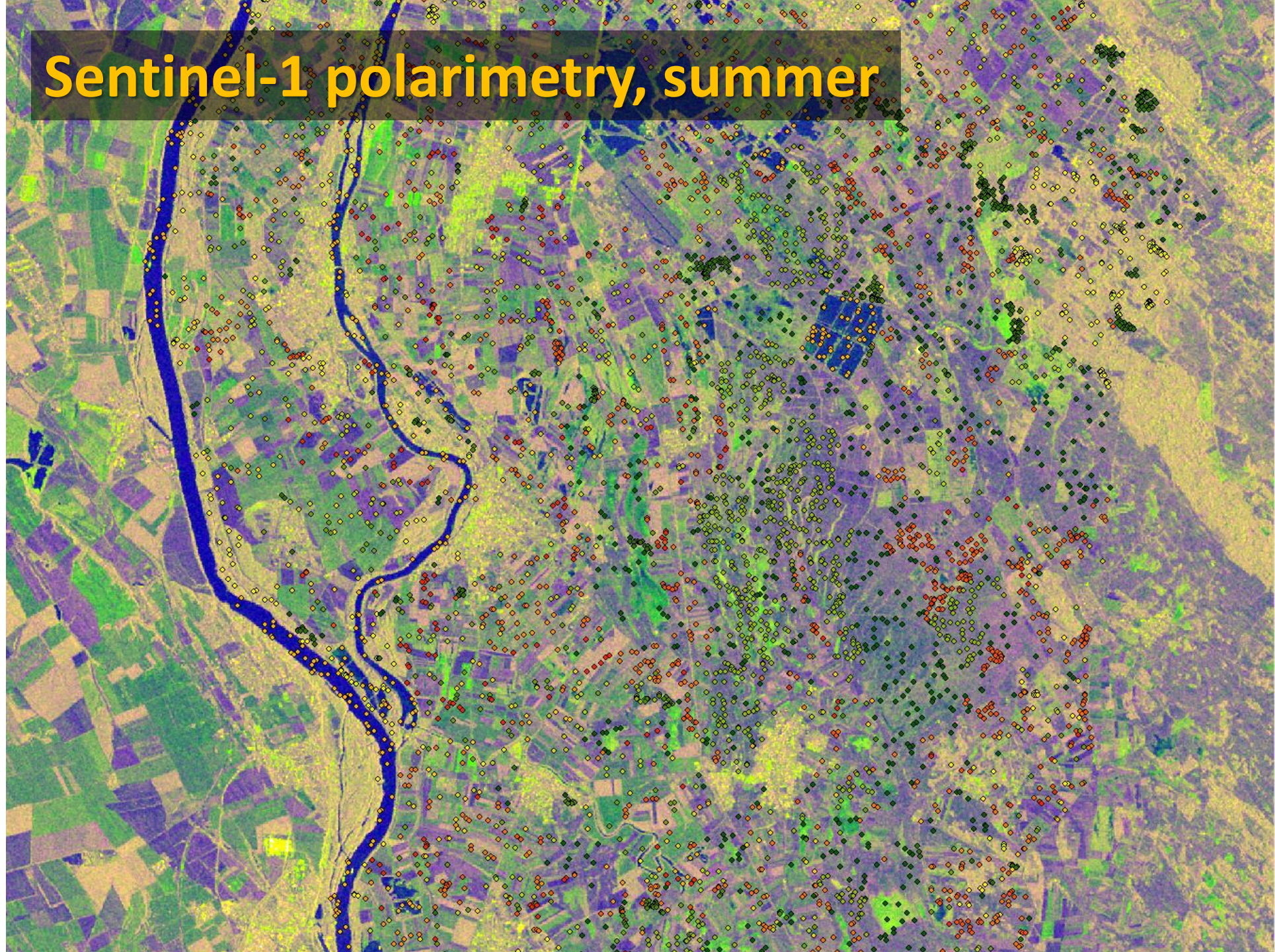
Sentinel-2 image, autumn



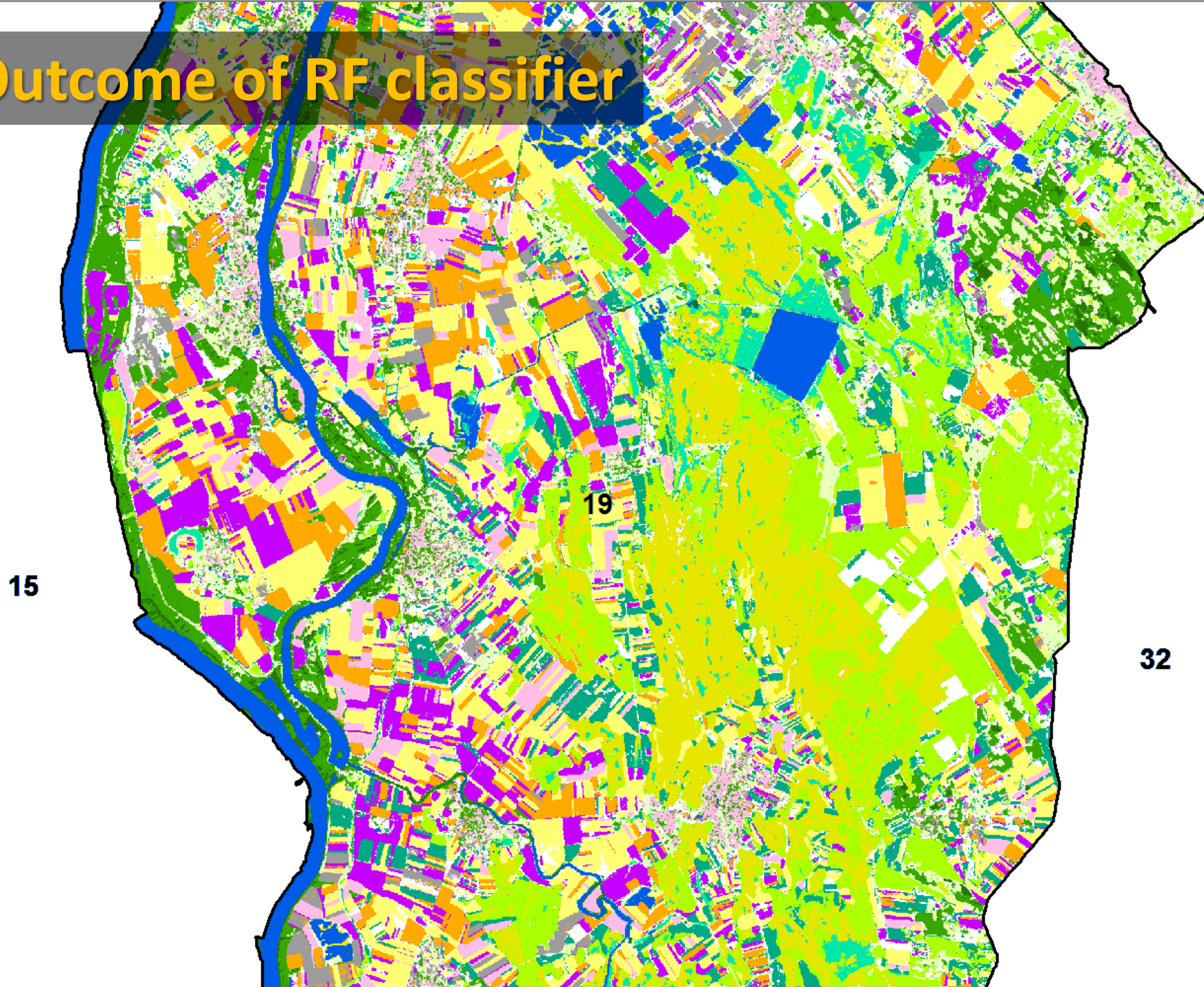
Sentinel-1 polarimetry, spring



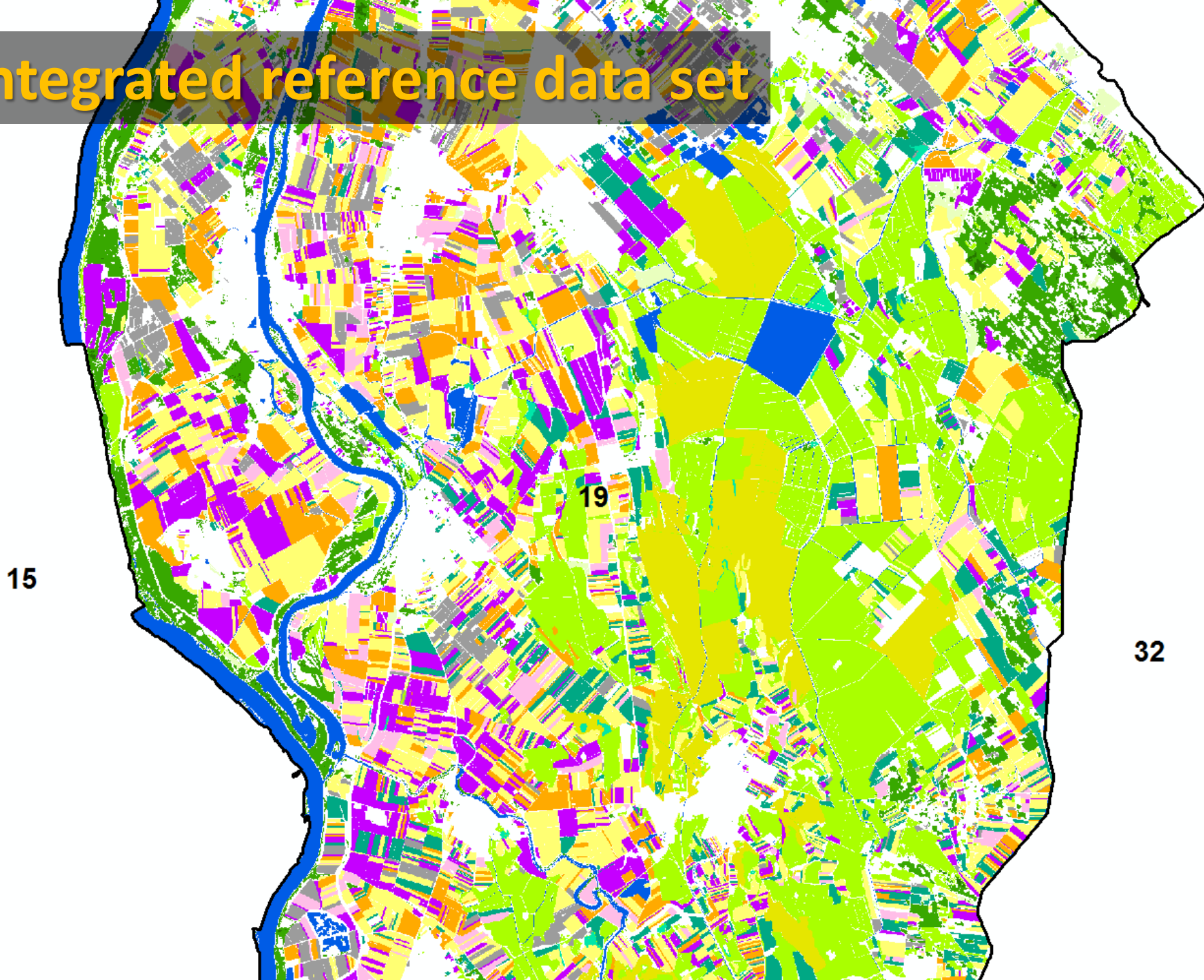
Sentinel-1 polarimetry, summer



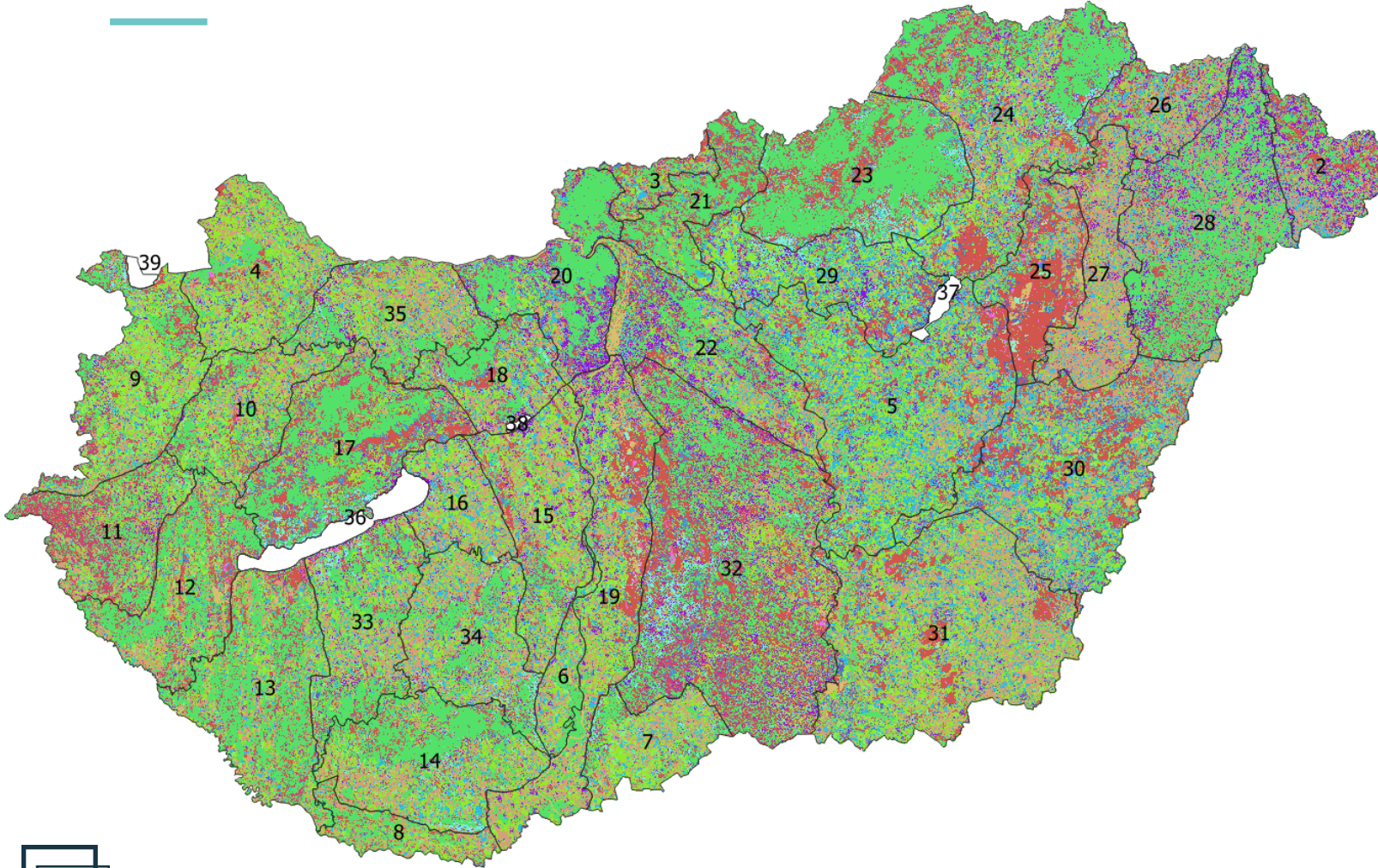
Outcome of RF classifier



