Improved soil moisture estimation with Sentinel-1 for arable land at the field scale

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Summary

This presentation describes an approach to retrieve a useful field-scale soil moisture estimate from Sentinel-1 C-band SAR at times when the vegetation in the field is growing so rapidly that the radar does not directly measure soil moisture as it cannot penetrate the canopy. The approach is a two-dimensional interpolation solution, building on the change detection method, which gives good results. This plugs a significant gap in the capability for remote sensing of soil moisture in the main growing season, for the benefit of farmers and agronomists.

If you have any suggestions or further questions then please contact me via email at john.e.beale@cranfield.ac.uk.

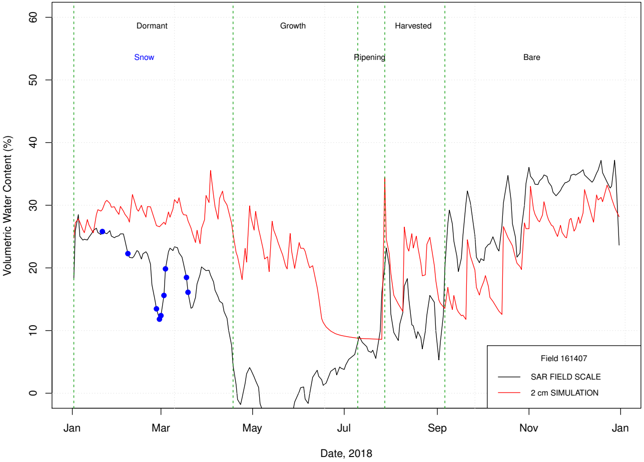
Outline

Introduction

- SAR data from satellites, such as ESA's Sentinel-1, are being exploited to estimate surface soil moisture (SM) at scale
- Change detection (CD) algorithms [1, 2, 3, 4], do not need model training or *a priori* information
- CD assumptions are not valid for arable fields [5, 6, 7]; typical errors in volumetric water content (VWC) are [8, 9]:
  - Up to 20 vol.% during the crop main growth period
  - 4 to 10 vol.% when the soil is bare
- Limited benefit to agriculture (5 vol.% desired)
- A new method of Inverse Distance and Confidence Weighting (IDCW) is proposed for implementing CD at field-scale that is effective for arable crops at all times of year

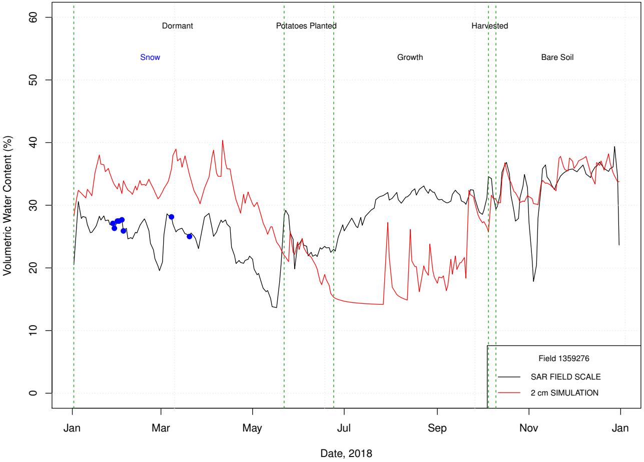
Arable Field Performance of CD Algorithm - Example 1

- Winter wheat field time series plot 2018 (#161407 at Fincham)
  - Field Scale SM estimate by CD (black)
  - 2 cm SM (red)
  - Crop and tillage activities - vertical, dotted, green lines
  - Blue dots - days of snow or ice
- CD estimate very low in spring/early summer
- Good match after ploughing (bare soil)



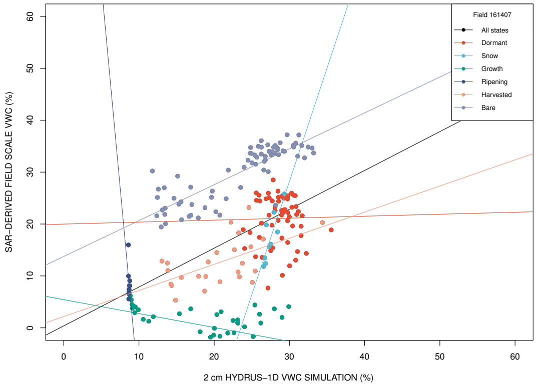
Arable Field Performance of CD Algorithm - Example 2

