Remote sensing for cropland soils at the regional scale

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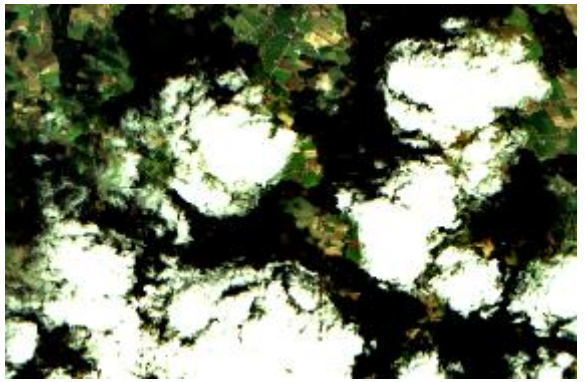
[2] Aristotle University of Thessaloniki (AUTH)
[3] Université catholique de Louvain (UCL)

Content:

- Introduction – Observing soils from optical satellite platforms
- Soil Composite Mapping – SCMaP and HISET
- SCMaP Product Suite
- Summary and Outlook

1. Introduction – Observing soils from optical satellite platforms

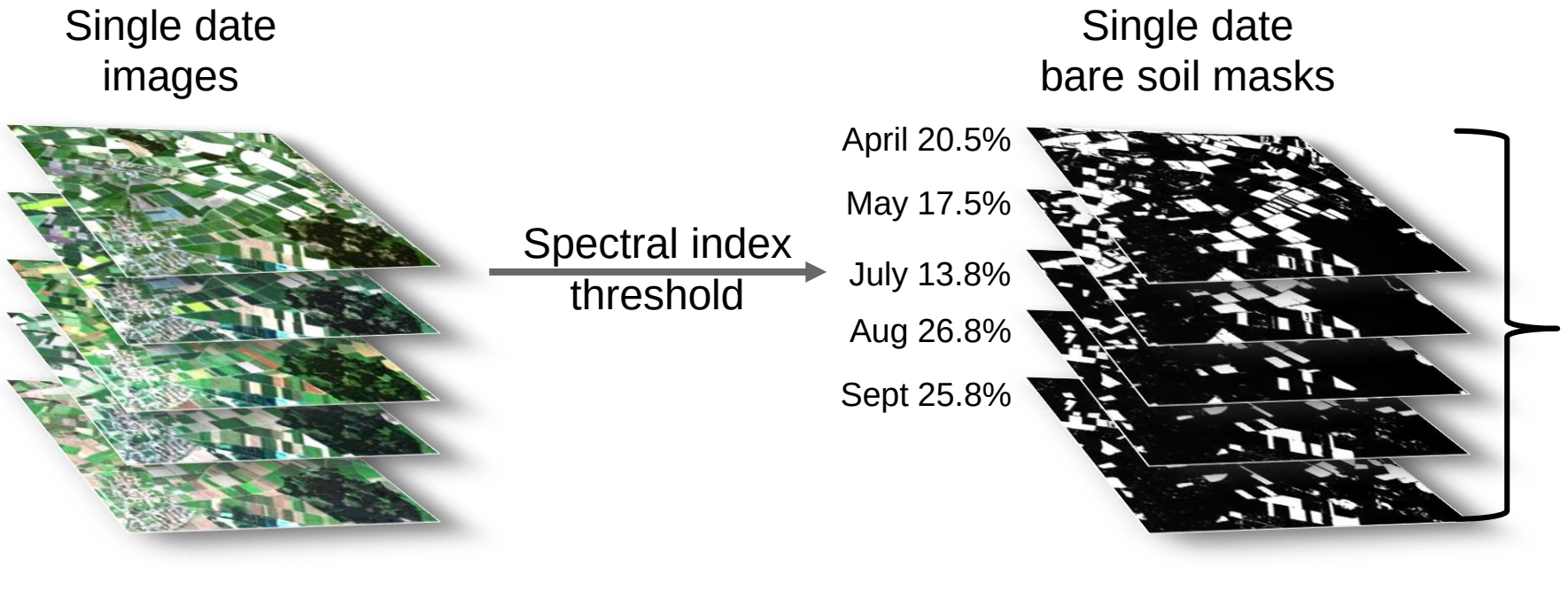
Clouds / Cloudshadow / …



Detecting bare soil

Disturbances:
Green and dry vegetation, stubbles, moisture, structure

1. Introduction – Basic idea



References

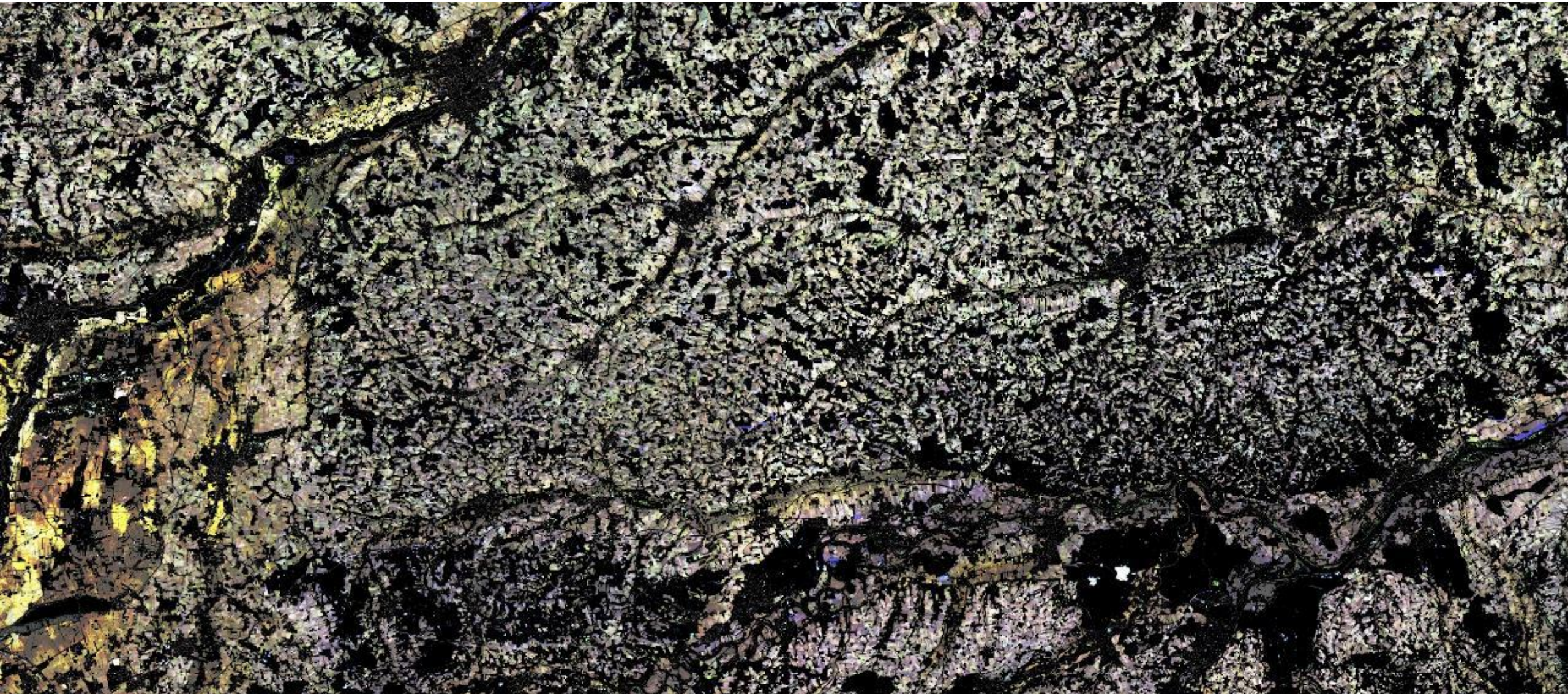
- Diek, S.; Fornallaz, F.; Schaepman, M.E.; De Jong, R. Barest Pixel Composite for Agricultural Areas Using Landsat Time Series. Remote Sens. 2017, 9, 1245.
- Rogge, D. et al. (2018). Building an exposed soil composite processor (SCMaP) for mapping spatial and temporal characteristics of soils with Landsat imagery (1984–2014), RSE, 205, 1-17.
- Demattê, J.A.M.; Fongaro, C.T.; Rizzo, R.; Safanelli, J.L. (2018). Geospatial Soil Sensing System (GEOS3): A powerful data mining procedure to retrieve soil spectral reflectance from satellite images. RSE, 212, 161–175.

Sentinel–2 mean reflectance composite (2017 – 2019), North-East of Munich

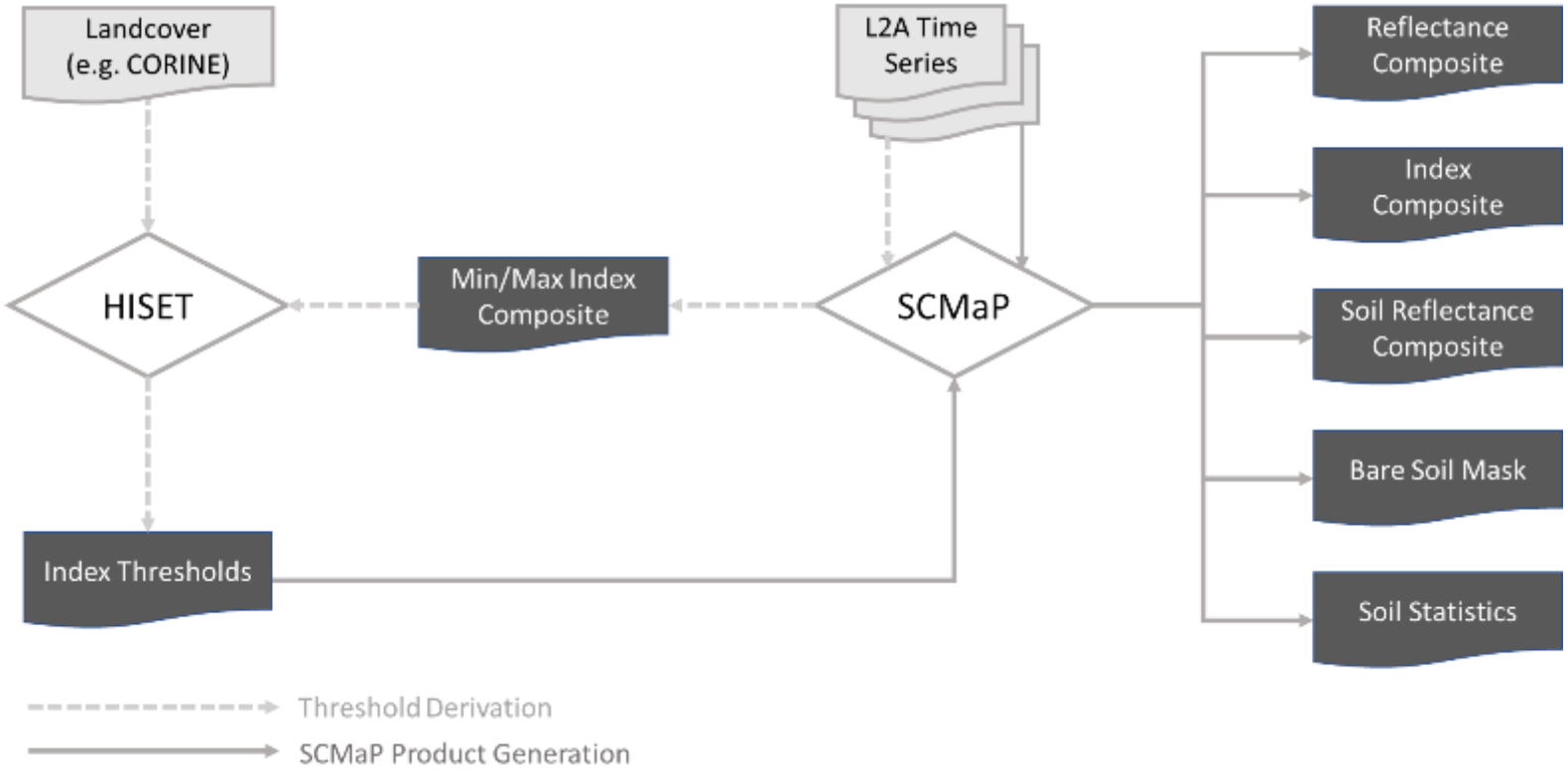
ESA WorldSoils: Exploring the S2 archive for Soil Information Retrieval

Sentinel–2 soil reflectance composite (2017 – 2019), North-East of Munich

ESA WorldSoils: Exploring the S2 archive for Soil Information Retrieval



2. Soil Composite Mapping – Overview



Soil **C**omposite **Ma**pping **P**rocessor (SCMaP)*

- Runs on different cloud platforms (LRZ, DIAS MUNDI, …)
- Input Landsat 4, 5, 7, 8, Sentinel-2A+B
- Currently 13 spectral indices (e.g. NBR I/II, NDVI, BSI, …)
- Automated index threshold derivation (HISET)
- Output = Product suite suitable for digital and spectral soil modelling

*References
Rogge, D. et al. (2018), Building an exposed soil composite processor (SCMaP) for mapping spatial and temporal characteristics of soils with Landsat imagery (1984–2014), RSE, 205, 1-17.

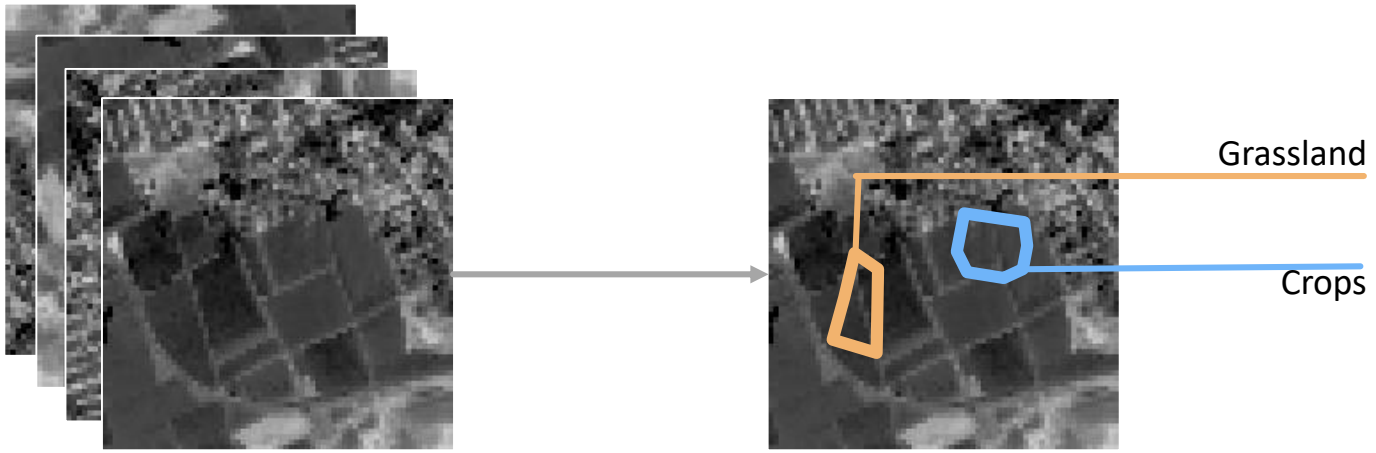
Heiden, U. et al. (2022), Soil Reflectance Composites—Improved Thresholding and Performance Evaluation. RS 2022, 14, 4526.

*References
Heiden, U. et al. (2022), Soil Reflectance Composites—Improved Thresholding and Performance Evaluation. Remote Sens. 2022, 14, 4526.