Integrated reference data set



Country-wide results, 2021



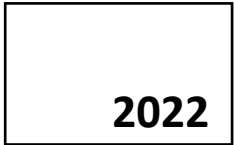
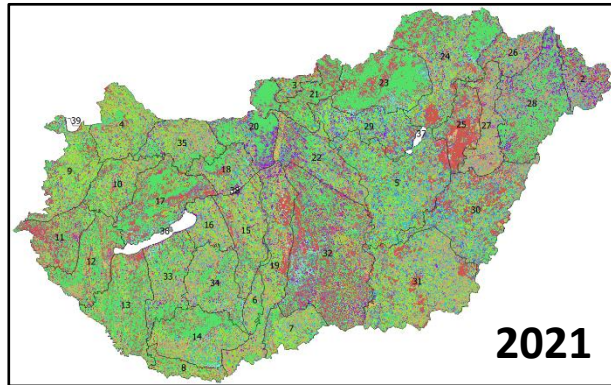
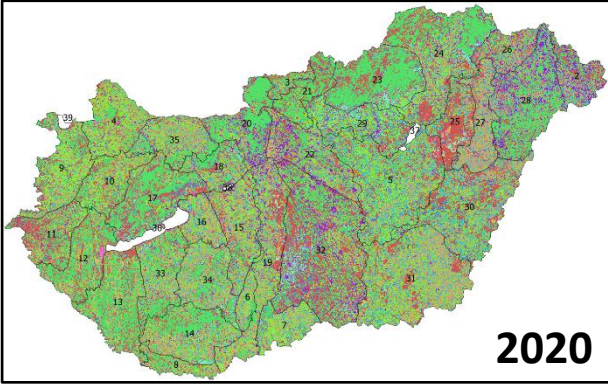
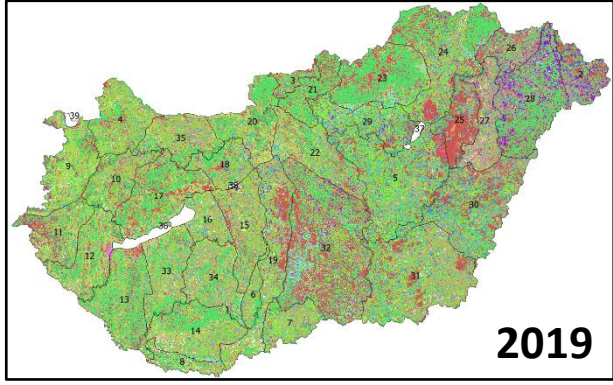
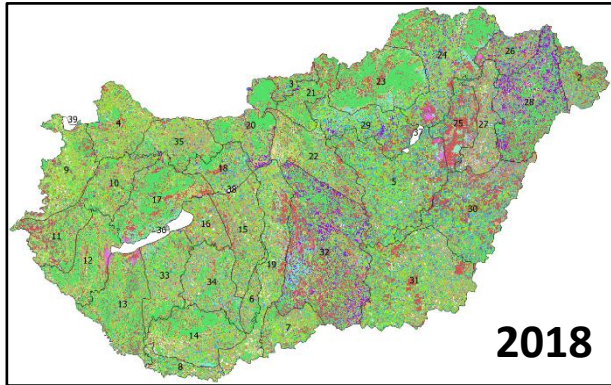