- Potato field time series plot 2018 (#1359276 at Spen Farm)
  - Field Scale SM estimate by CD (black)
  - 2 cm SM (red)
  - Crop and tillage activities - vertical, dotted, green lines
  - Blue dots - days of snow or ice
- CD estimate very high in summer
- Good match after harvesting (bare soil)

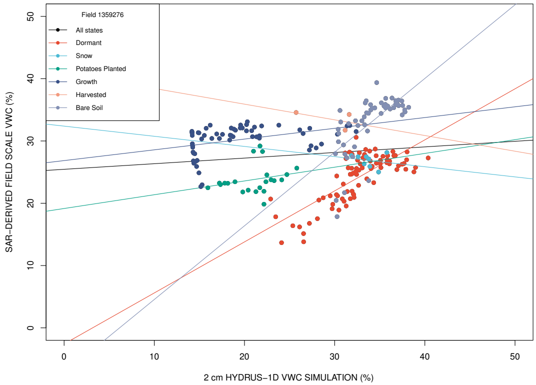


Arable Field Performance of CD Algorithm - Regression

Winter Wheat



Potatoes



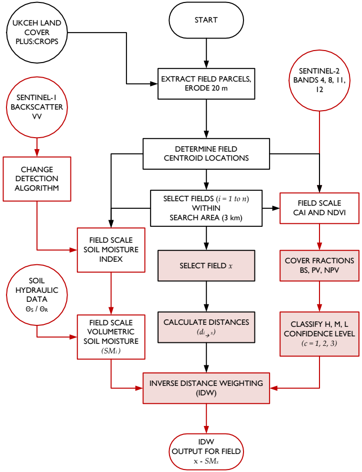
Arable Fields Summary of Performance

Crop Type	Year Round	Winter Dormancy	Growth Phase	Ripening	Post-harvest/Cut	Bare Soil
Winter Wheat (Trad. Till)	LOW	LOW	NONE	LOW	MEDIUM	HIGH
Winter Wheat (Min. Till)	MEDIUM	MEDIUM	LOW	MEDIUM	MEDIUM	HIGH
Oil-seed Rape	MEDIUM	LOW	NONE	NONE	MEDIUM	MEDIUM
Grass (Pasture)	HIGH					
Grass (Ley)	LOW	HIGH	LOW		HIGH	
Potatoes	LOW	HIGH	LOW		LOW	HIGH

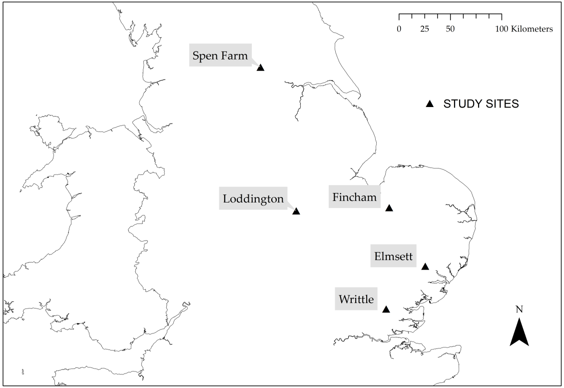
- Using C-band Sentinel-1 SAR data, CD has no capability to estimate SM in most arable crops at a crucial time of crop development
- An alternative strategy must be found to provide a soil moisture capability during these periods.

Materials and Methods

- Field geospatial information
  - Boundaries (erode 20 m)
  - Centroid locations
- Classify by CD confidence level, *c*
- Field-scale SM estimate, SM_i, by CD
- Spatial interpolation and confidence weighting
- Alternative field-scale SM estimate SM_x for field *x*