2. Soil Composite Mapping – Thresholds to detect bare soils

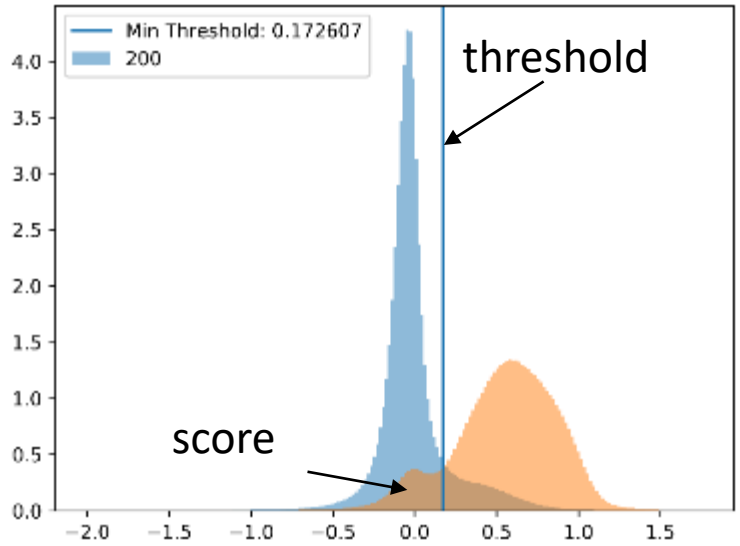
Histogram **SE**paration **T**hreshold (HISET) Method

1. Index calculation for each single scene
2. Index mean composite generation
3. Selection of specific LC classes (e.g. CORINE for Europe, Copernicus Landcover, ESA WorldCover)
4. Temporal behaviour of LC classes (PDF: normalised histogram)
5. Threshold calculation + Quality score



Index per scene

Min **index** composite



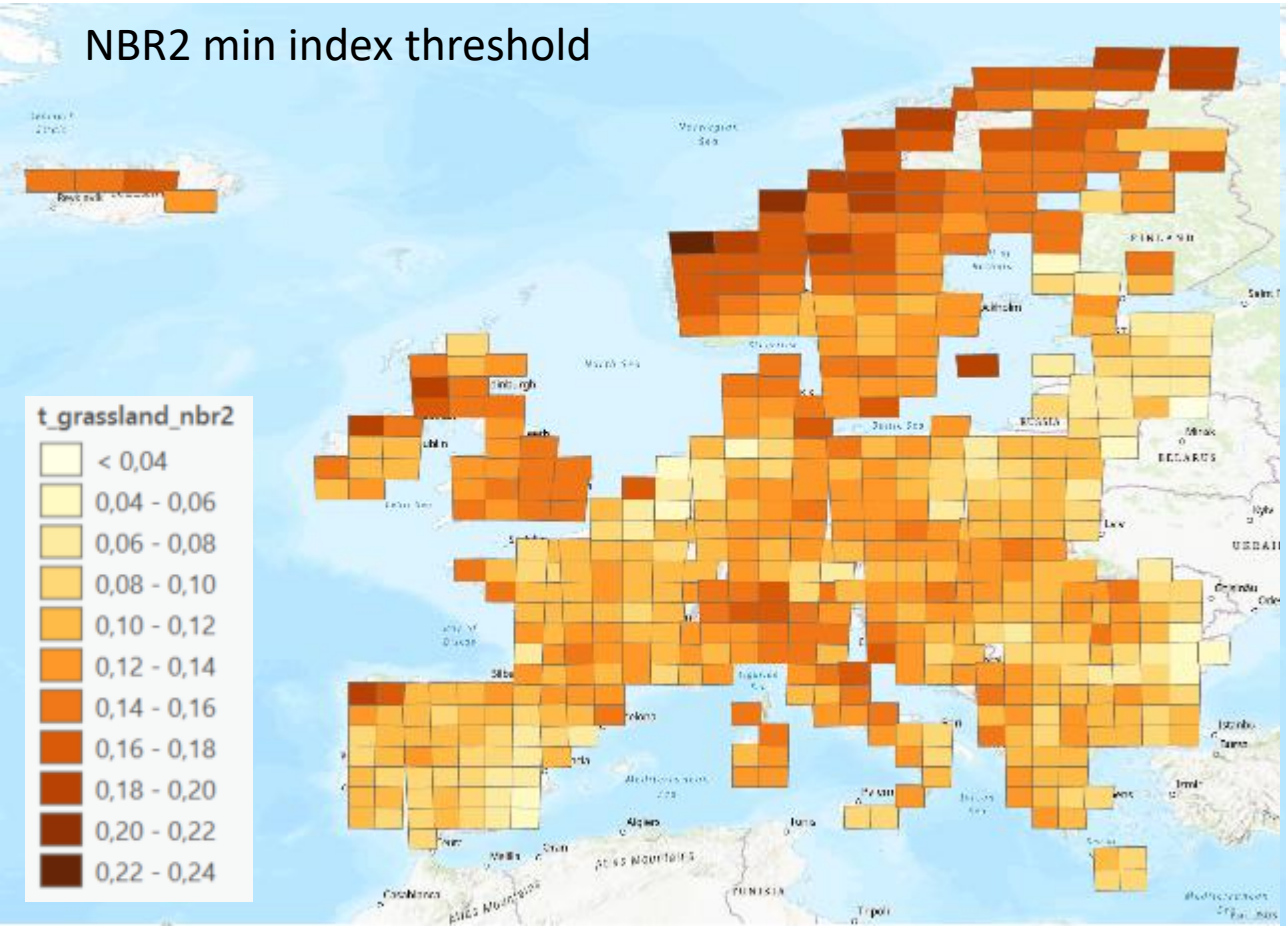
Index value in the Min index composite

2. Soil Composite Mapping – HISET Results for Europe

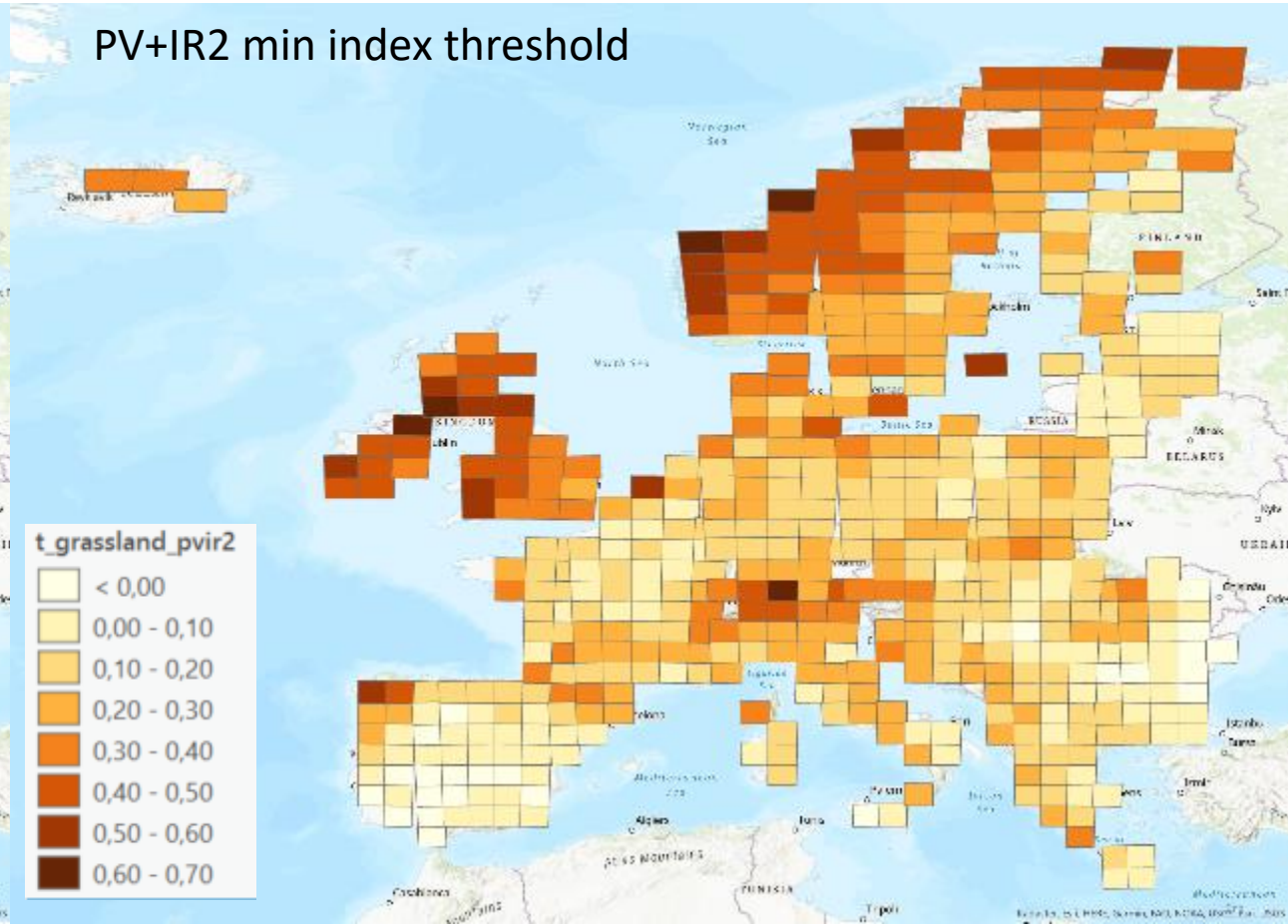
Threshold$_{min}$ to separate bare soils from dry vegetation -> suggested LC: crops and grassland

Threshold$_{max}$ to separate bare soils from urban areas -> suggested LC: crops and urban

NBR2 min index threshold



PV+IR2 min index threshold

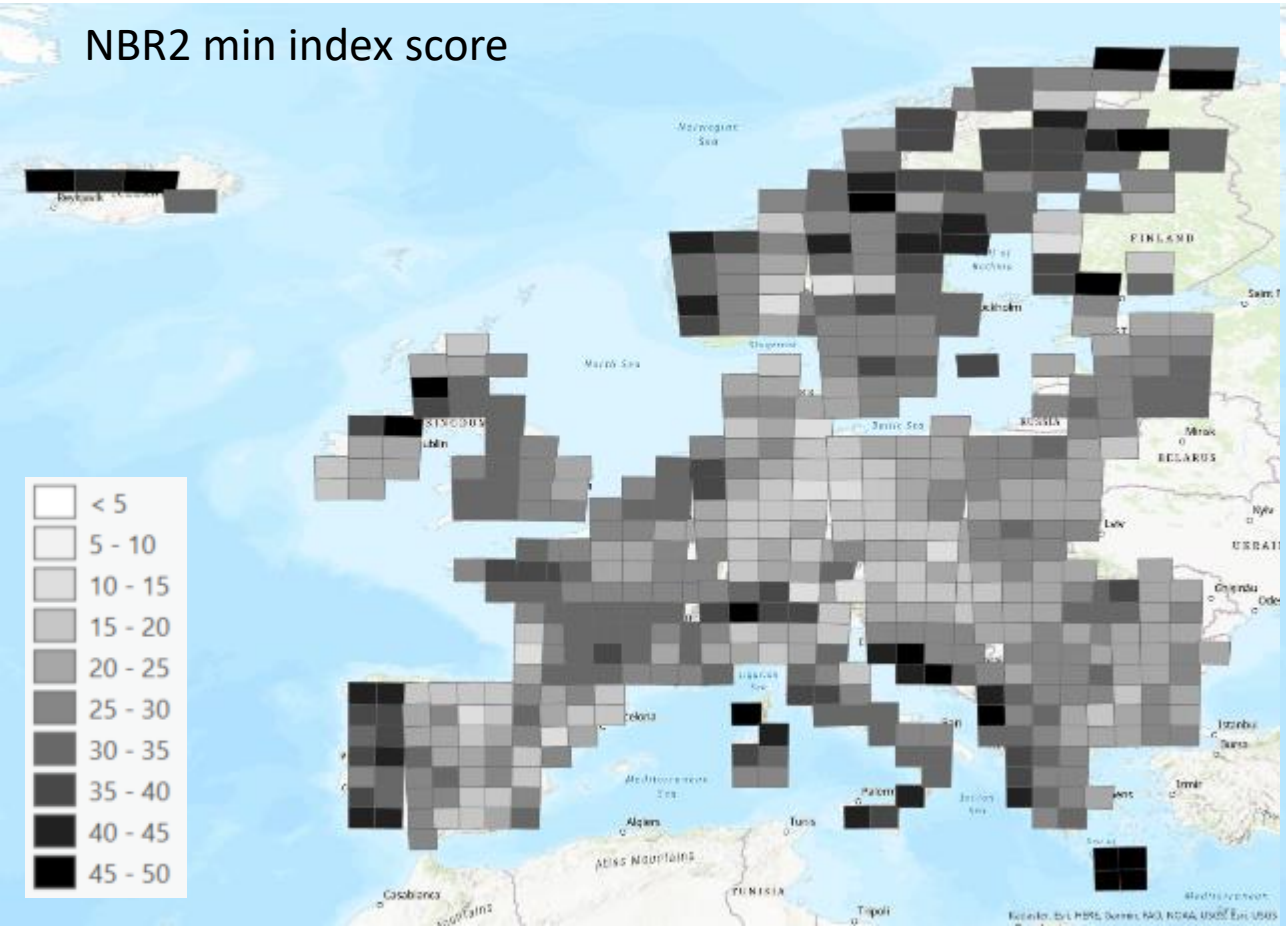


2. Soil Composite Mapping – HISET Results for Europe

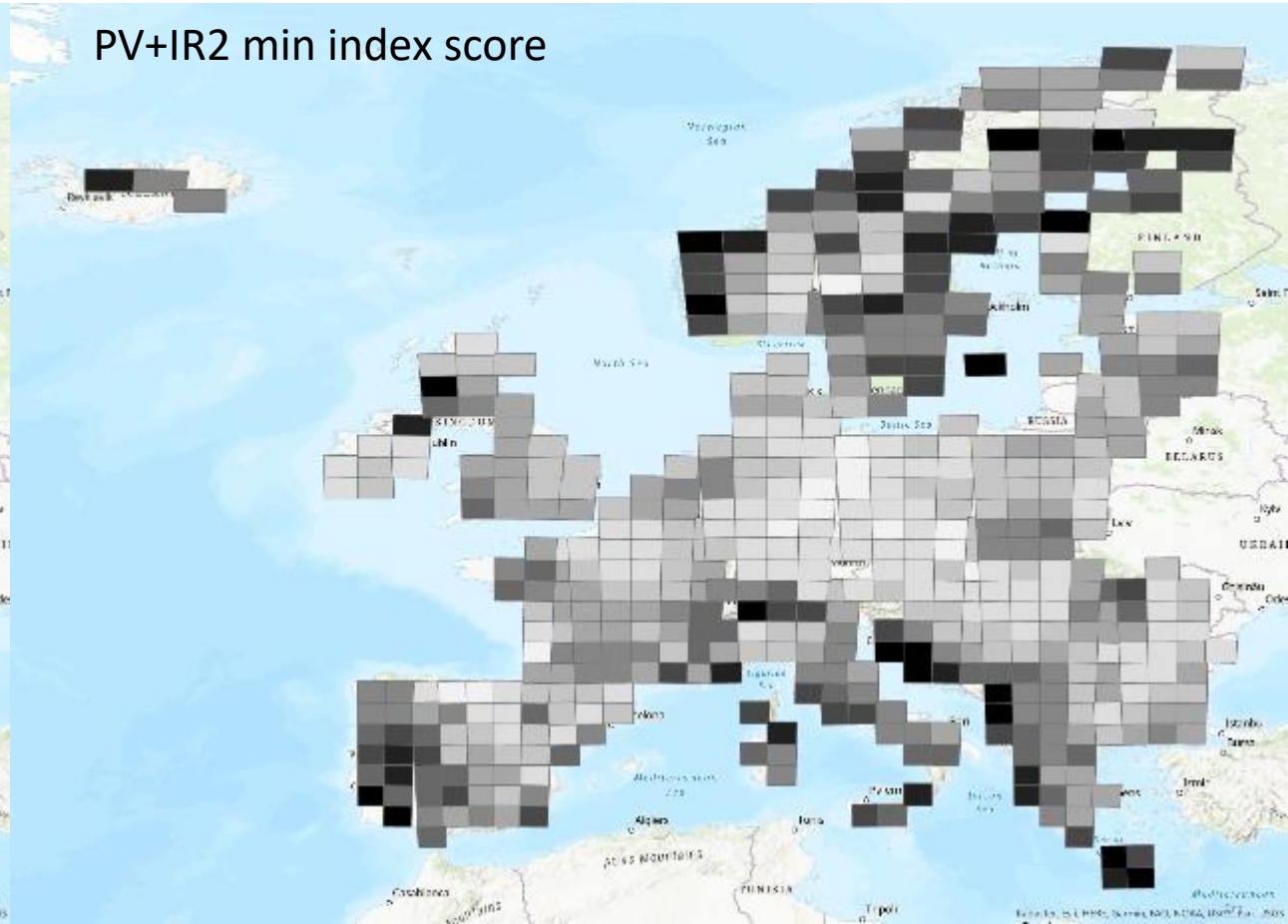
Threshold$_{min}$ to separate bare soils from dry vegetation -> suggested LC: crops and grassland

Threshold$_{max}$ to separate bare soils from urban areas -> suggested LC: crops and urban

NBR2 min index score



PV+IR2 min index score



3. SCMaP Product Suite

Tziolas, N. et al. (submitted): **Convolutional neural networks for soil organic carbon mapping from Earth Observation data,** a case study in Bavaria state.

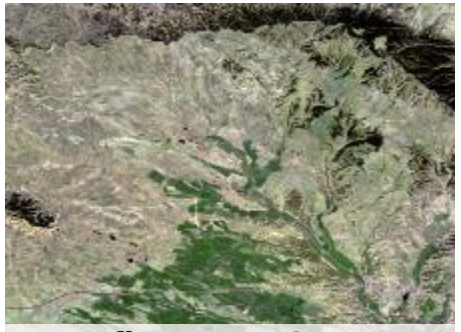
Dvorakova, K., et al. (2023): **Improving soil organic carbon predictions from a Sentinel–2 soil composite by assessing surface conditions and uncertainties**, Geoderma, 429, 116128.

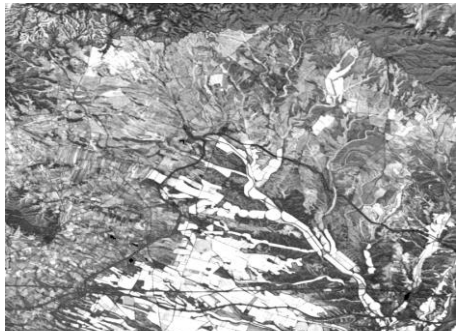
Möller, M. et al. (2022): **Scale-Specific Prediction of Topsoil Organic Carbon Contents Using Terrain Attributes and SCMaP Soil Reflectance Composites**. RS, 14, 2295.