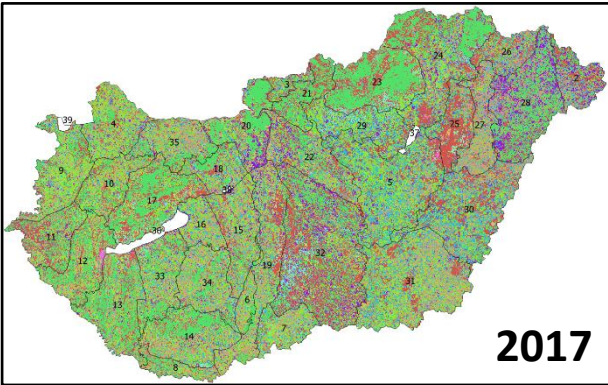
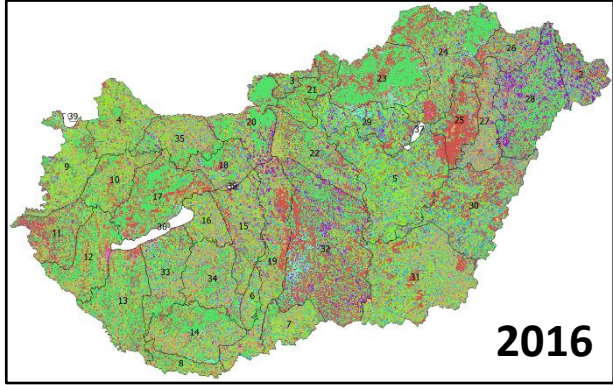
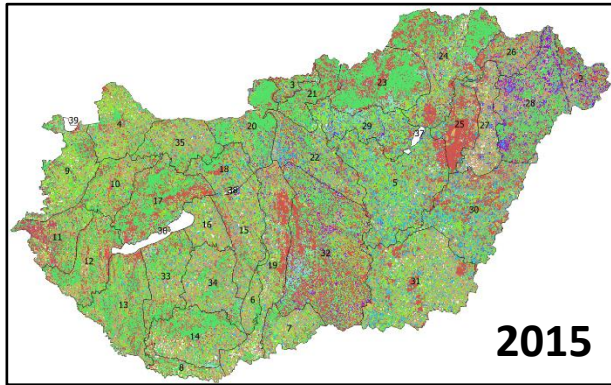
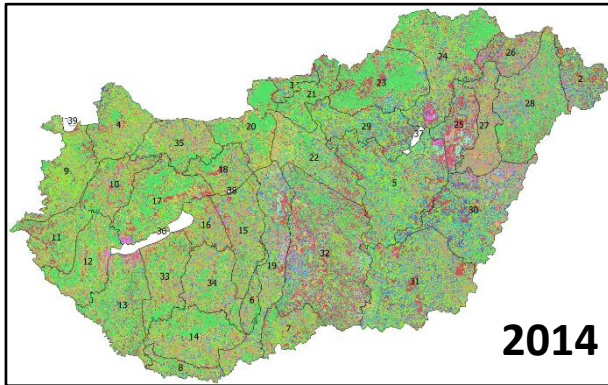
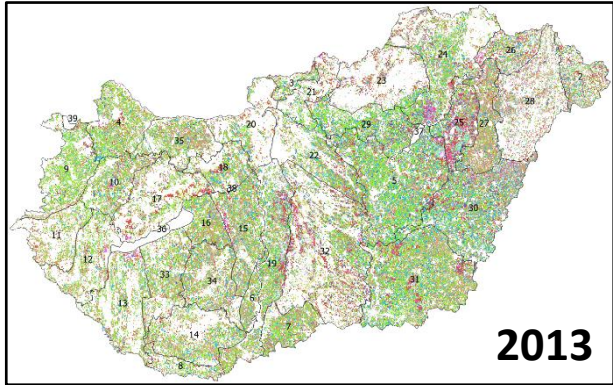
Zone	p_0 (%)	Zone	p_0 (%)	Zone	p_0 (%)
2	90,76	14	96,95	26	92,33
3	93,88	15	97,33	27	97,19
4	96,28	16	98,18	28	94,76
5	94,97	17	87,88	29	94,56
6	98,08	18	96,03	30	95,83
7	97,57	19	93,33	31	97,52
8	96,88	20	92,89	32	91,01
9	96,27	21	93,98	33	96,67
10	93,98	22	94,71	34	97,21
11	95,25	23	89,99	35	96,41
12	94,21	24	92,02		
13	95,84	25	81,62		