Zepp, S. et al. (2021): **Estimation of soil organic carbon contents in croplands of Bavaria from SCMaP soil reflectance composites**, RS,


Reflectance Comp. (Maximum Index)


Reflectance Comp. (Minimum Index)

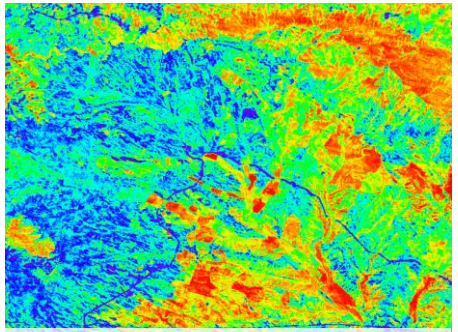

Reflectance Comp. (Mean)

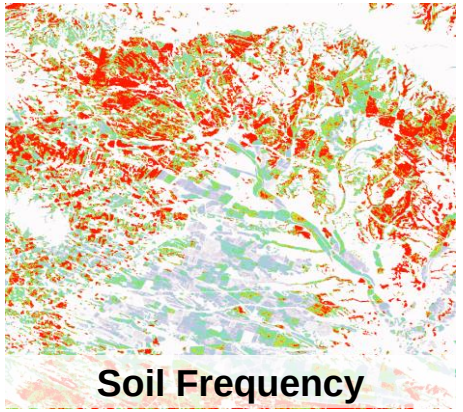

Index Composite (Stats)

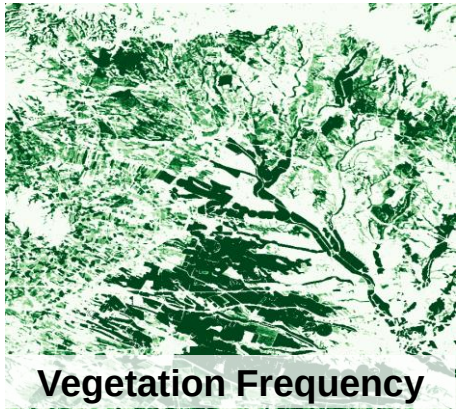

Soil Reflectance Composite

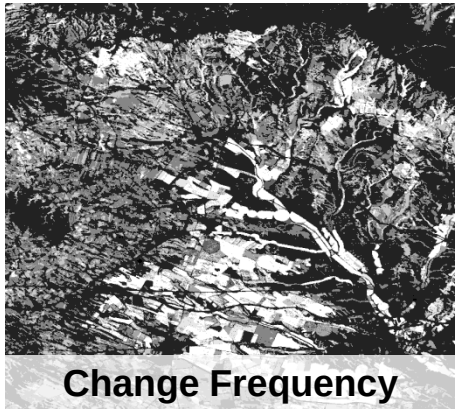

Soil Reflectance Composite (Normalised)


Mean Albedo


No. of Valid Inputs


Soil Frequency


Vegetation Frequency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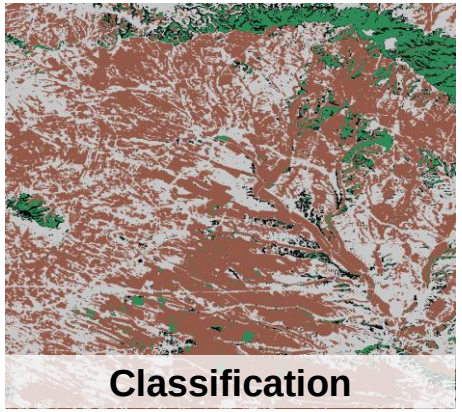
Classification

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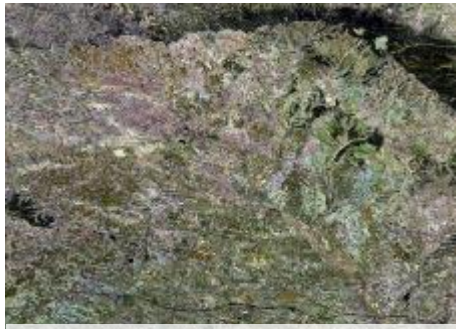
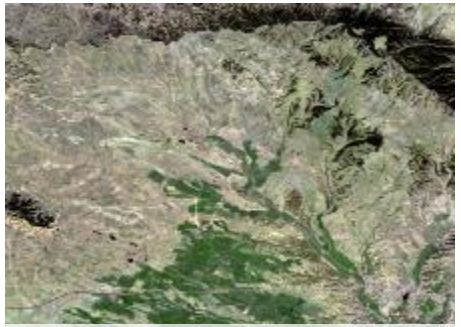
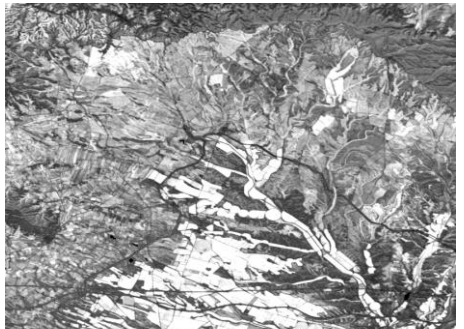

Reflectance Comp. (Minimum Index)

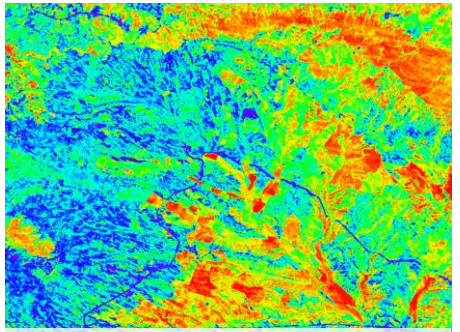

Reflectance Comp. (Mean)


Index Composite (Stats)


Soil Reflectance Composite


Soil Reflectance Composite (Normalised)


Mean Albedo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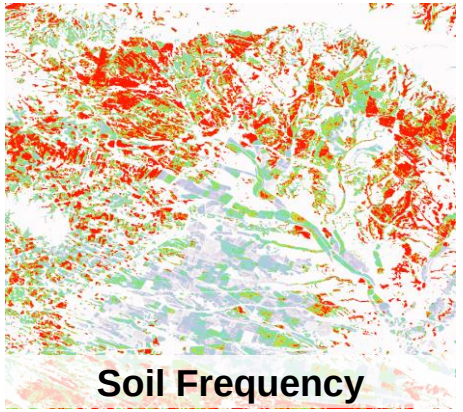
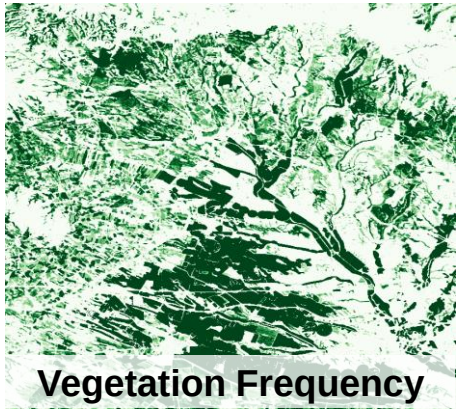
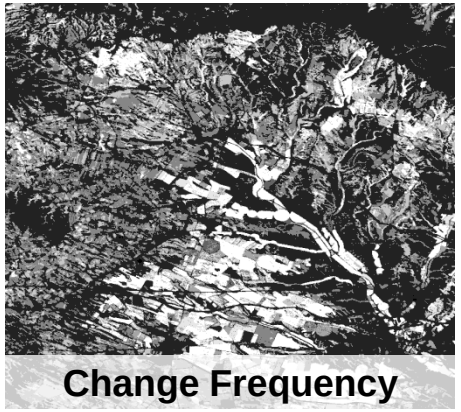
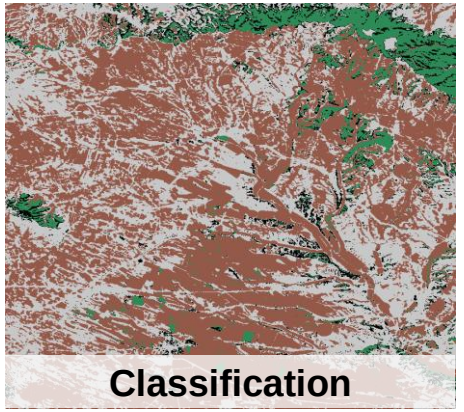
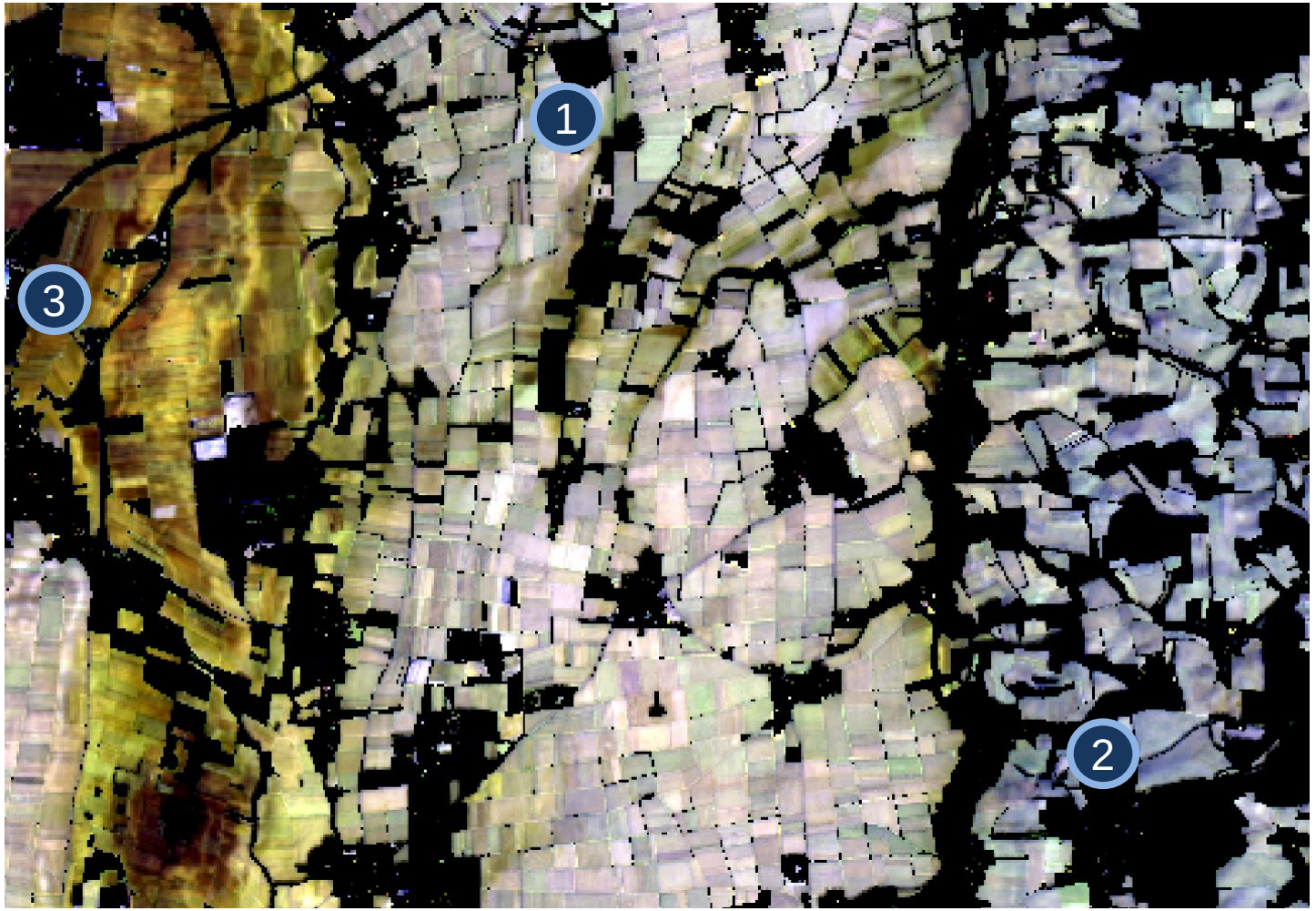

Soil Frequency


Vegetation Frequency


Change Frequency

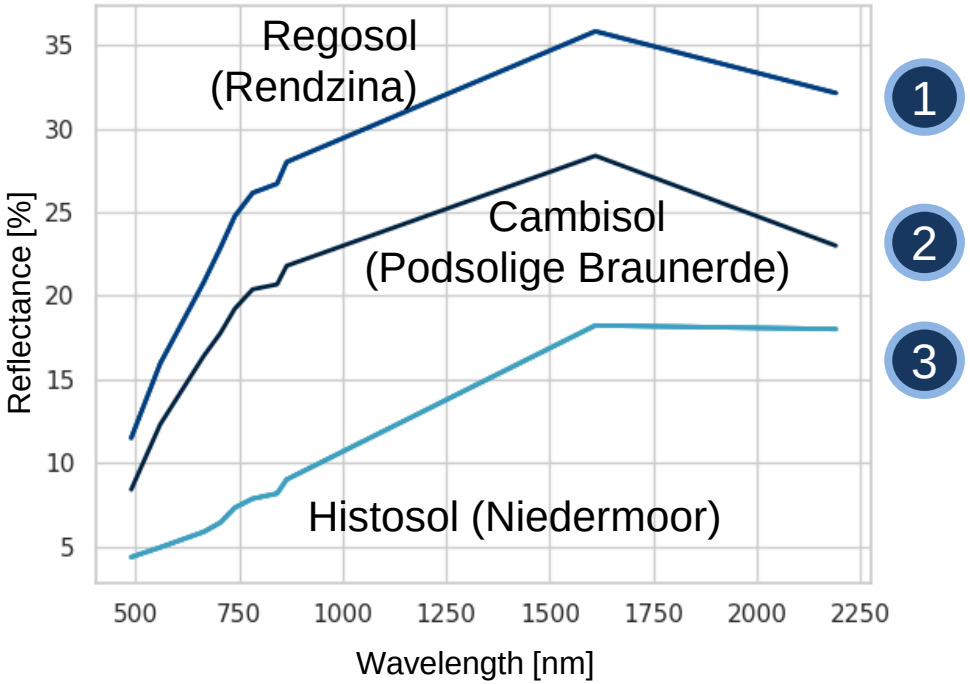

Classification

3. SCMaP Product Suite – SRC Examples



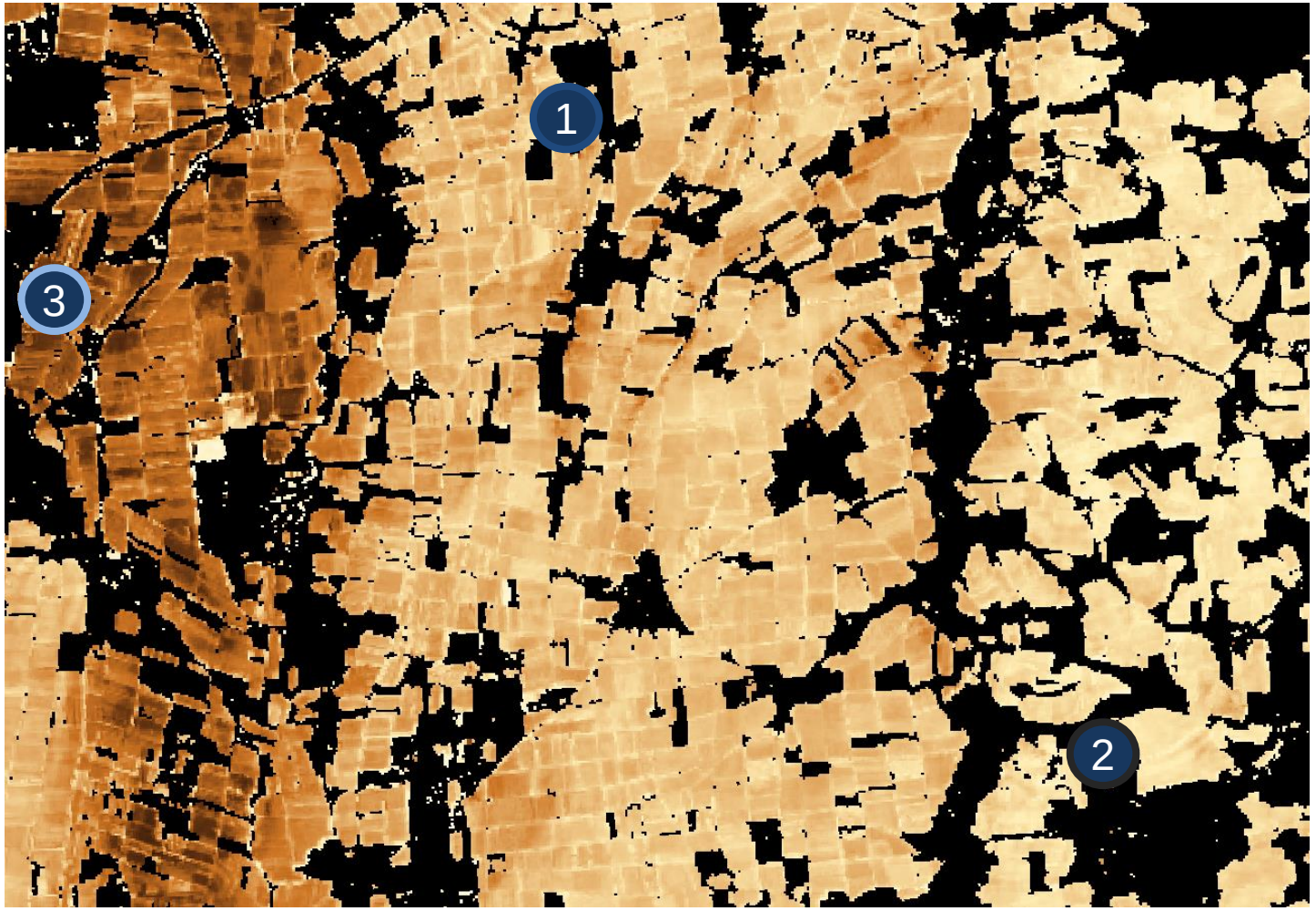
Processing Parameter:

- Sentinel-2
- L2A input processed by MAJA
- Month 03 – 10; 2018 – 2020



DLR

3. SCMaP Product Suite - SRC Examples



SOC prediction using a combined CNN and ANN model*

Processing Parameter:

- Sentinel-2
- L2A input processed by MAJA
- Month 03/04/05/; 2015 – 2020

SOC content [gC / kg]

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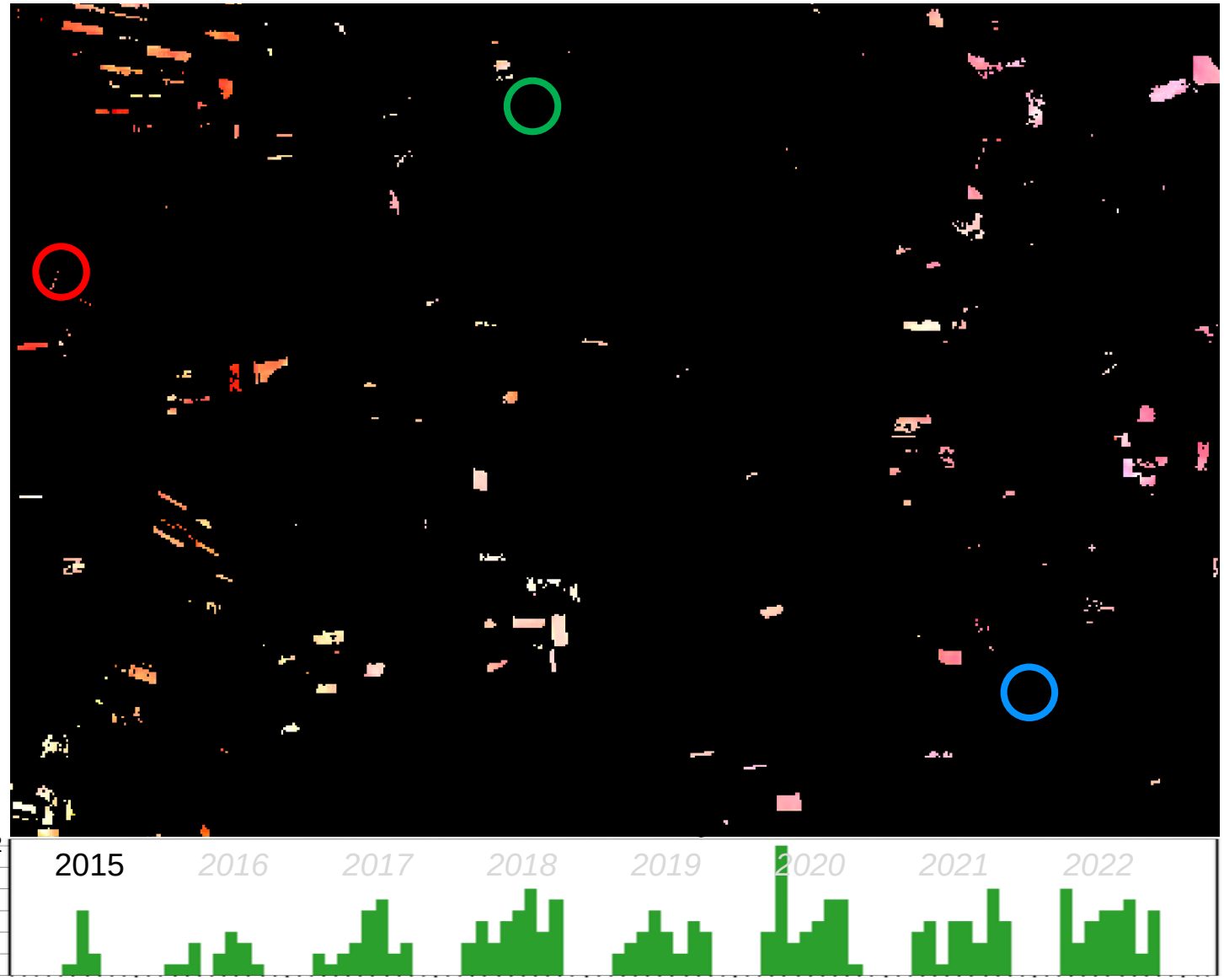
*Tziolas, N. et al. (submitted): **Convolutional neural networks for soil organic carbon mapping from Earth Observation data,** a case study in Bavaria state.

DLR

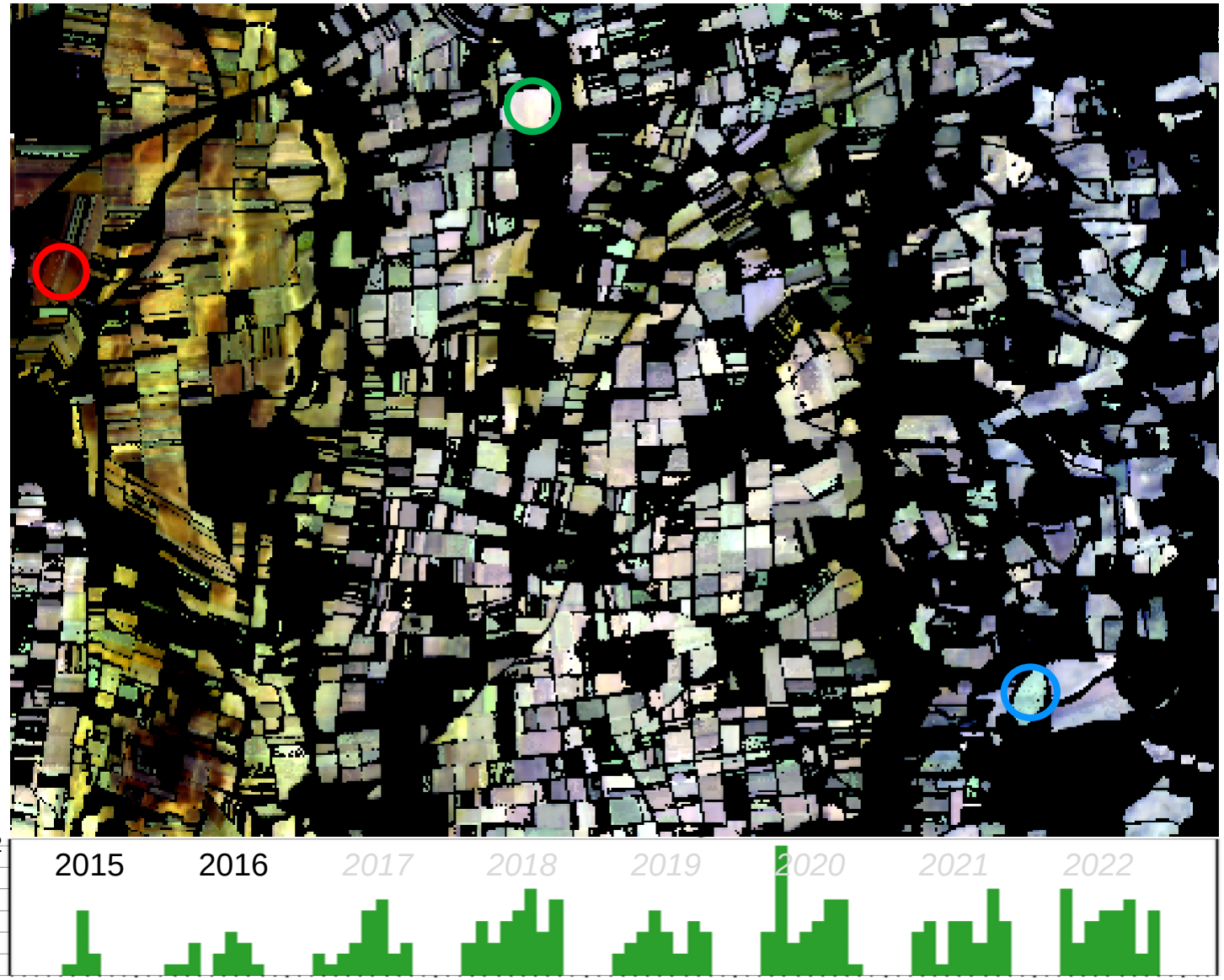
3. SCMaP Product Suite – SRC Examples

2015

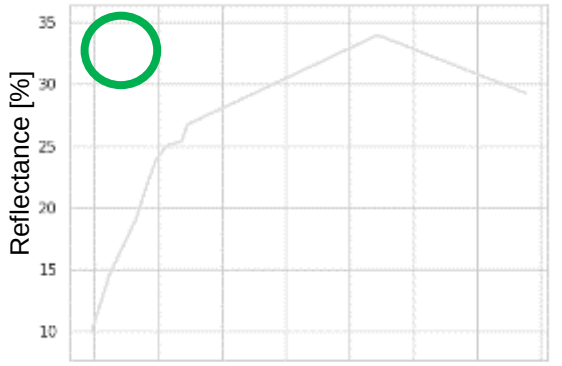
Mean number of bare soil pixels

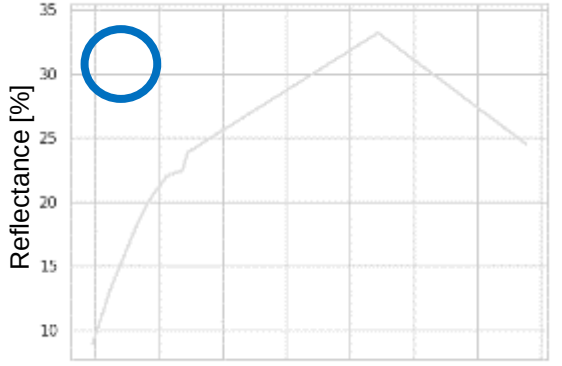


3. SCMaP Product Suite – SRC Examples



2015 – 2016





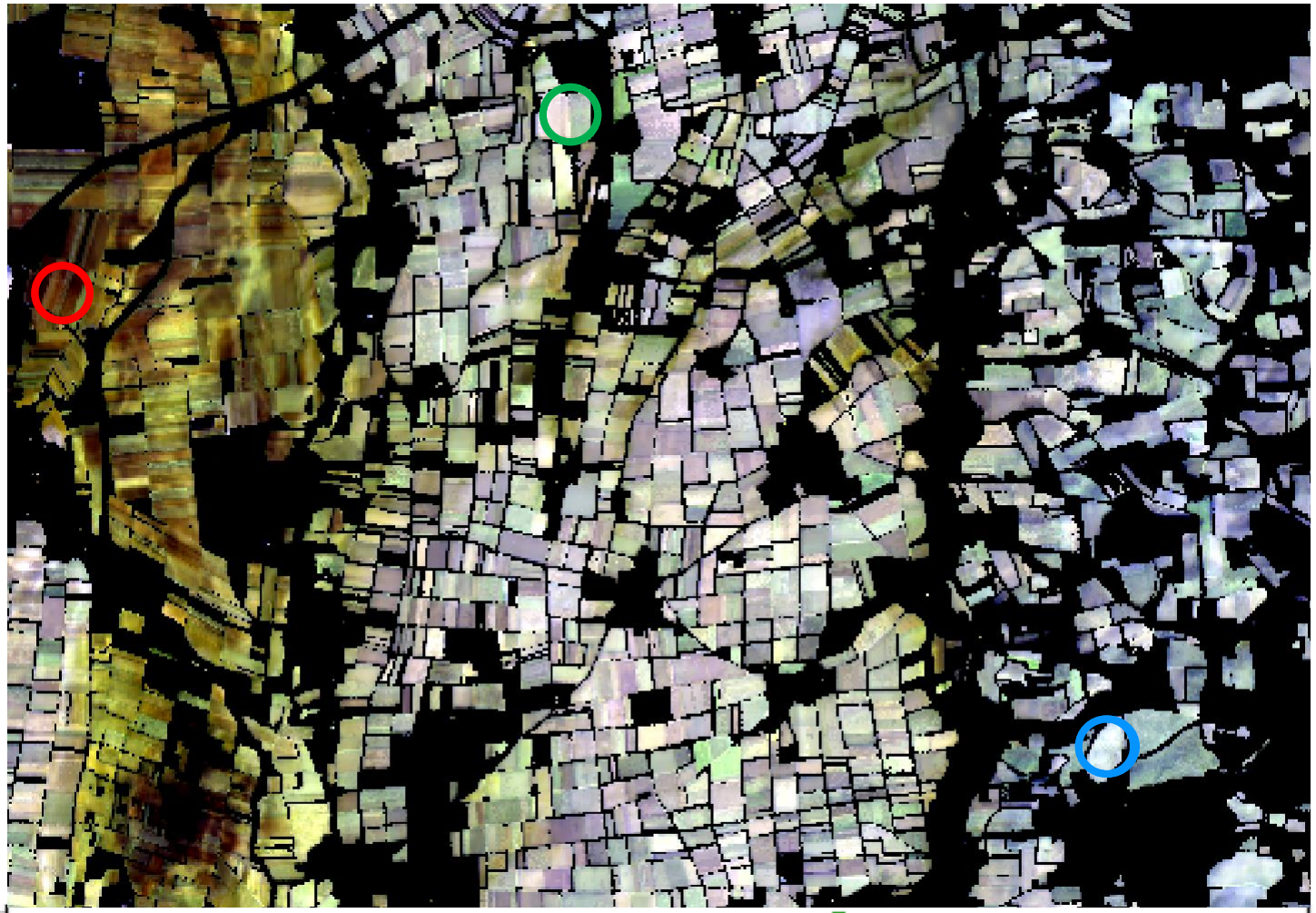
Mean number of bare soil pixels

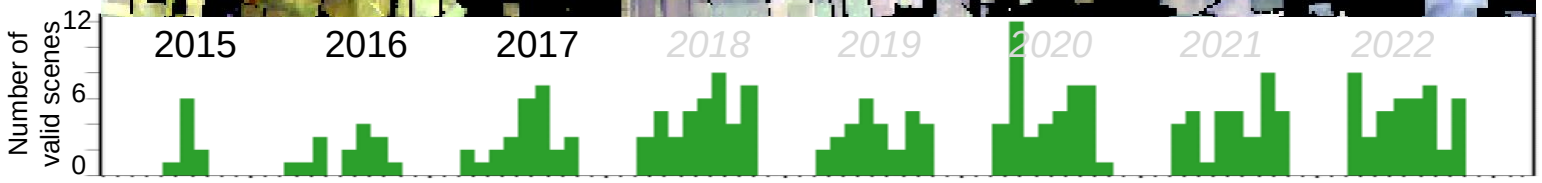
5,0

4,6

3,1

3. SCMaP Product Suite - SRC Examples

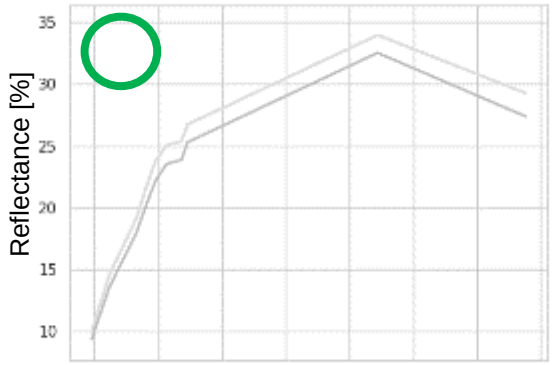




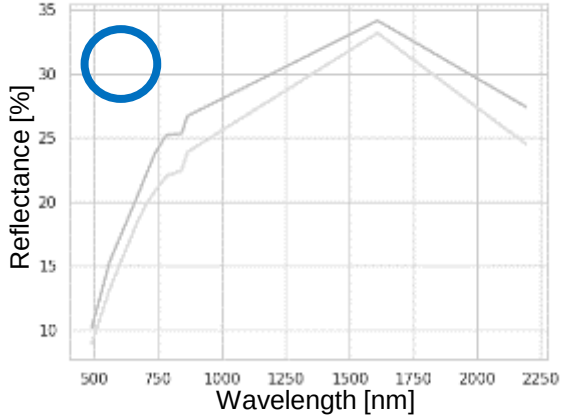
2015 – 2017

Mean number of bare soil pixels

11,4

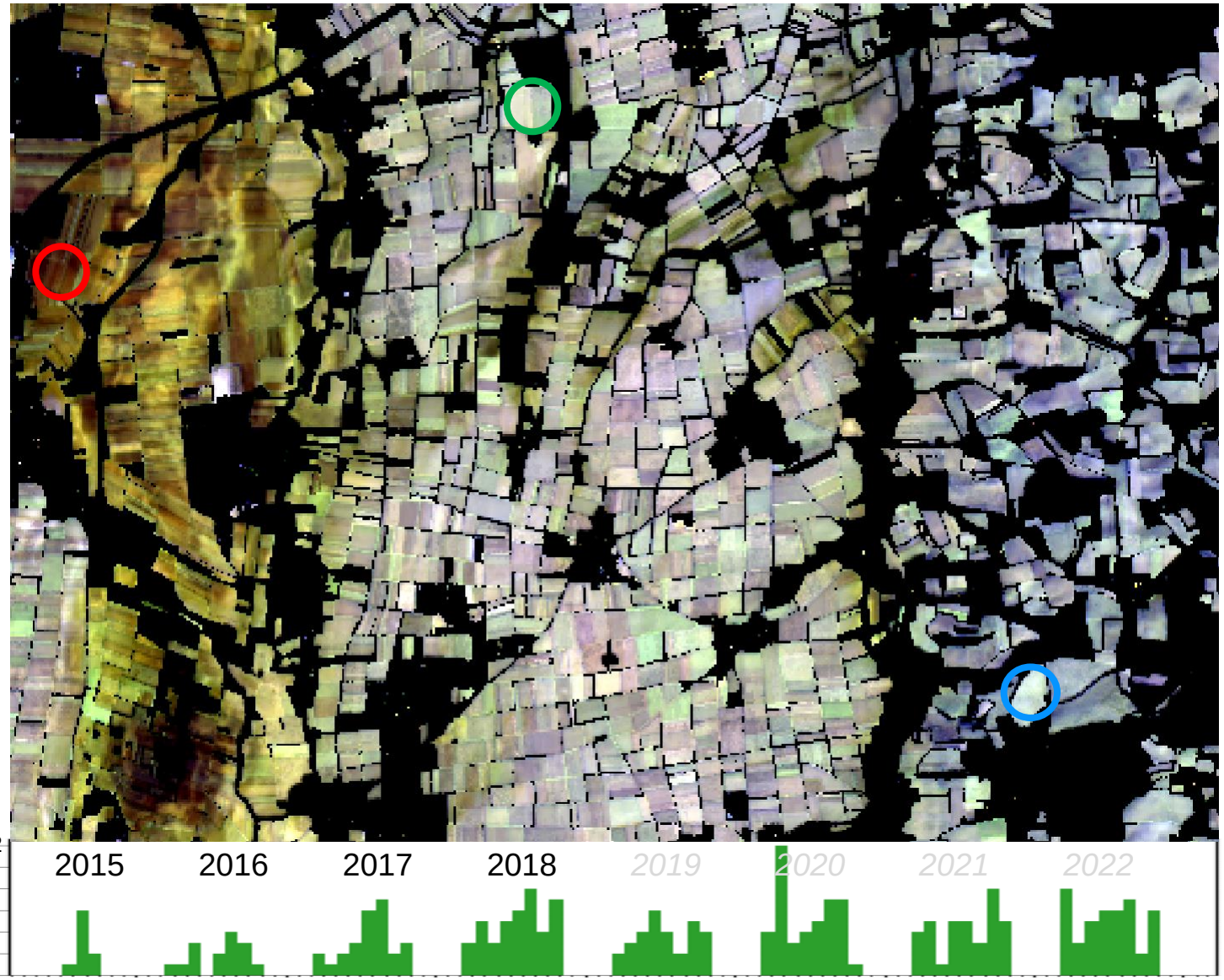


8,5



8,5

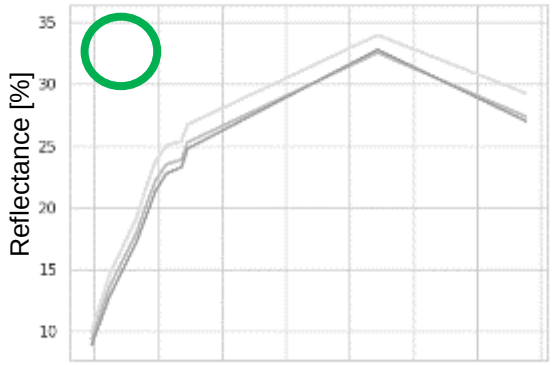
3. SCMaP Product Suite - SRC Examples



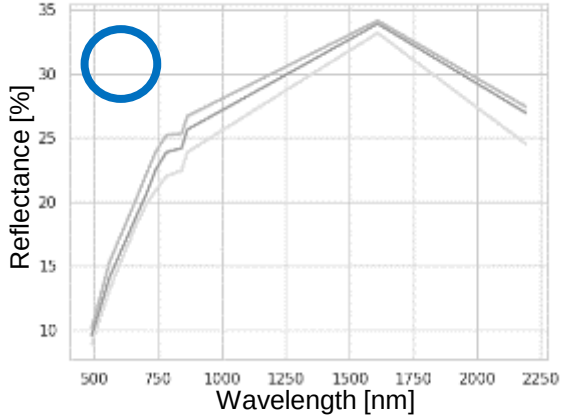
2015 – 2018

Mean number of bare soil pixels

21,4

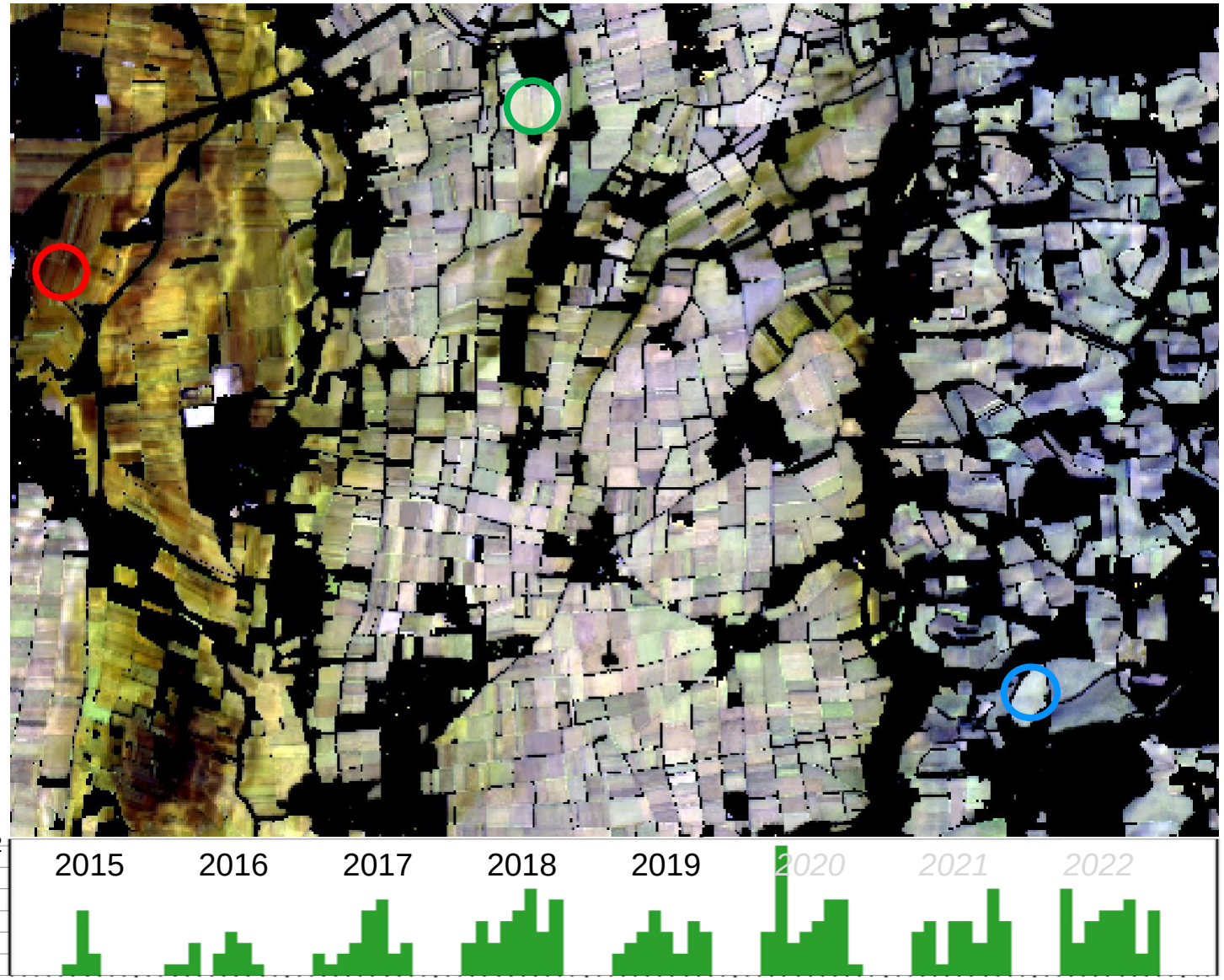


12,8

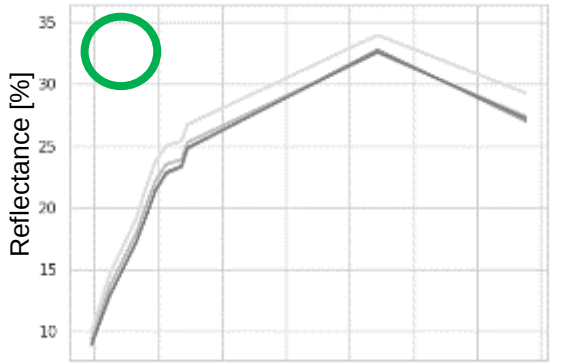


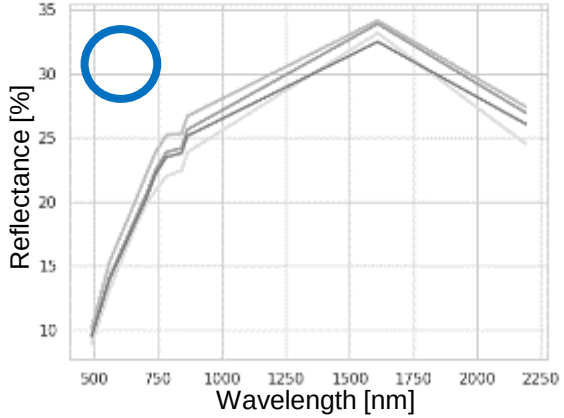
15,5

3. SCMaP Product Suite - SRC Examples



2015 – 2019





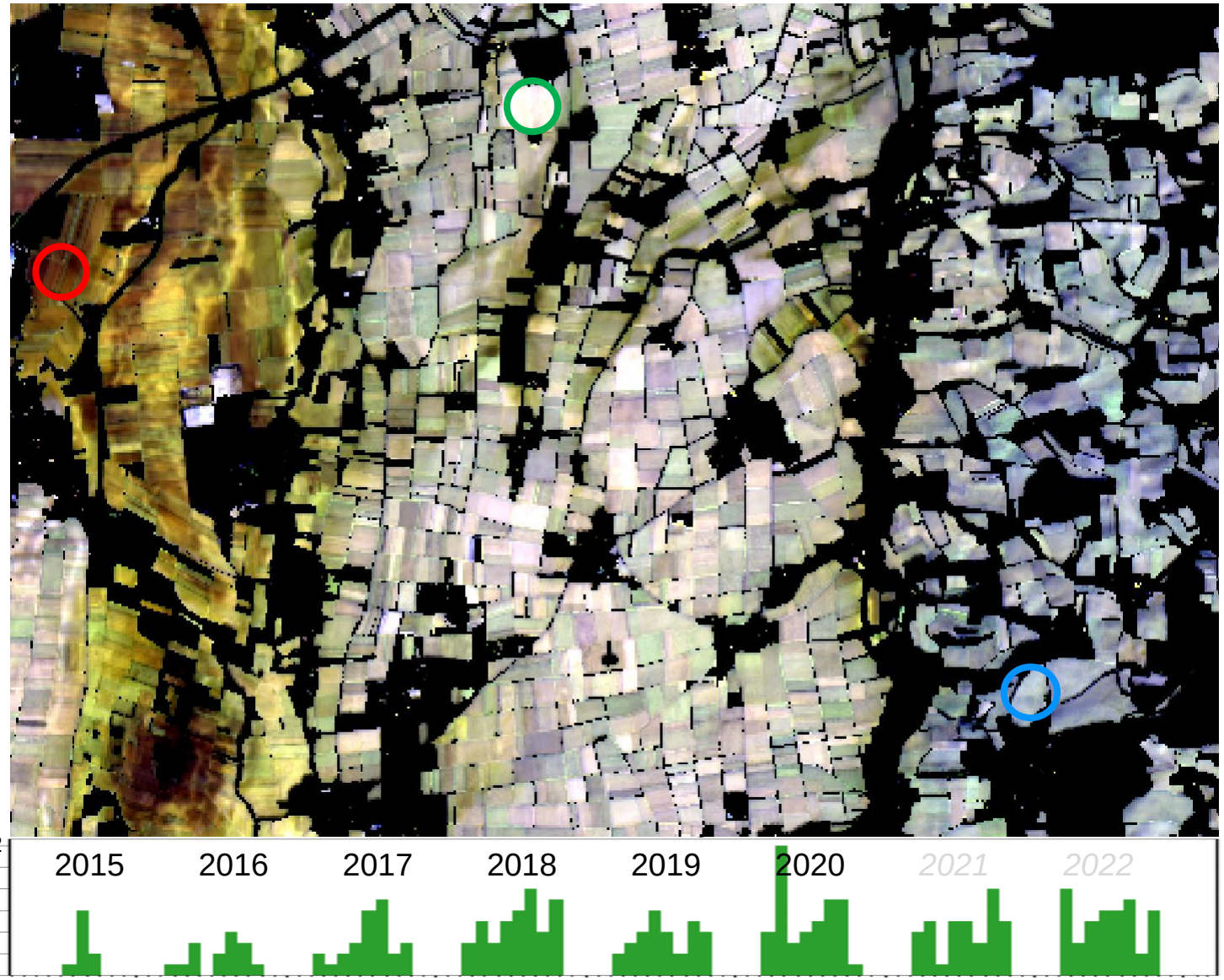
Mean number of bare soil pixels

31,6

16,6

20,8

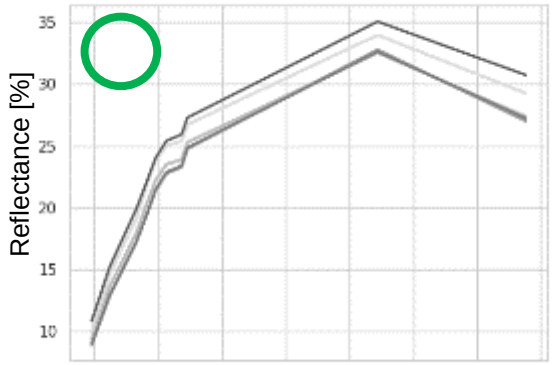
3. SCMaP Product Suite - SRC Examples



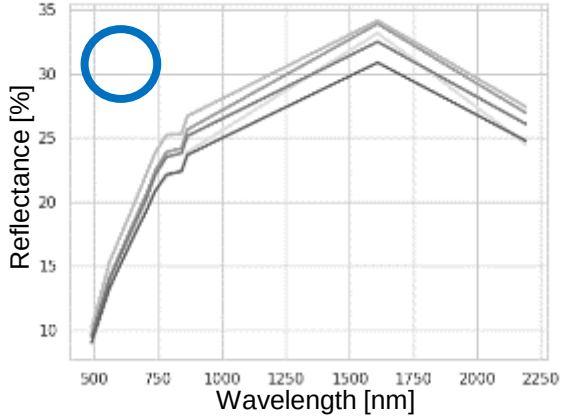
2015 – 2020

Mean number of bare soil pixels

48,1

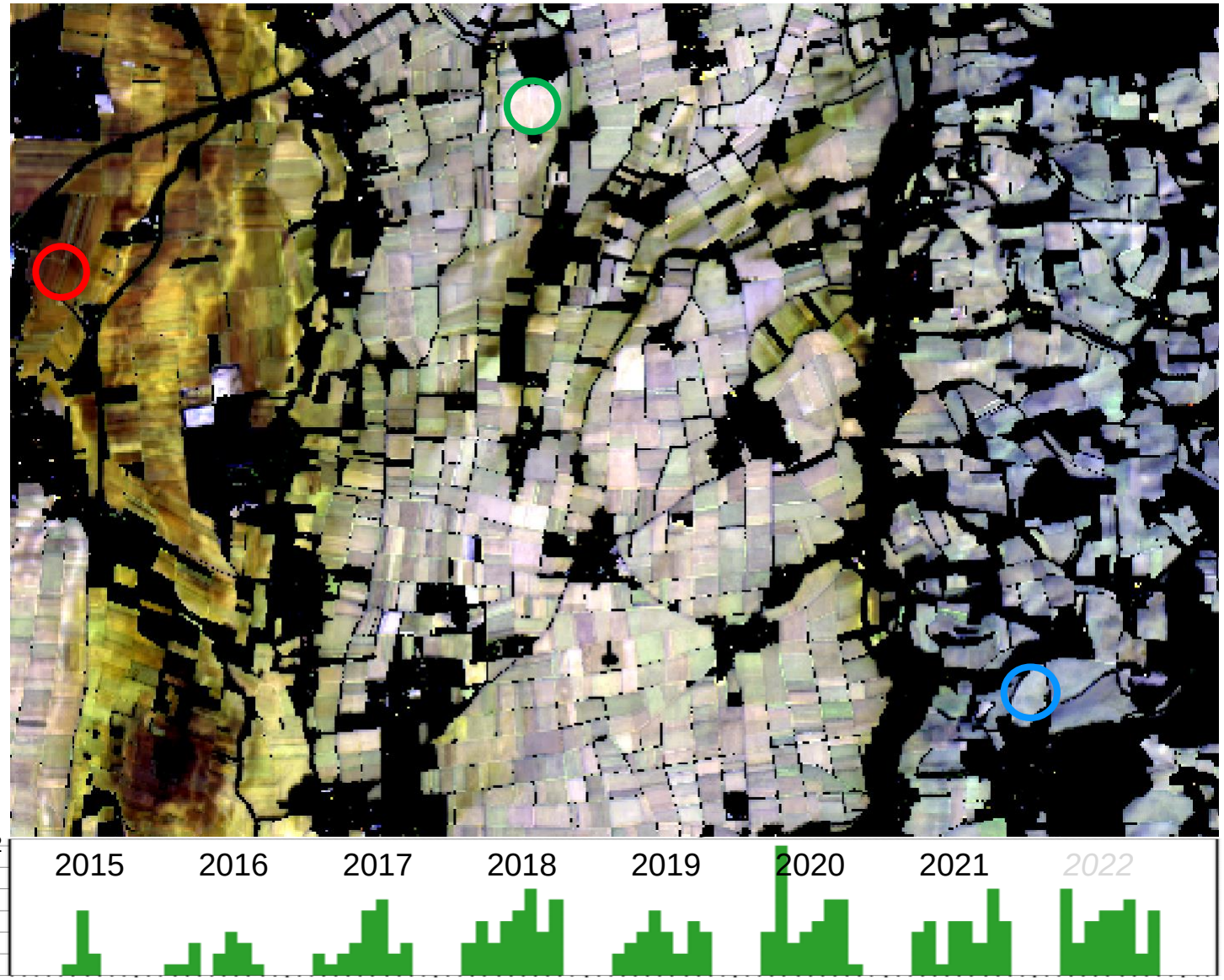


33,5



26,4

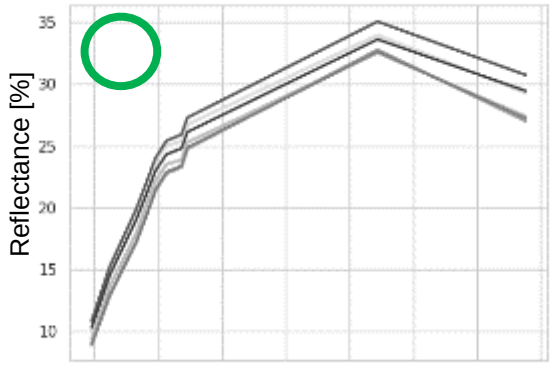
3. SCMaP Product Suite - SRC Examples



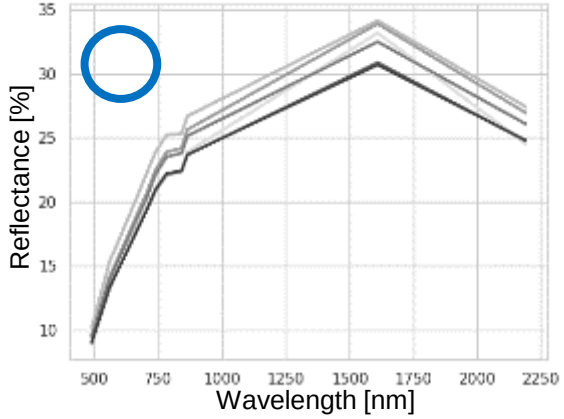
2015 – 2021

Mean number of bare soil pixels

61,4