Categories	
Winter cer.	Soy
Spring cer.	Deciduous forest
Maize	Needleleaf forest
Sunflower	Surface waters
Sugarbeet	Tobacco
Alfalfa	Grassland
Peas	Uncultivated grassland
Potato	Wet grassland
Rapeseed	Alkaline grassland
Vineyards	Grassland with herbaceous weeds
Orchards	Grassland with arboreal vegetation
Oil seed pumpkin	Other

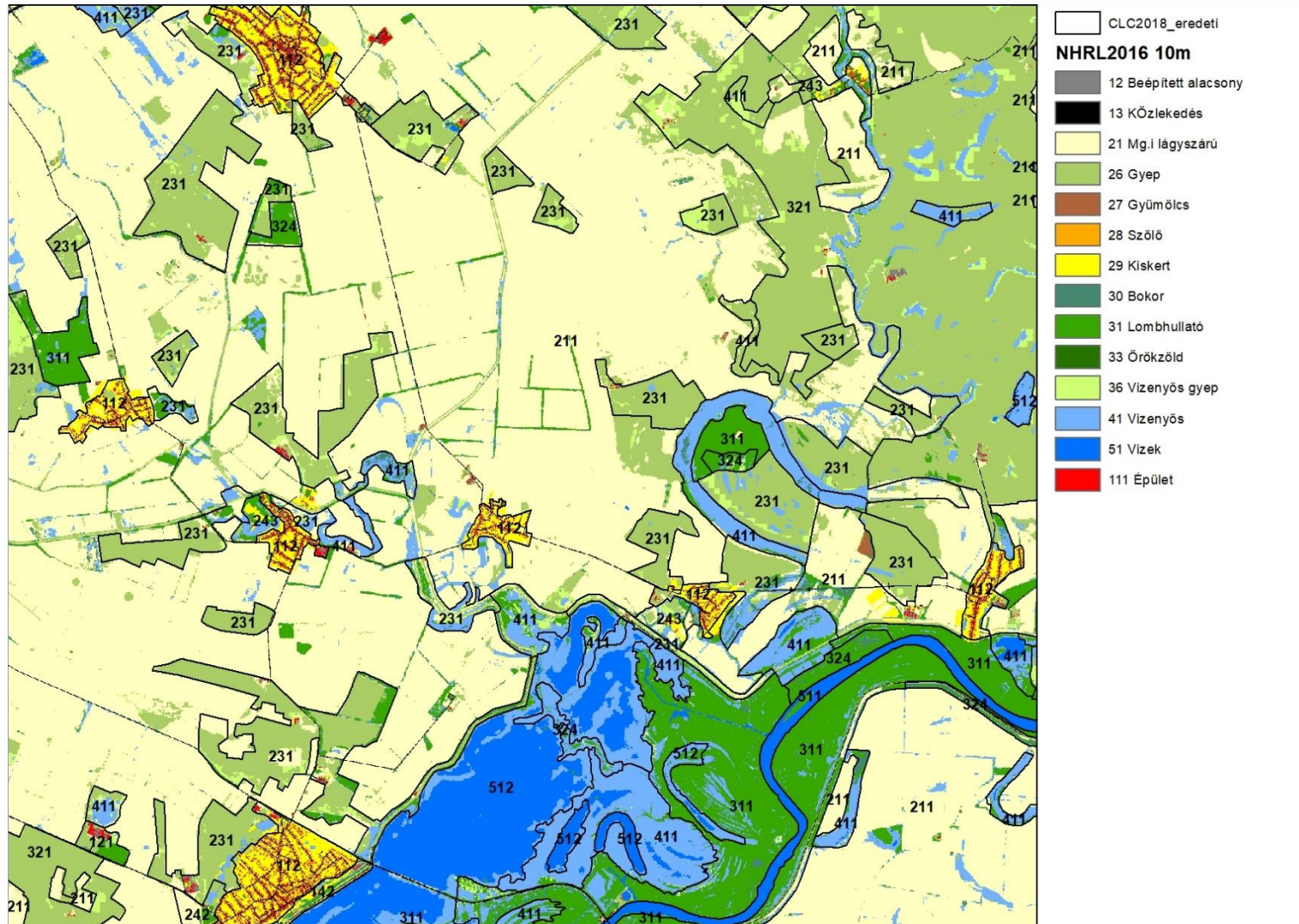




Country-wide results, 2013-21



National High Resolution Land Cover (NHRL)

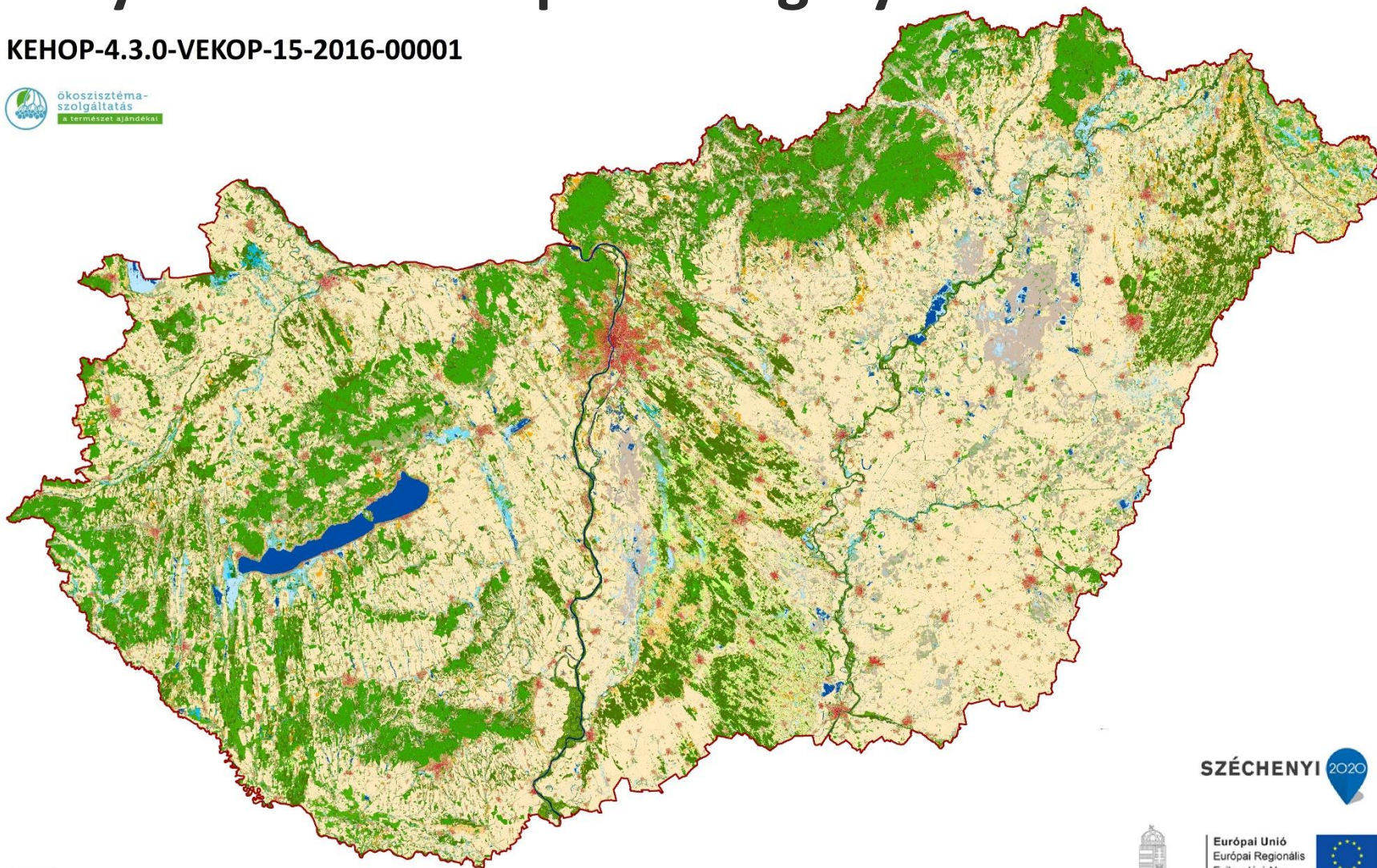


Tisza-tó és környéke

- ✓ Data integration & RF classification: Sentinel-1&2 (radar and optical) time series, thematic data sets
- ✓ Yearly data (2016-2021 ready)
- NHRL2022 under construction
- Visual and manual harmonization within time series
- Used in a large number of applications

Ecosystem Base Map of Hungary

KEHOP-4.3.0-VEKOP-15-2016-00001



Jelkulcs

- 1 110 : Alacsony épület
- 1 120 : Magas épület
- 1 210 : Szilárd burkolatú utak
- 1 220 : Földutak
- 1 230 : Vasutak
- 1 310 : Egyéb burkolt vagy burkolatlan mesterséges felületek
- 1 410 : Zöldfelületek mesterséges környezetben fákkal
- 1 420 : Zöldfelület mesterséges környezetben fák nélkül
- 2 100 : Szántóföldek
- 2 210 : Szőlők
- 2 220 : Gyümölcsösök, bogdosók
- 2 230 : Energiaültetvények
- 2 310 : Komplex művelési szerkezet épületekkel
- 2 320 : Komplex művelési szerkezet épületek nélkül
- 3 110 : Nyílt homokpuszta gyepek
- 3 120 : Zárt gyepek homokon
- 3 200 : Szikes és szikesedésre hajlamos gyepek
- 3 310 : Sziklakibúvással tarkított mészkezdő gyepek
- 3 320 : Sziklakibúvással tarkított egyéb gyepek
- 3 400 : Zárt gyepek kötött talajon vagy domb és hegyvidéken
- 3 500 : Máshová nem besorolható lágyszárú növényzet
- 4 101 : Bükkösök
- 4 102 : Gyertyános kocsánytalan tölgyesek
- 4 103 : Cseresek
- 4 104 : Molyhos tölgyesek
- 4 105 : Ny-Dunántúli erdőfenyvesei
- 4 106 : Ny-Dunántúli erdőfenyő-elegyes lombosok
- 4 107 : Hazai nyárasok
- 4 108 : Hegy- és dombvidéki pionír erdők
- 4 109 : Gyertyános kocsányos tölgyesek
- 4 110 : Elegetlen és kőselegyes kocsányos tölgyesek
- 4 111 : Egyéb, többletvízhatástól független őshonos dominanciájú erdők
- 4 112 : Egyéb elegyes lombosok
- 4 201 : Puhafás ártéri erdők
- 4 202 : Keményfás ártéri erdők
- 4 301 : Elegetlen és kőselegyes kocsányos tölgyesek TVHA
- 4 302 : Égeresek
- 4 303 : Többletvízhatás alatti gyertyános kocsányos tölgyesek
- 4 304 : Ártéri kívüli fűzések
- 4 305 : Ártéri kívüli, többletvízhatás alatti nyárasok
- 4 306 : Nyíresek
- 4 307 : Többletvízhatással érintett cseresek
- 4 308 : Egyéb, többletvízhatással érintett őshonos dominanciájú erdők
- 4 309 : Egyéb, többletvízhatással érintett elegyes lombosok
- 4 401 : Tülevölgyek dominált ültetvények
- 4 402 : Akác dominált ültetvények
- 4 403 : Nemesnyár- és fűz dominált ültetvények
- 4 404 : Egyéb idegenhonos lombos fajok dominált erdők
- 4 501 : Pusztavég
- 4 502 : Folyamatban lévő felújítás
- 4 600 : Máshová nem besorolható fás száraz növényzet
- 5 110 : Vízben álló mocsári/lápi növényzet
- 5 120 : Időszakos vízhatás alatt álló gyepek valamint lágyszárú és mocsári
- 5 200 : Lágyszárú és mocsári
- 6 100 : Állóvizek
- 6 200 : Vízfolyások

SZÉCHENYI 2020



Európai Unió
Európai Regionális
Fejlesztési Alap



BEFEKTETÉS A JÖVŐBE



MTA
ÖKOLÓGIAI
KUTATÓKÖZPONT



MTA ATK TAKI

Current development: Application of Convolutional Neural Networks (CNNs)



Convolutional Neural Networks

- **Why CNN?**

- Widespread, universal Deep Learning algorithm supported by a large number of scientific papers
- Expected to provide good results also with fewer reference data
- Temporality can be taken into account (1D, 3D convolution)

- **Objective:** test applicability of 1D/2D/3D CNNs for LC mapping

- **Tools: Python – Tensorflow – Keras**

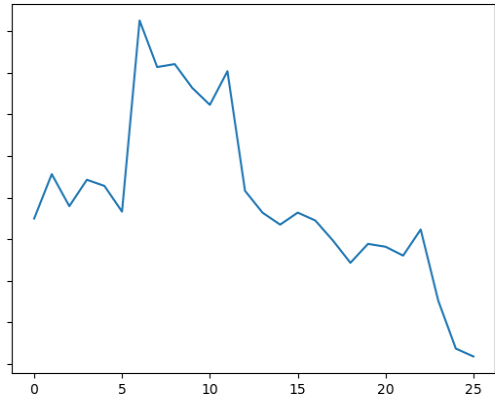
- Reference data and satellite imagery series divided into tiles and used as input for the neural network

- **Challenges:**

- Extreme memory consumption
- Execution times highly dependent on hyperparameter settings
- Tremendous amount of hyperparameter combinations, their effects on results and executions times can only be analyzed through extensive testing

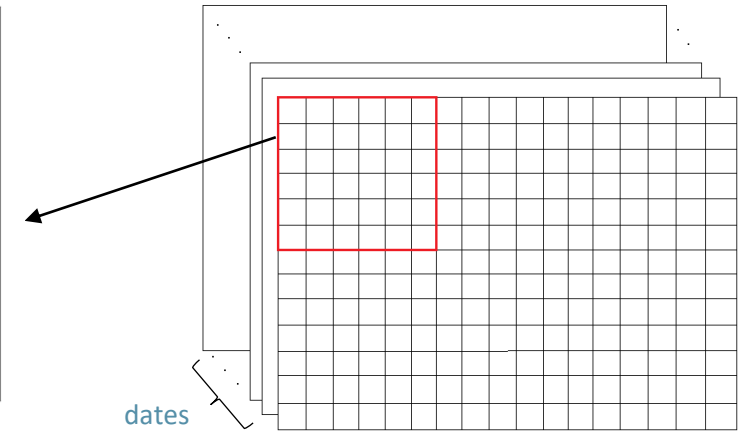
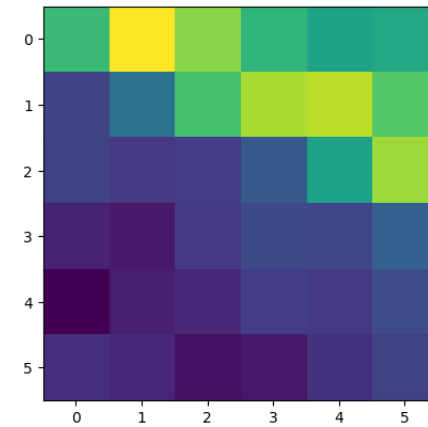
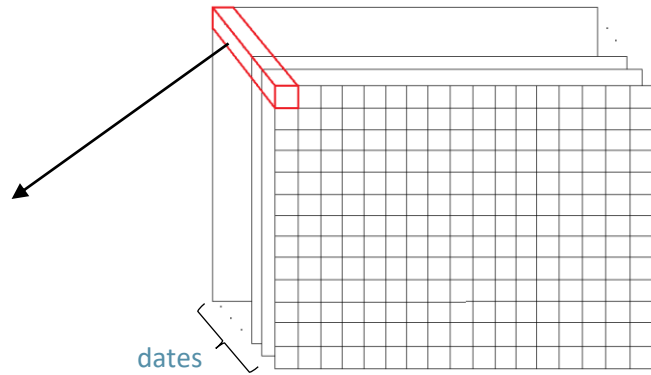


Methods – Input structures (one spectral band)