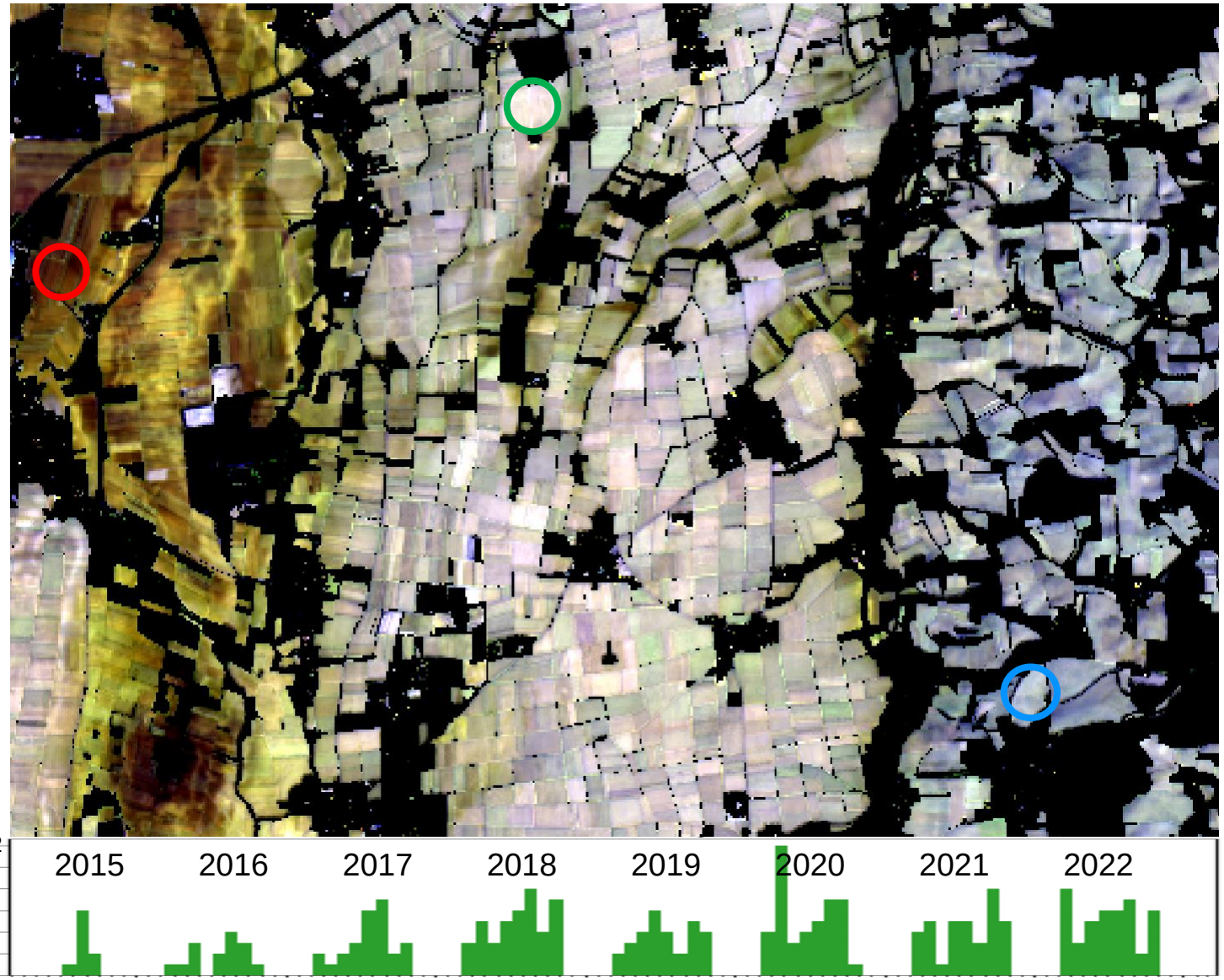


40,4



32,0

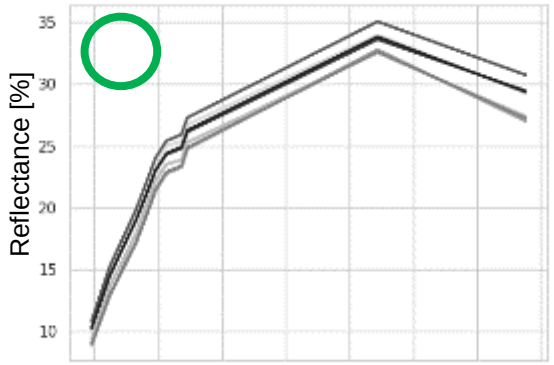
3. SCMaP Product Suite - SRC Examples



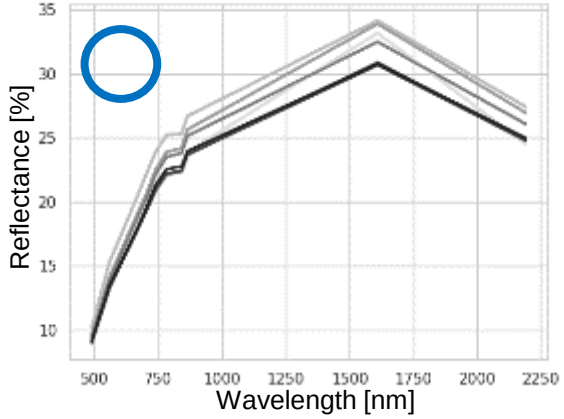
2015 – 2022

Mean number of bare soil pixels

74,2



42,8



34,8

3. SCMaP Product Suite - Conclusion

Soil Reflectance Composites (SRC)

- The shorter the temporal length – the less pixels are available for calibrating soil models
- The longer the temporal length – the less seasonal variability / field to field differences
- The definition of the temporal length depends on the bare soil dynamic in the specific area

3. SCMaP Product Suite

Tziolas, N. et al. (submitted): **Convolutional neural networks for soil organic carbon mapping from Earth Observation data,** a case study in Bavaria state.

Dvorakova, K., et al. (2023): **Improving soil organic carbon predictions from a Sentinel–2 soil composite by assessing surface conditions and uncertainties**, Geoderma, 429, 116128.

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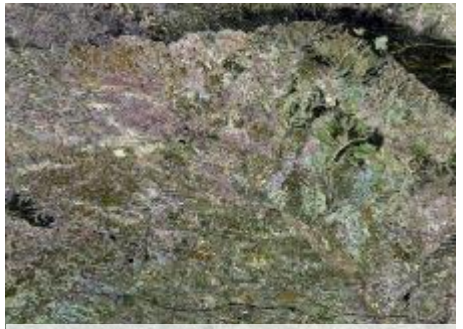
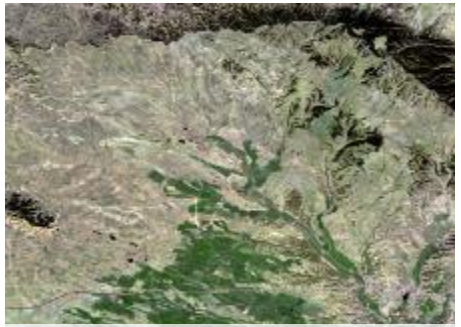
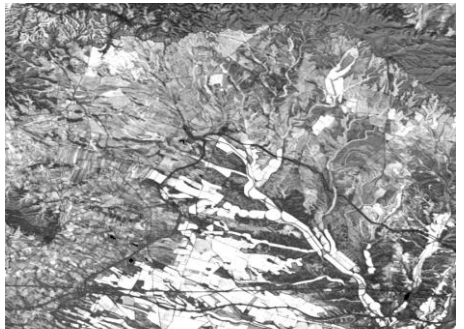
Reflectance Comp. (Maximum Index)


Reflectance Comp. (Minimum Index)

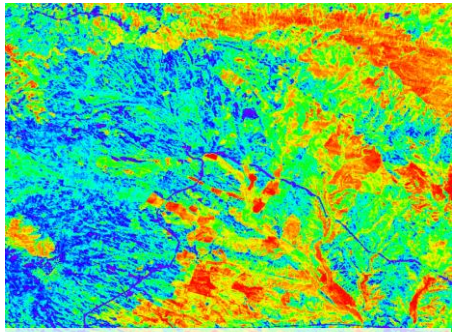

Reflectance Comp. (Mean)

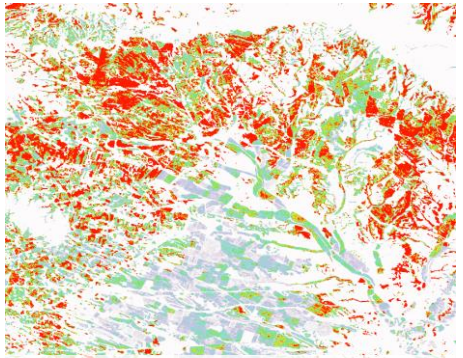

Index Composite (Stats)

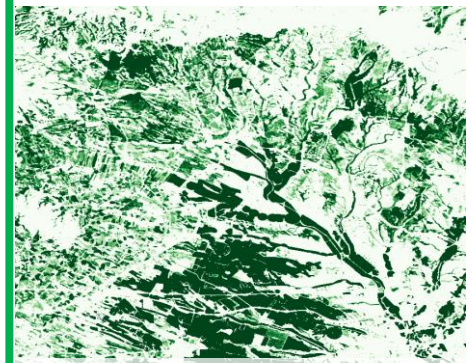

Soil Reflectance Composite

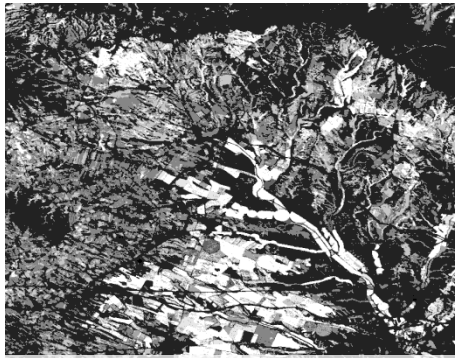

Soil Reflectance Composite (Normalised)

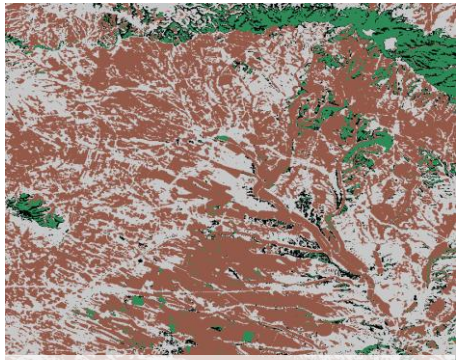

Mean Albedo


No. of Valid Inputs


Soil Frequency


Vegetation Frequency


Change Frequency


Classification

DLR

3. SCMaP Product Suite – Soil Frequency

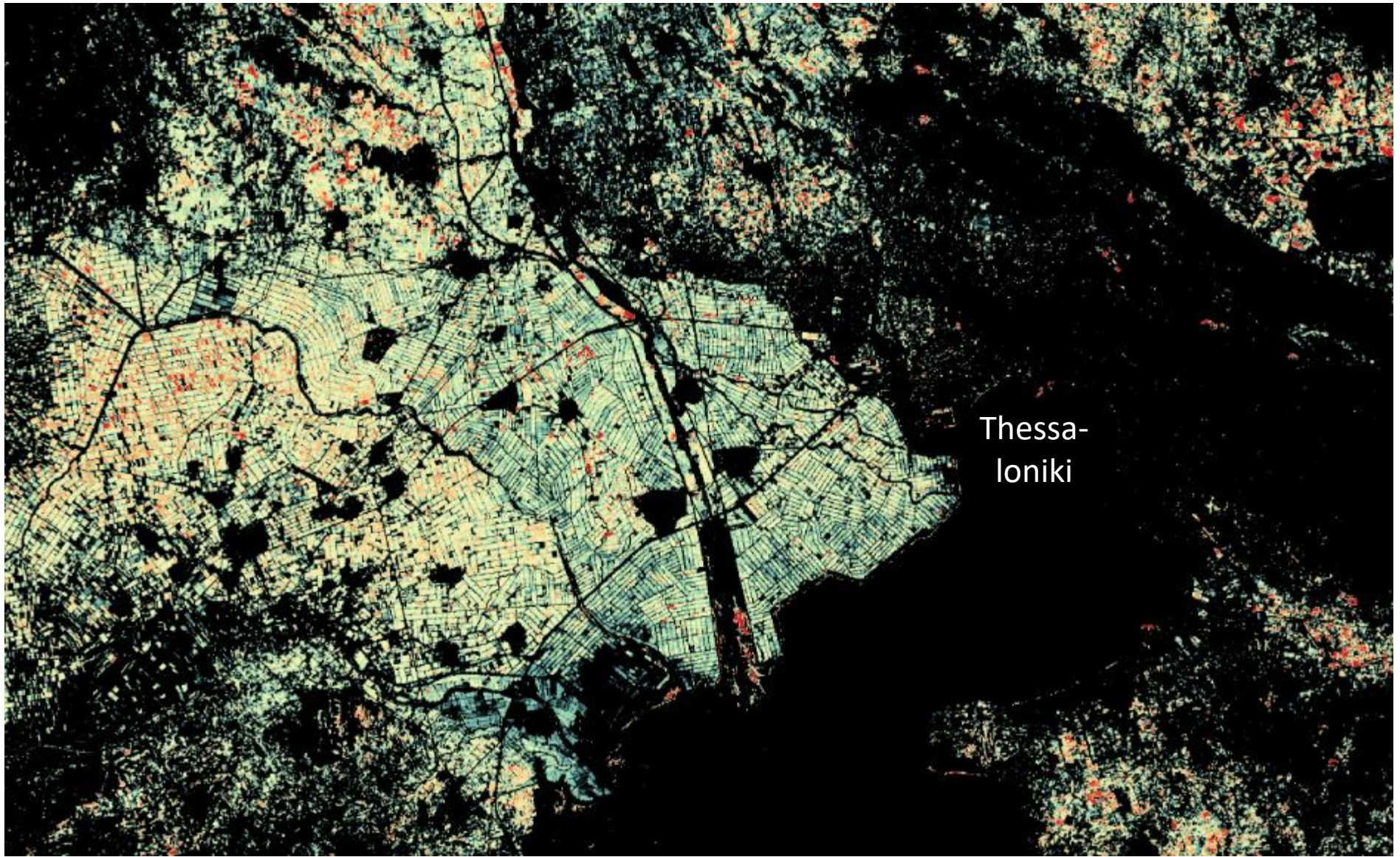
Sentinel-2

2018–2020
Feb – Nov

Cloudless
mosaic

DLR

3. SCMaP Product Suite – Soil Frequency



Sentinel-2

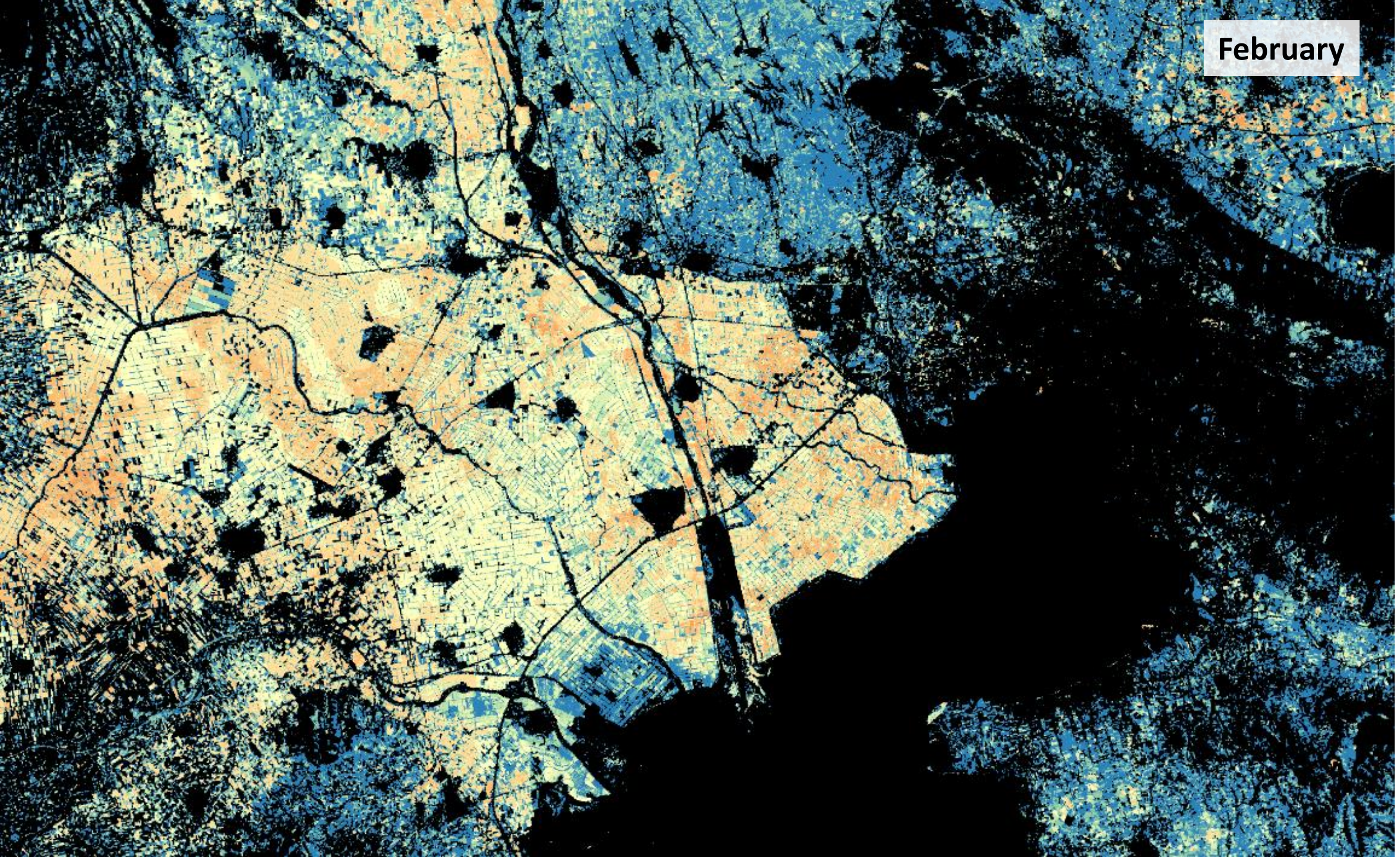
2018–2020
Feb – Nov

Bare soil
frequency

70 %

0 %

DLR



Bare soil count

17

1

Bare soil count

17

1

Bare soil count

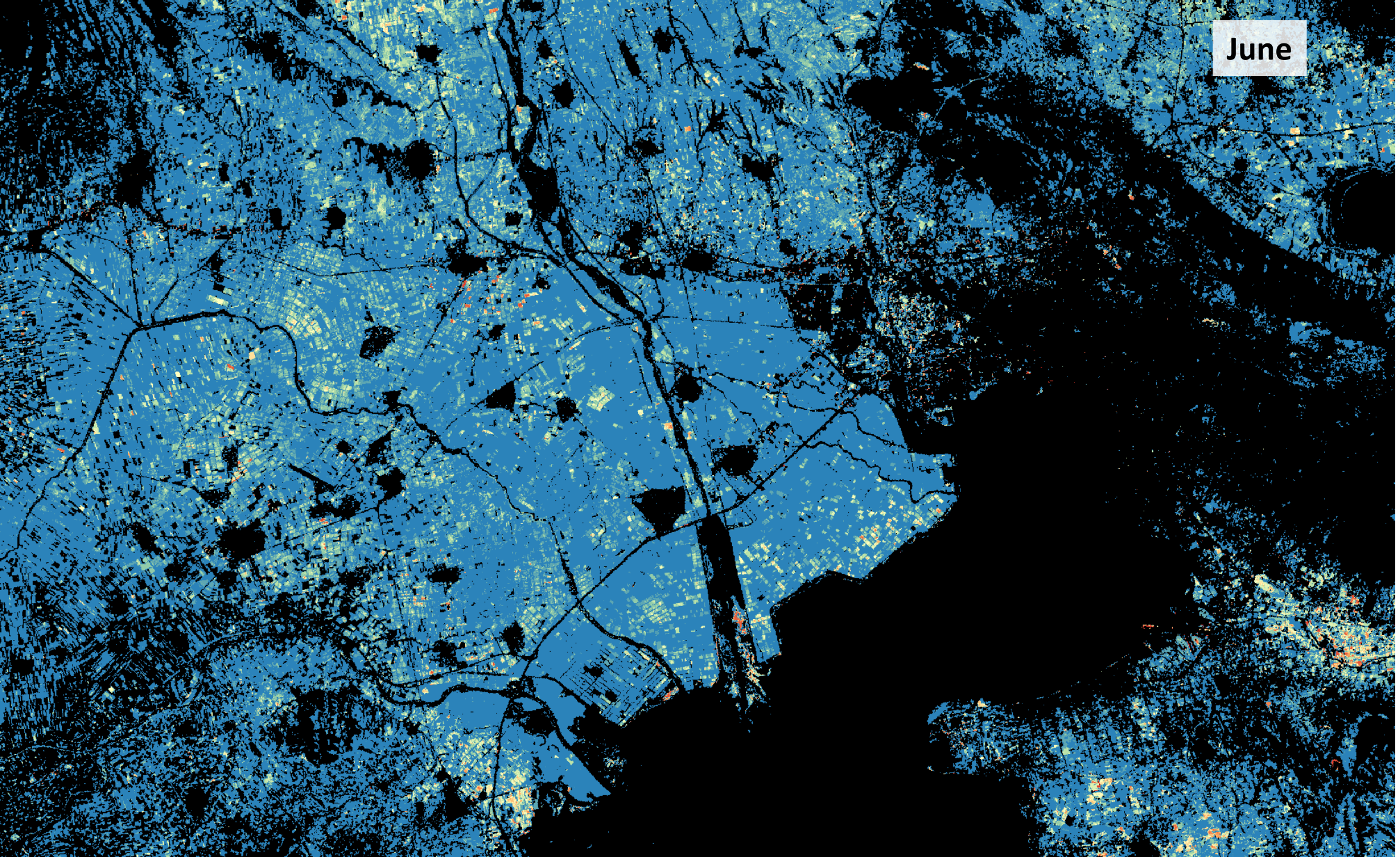
17

1

Bare soil count

17

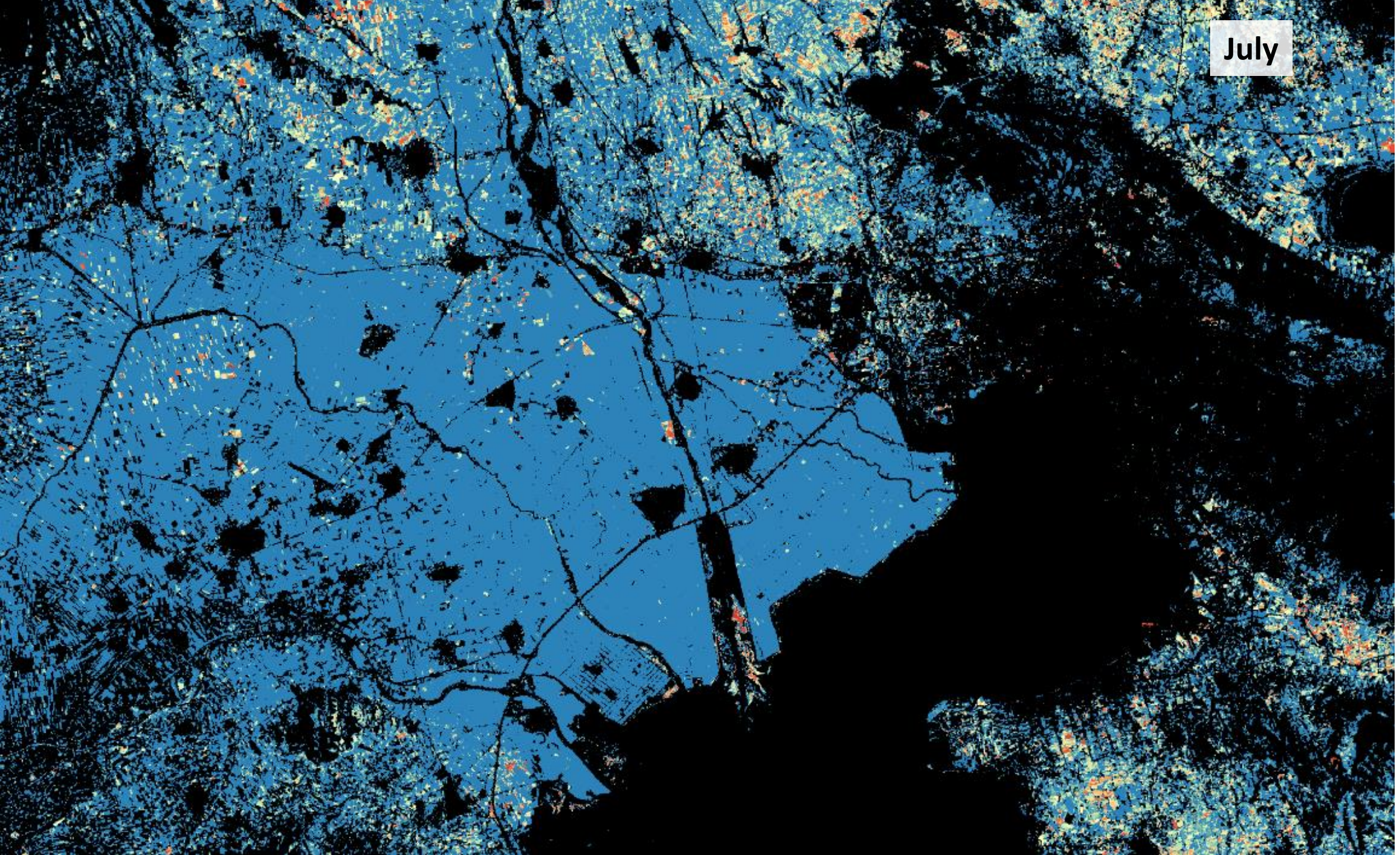
1



Bare soil count

17

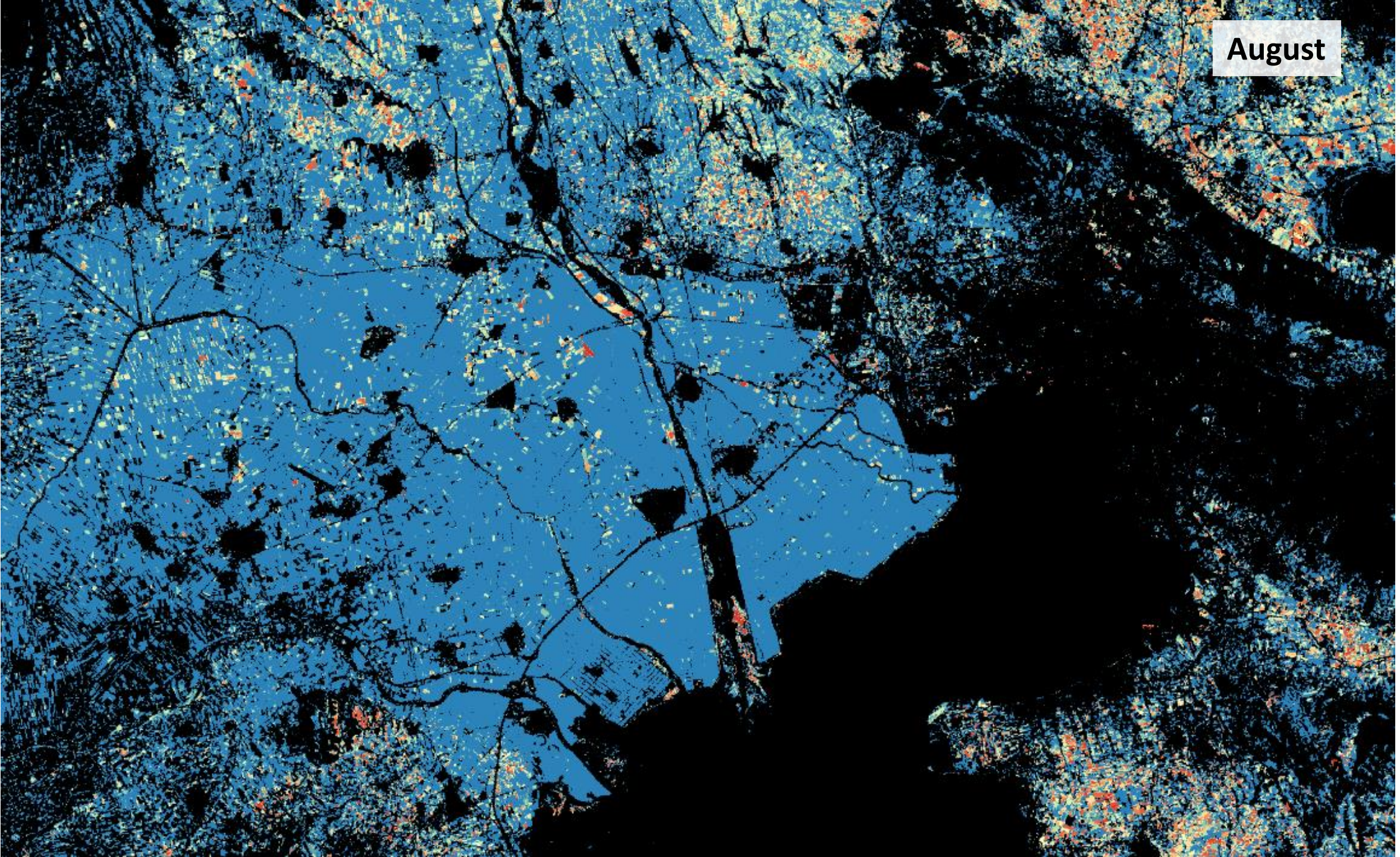
1



Bare soil count

17

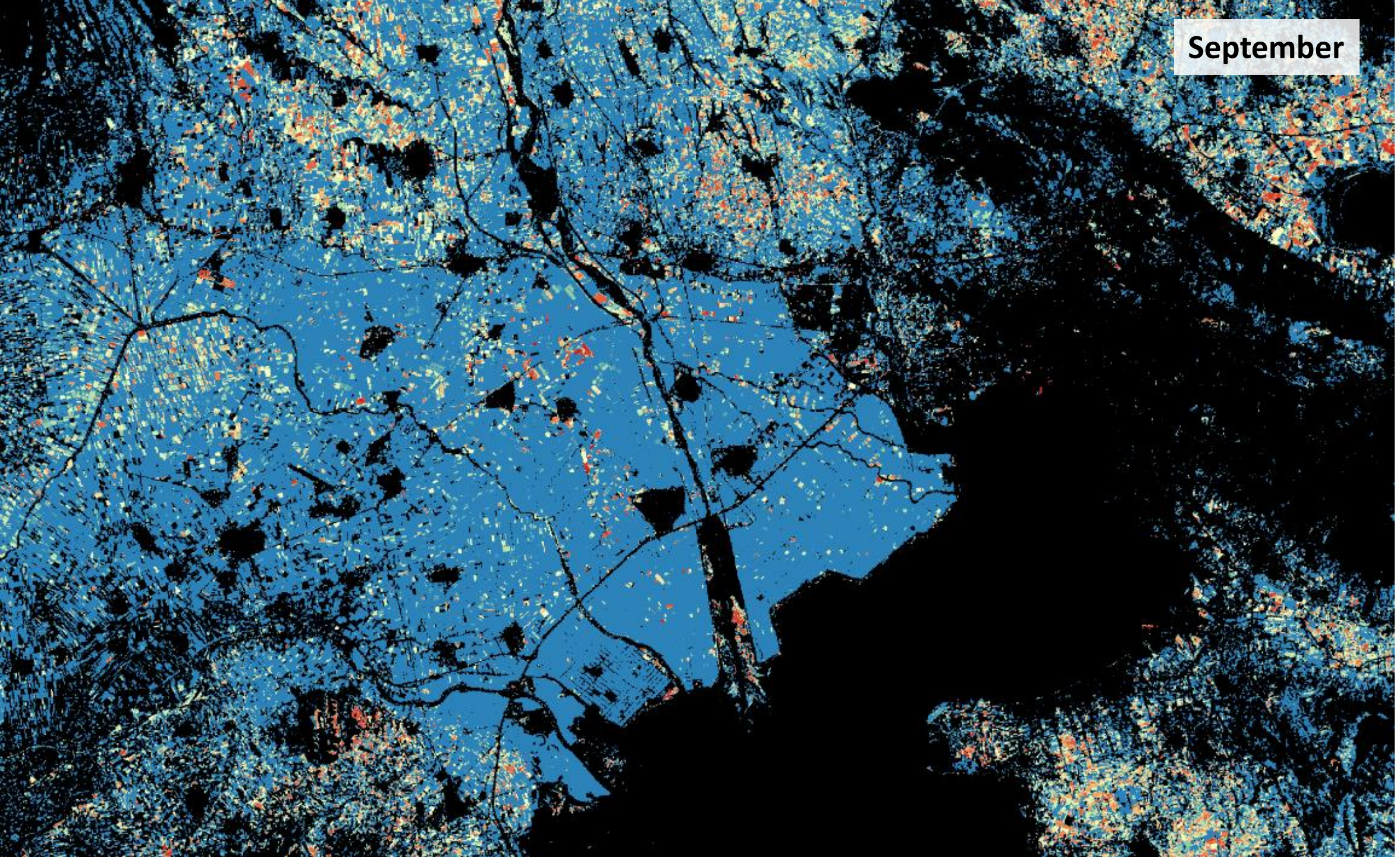
1



Bare soil count

17

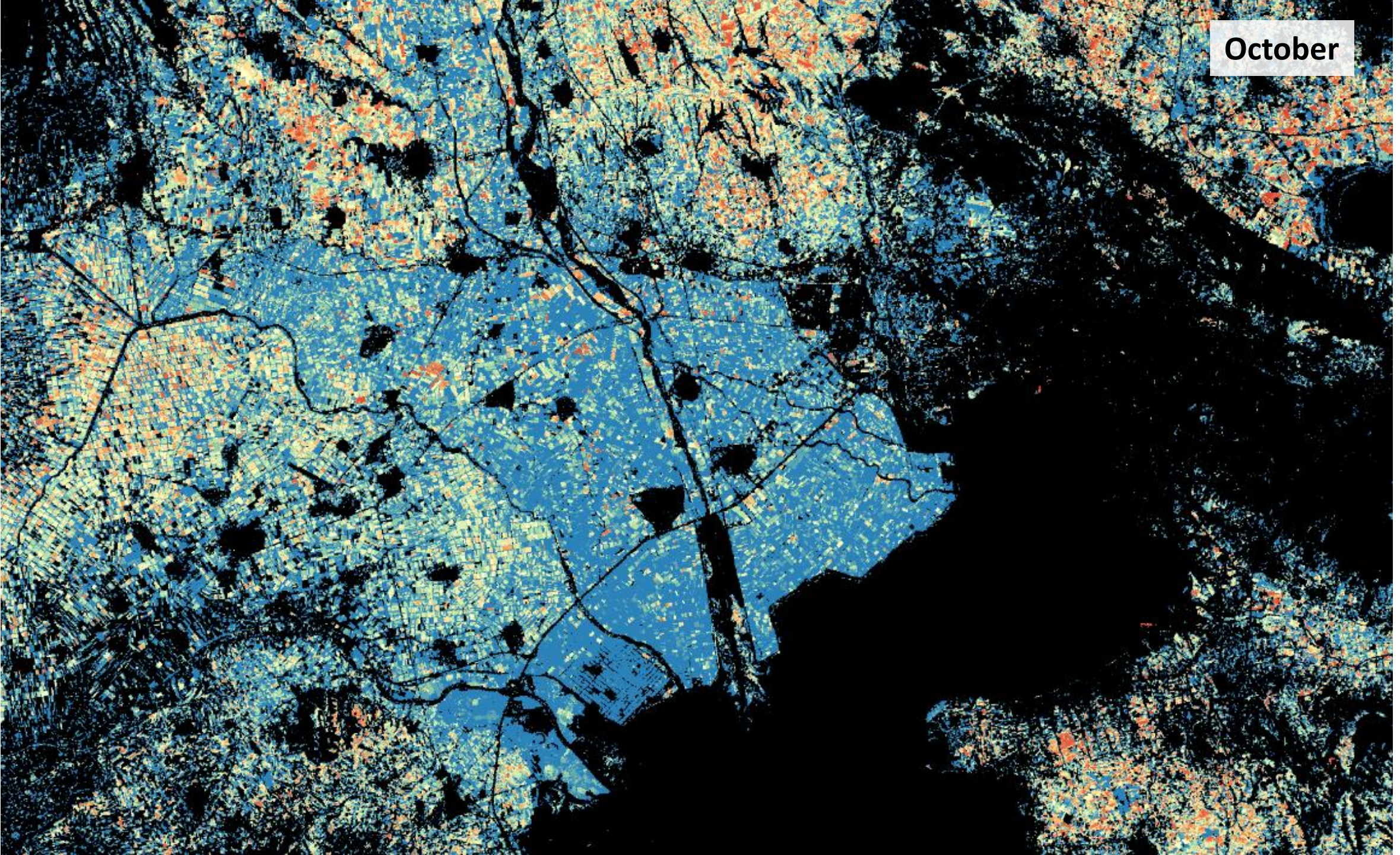
1



Bare soil count

17

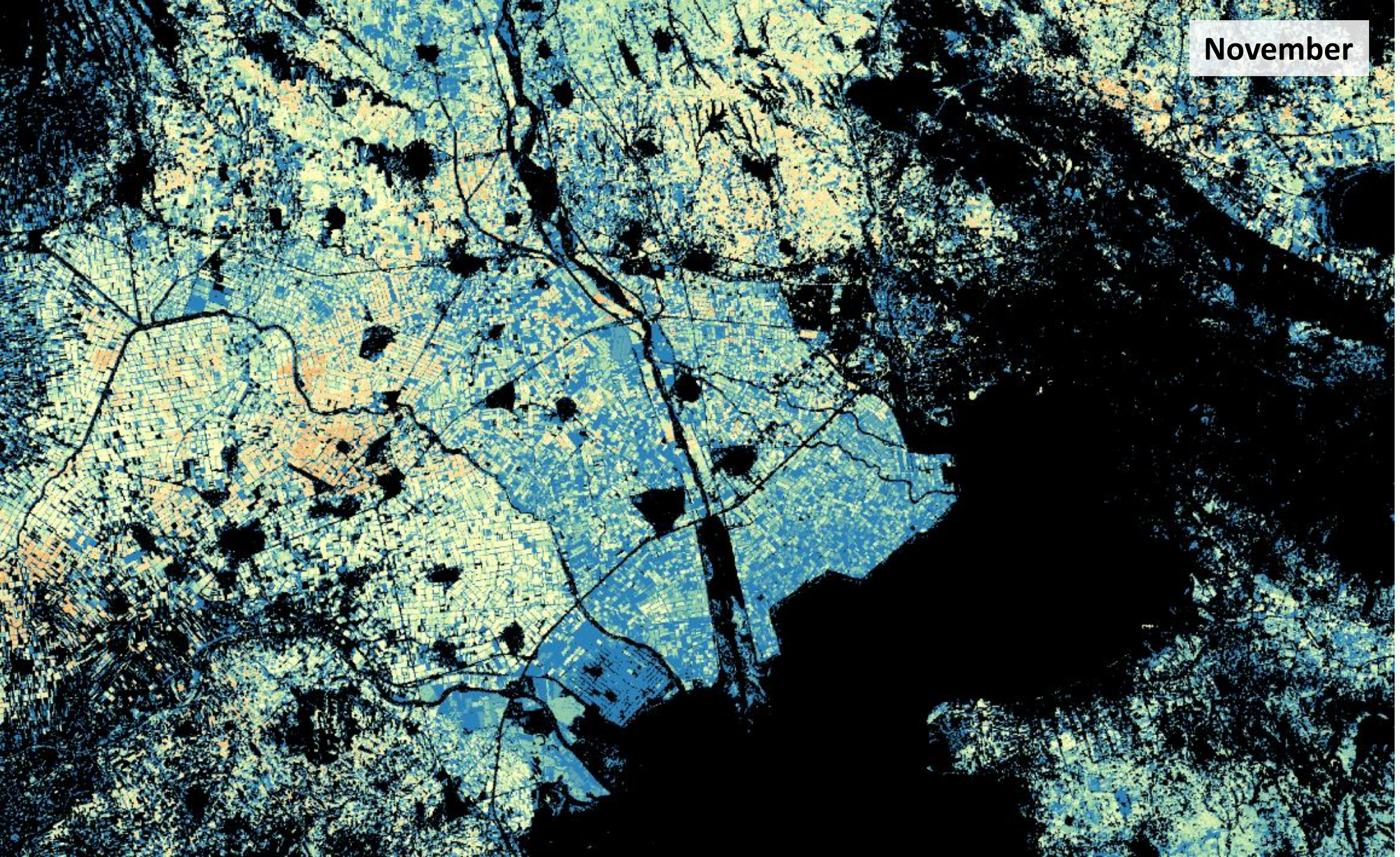
1



Bare soil count

17

1



Bare soil count

17

1

3. SCMaP Product Suite - Conclusion

Soil Reflectance Composites (SRC)

- The shorter the temporal length – the less pixels are available for calibrating soil models
- The longer the temporal length – the less seasonal variability / field to field differences
- The definition of the temporal length depends on the bare soil dynamic in the specific area