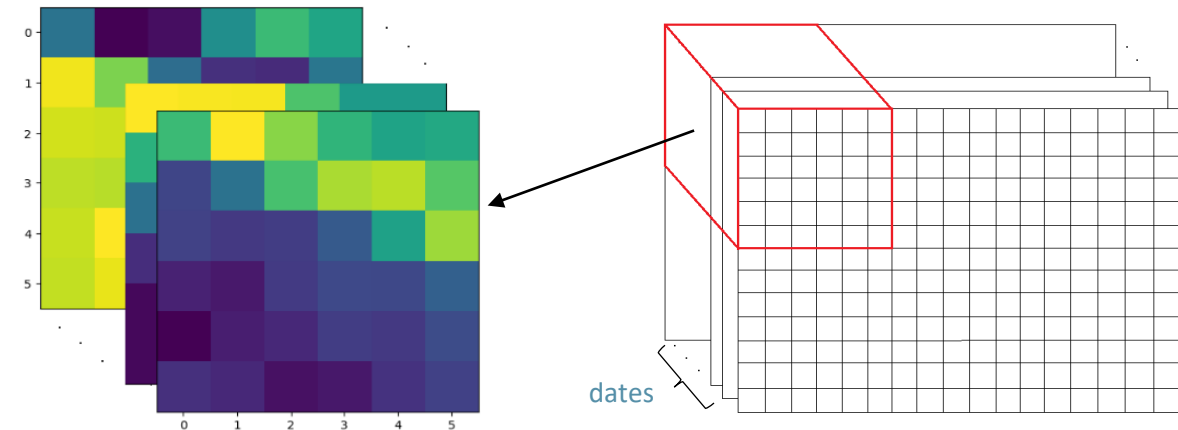
1D model

Time series of each pixel



2D model

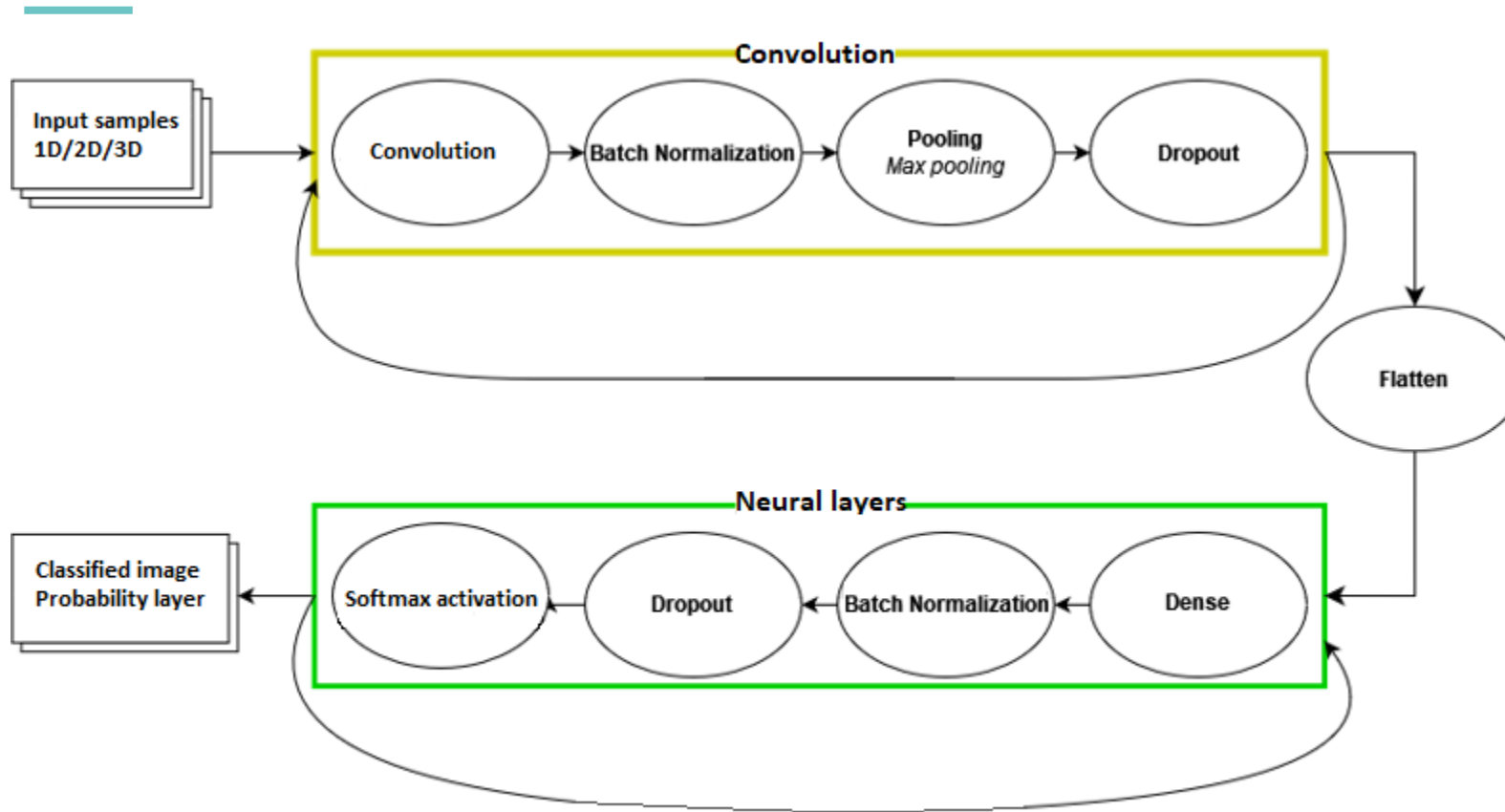
- Immediate environment of each pixel ($n \times n$ tile)
- Considers the values of each date as independent parameters