Soil Frequency

- Shows length of soil exposure
- Important information for analysing soil erosion and carbon sequestration processes
- Depends on crop type, agricultural practices, soil type

3. SCMaP Product Suite

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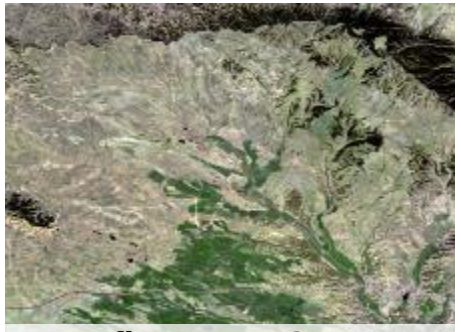
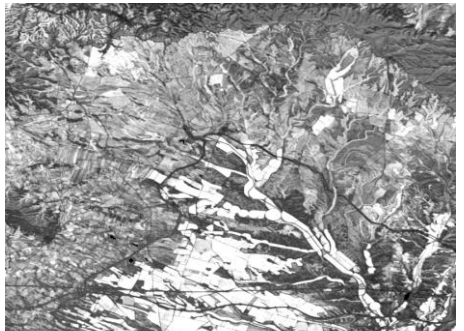
Reflectance Comp. (Maximum Index)


Reflectance Comp. (Minimum Index)

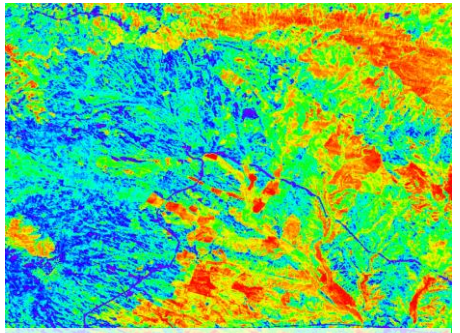

Reflectance Comp. (Mean)

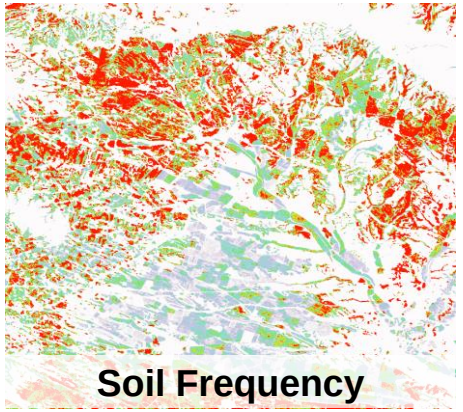

Index Composite (Stats)

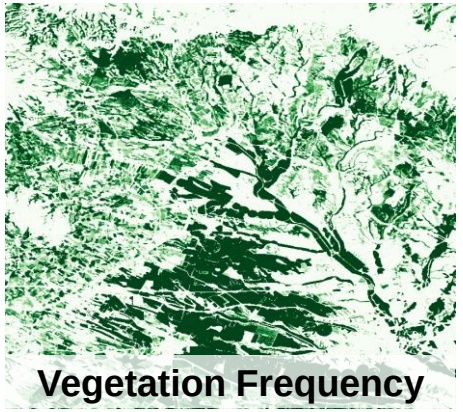

Soil Reflectance Composite

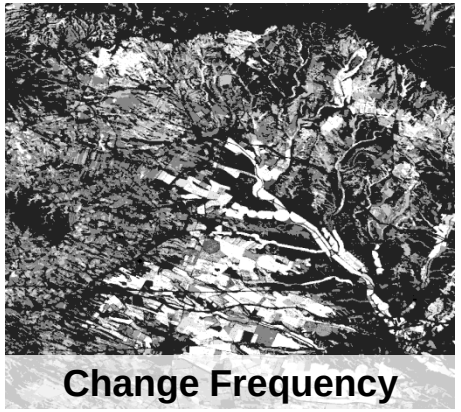

Soil Reflectance Composite (Normalised)

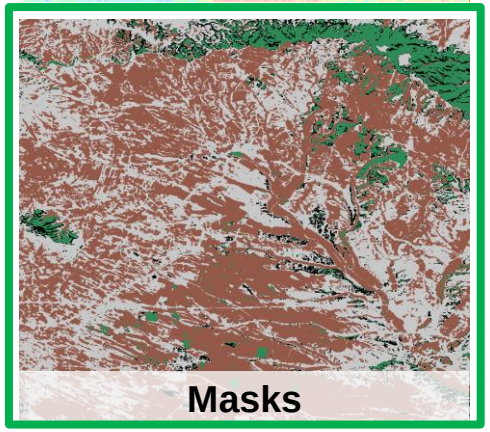

Mean Albedo


No. of Valid Inputs


Soil Frequency

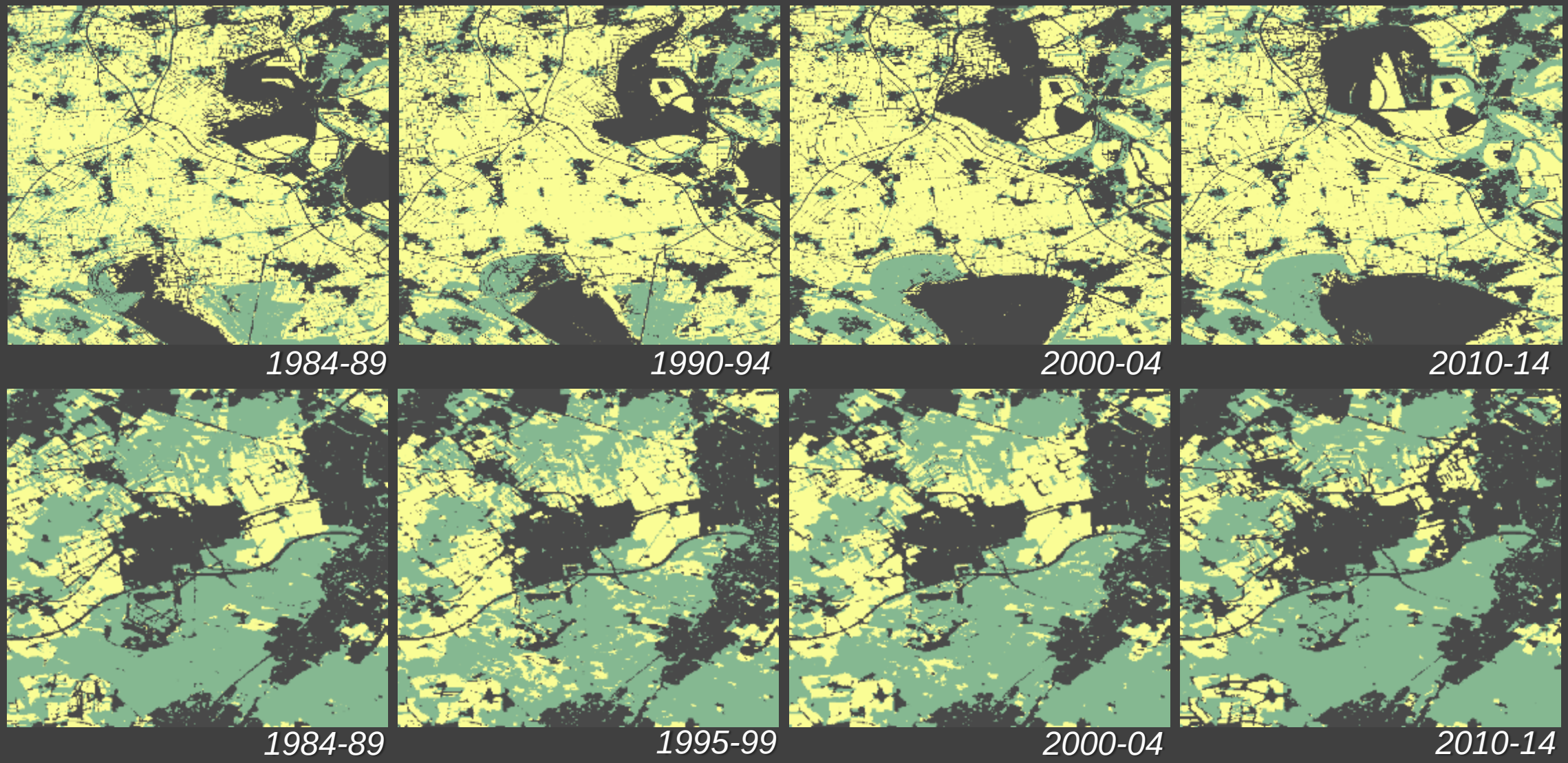

Vegetation Frequency


Change Frequency

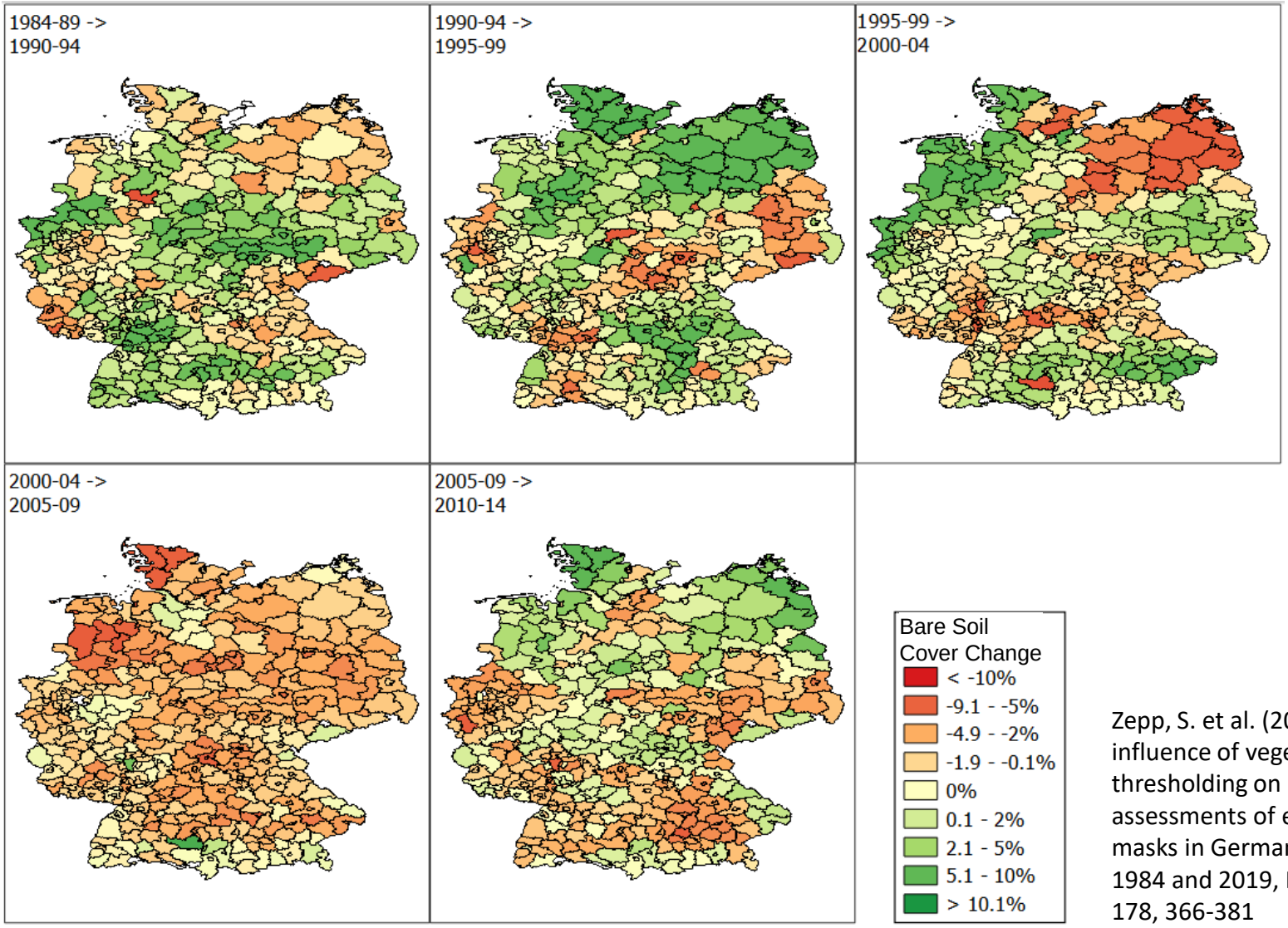

Masks

3. SCMaP Product Suite – SCMaP Masks (Landsat)

Zepp, S. et al. (2021): The influence of vegetation index thresholding on EO-based assessments of exposed soil masks in Germany between 1984 and 2019, ISPRS Journal, 178, 366-381



3. SCMaP Product Suite – SCMaP Masks



- Area of the bare soil mask per county for Germany
- Compared each 5 year period
- In 2005/2006: EU expanded the fallowing scheme* – impacts especially vegetable and sugar-beet crops in the NW of Germany

Source:https://de.wikipedia.org/wiki/Fl%C3%A4chenstilllegung

Zepp, S. et al. (2021): The influence of vegetation index thresholding on EO-based assessments of exposed soil masks in Germany between 1984 and 2019, ISPRS Journal, 178, 366-381

Summary and Outlook

- Operational processor SCMaP creates advanced input data base for characterisation of soils
- Uses optical remote sensing data such as Sentinel-2 and Landsat
- Runs platform independent and fully automated
- Tested and validated for large areas (Germany, different regions in Europe, Canada)

- SCMaP is and will be used in different international projects:
  - ESA WorldSoils (GMV) – Development of an operational system to measure SOC
  - EU MRV4SOC (GMV) – Generating an operational MRV systems for European soils
  - EU FPCUP (DLR) – Proposing soil products showing soil health as new Copernicus service
  - EU DESIRA (ISRIC) – Soil information for Africa

- Expand to hyperspectral satellite data (e.g. PRISMA, EnMAP, DESIS)

Thank you for your attention!
Question?

Contact: uta.heiden@dlr.de