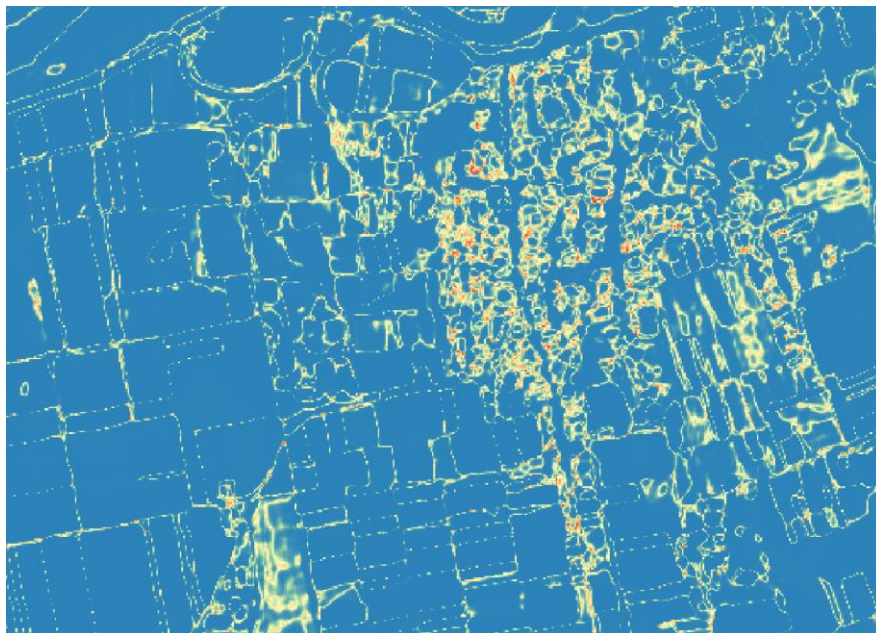
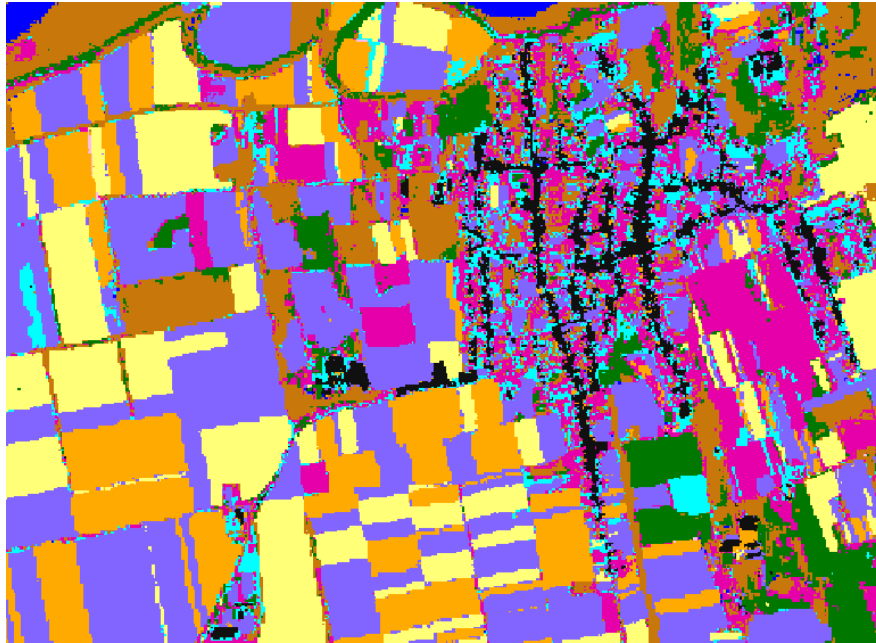
3D model

Spatially extended time series of each pixel and their immediate environment ($\text{dates} \times n \times n$ tile)

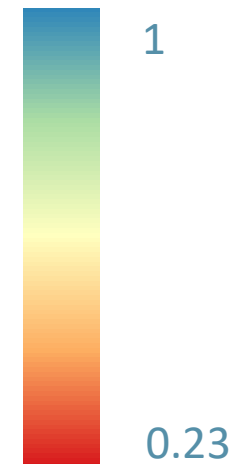
Methods – Basics of Convolutional Neural Networks



Results



Probabilities



Accuracies

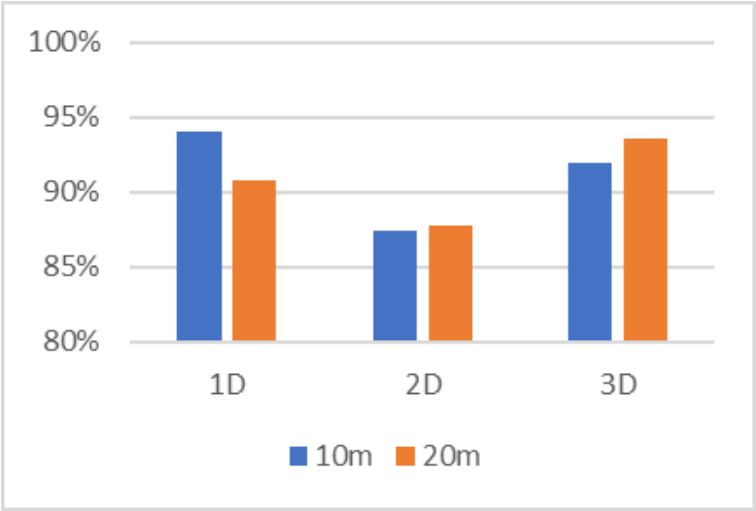


Chart: Overall accuracy of each base model in 10 and 20 metres spatial resolution

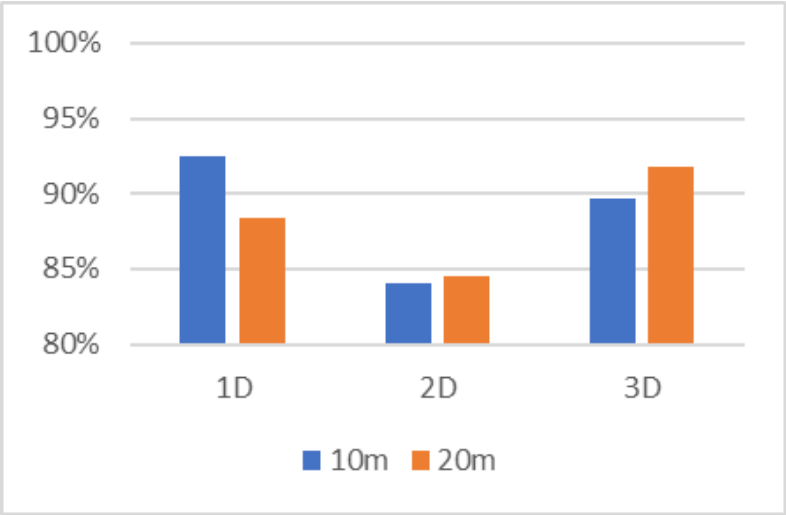


Chart: Kappa accuracy of each base model in 10 and 20 metres spatial resolution

Model	Spatial resolution			
	10m		20m	
	Overall accuracy [%]	Kappa accuracy [%]	Overall accuracy [%]	Kappa accuracy [%]
1D	94.1	92.5	90.8	88.4
2D	87.4	84.0	87.8	84.5
3D	91.9	89.7	93.6	91.8

Table: Overall and Kappa accuracy of each base model in 10 and 20 metres spatial resolution



Thank you!



CONTACT

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