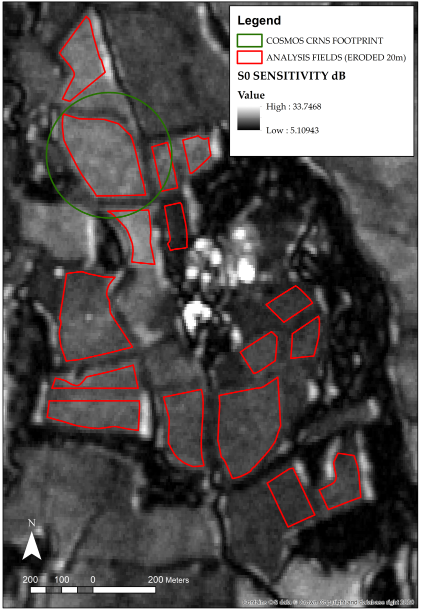
Test Sites



- Five test sites
  - Arable farming
  - Locations within the COSMOS-UK network [10]
  - Soil hydraulic parameters and 2 cm soil moisture profiles for 2018 were calculated for Beale et al. [9]
- Processing extents (at each site)
  - 3 km for IDCW (> 100 fields at each test site)
  - 5 km for Sentine1-1 and Sentinel-2 analysis
  - 8 to 10 assessment fields selected

Data

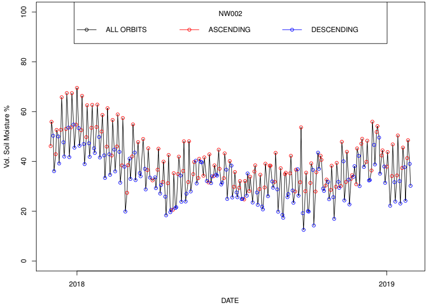
- UKCEH Land Cover Plus:Crops 2018 [11] (LCPC) for field boundaries - eroded by 20 m to exclude field margins, hedges and buildings
- Field scale SM derived from C-band SAR (Sentinel-1 GRD Level 1 IW VV) using CD algorithm [3, 4] implemented in Google Earth Engine (GEE), and scaled to volumetric SM [9].
- Sentinel-2 Level 2 MSI data for confidence level assessment
- Reference soil moisture at 2 cm depth [9]



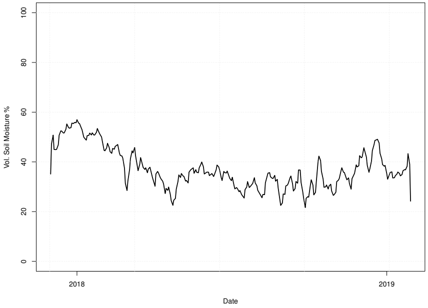
Filtering of field-scale SAR-derived SM

Potential causes

- The presence of scattering centres
- Structured soil surface roughness
- Errors in normalisation of backscatter
- SM differences due to times of day
- Layover affects

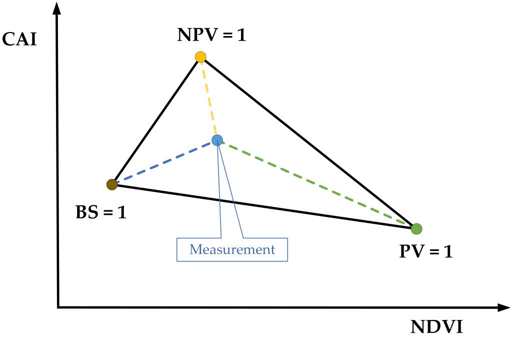


After smoothing Savitzky-Golay filtering (window of 7, 3rd order)



CD confidence level classification (1)

- Based the relative fractional land cover of bare soil (BS), photosynthetically active vegetation (PV) and non-photosynthetically active vegetation (NPV)
- Triangle space method adapted from Yue and Tian [12]



Vegetation indices – Sentinel-2 bands

$$NDVI = \frac{(NIR - red)}{(NIR + red)} = \frac{(B8 - B4)}{(B8 + B4)}$$

Surrogate of Cellulose Absorption Index (CAI) [13] proposed for Sentinel-2 [14]:

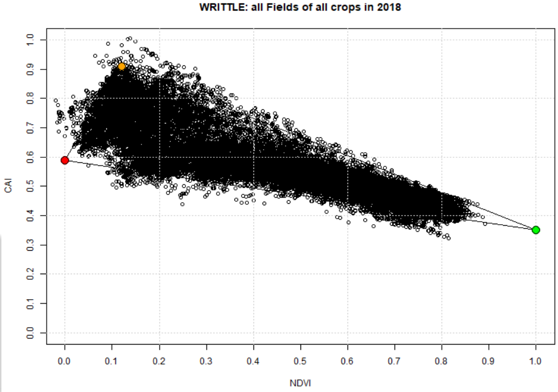
$$CAI^{*} = \frac{B12}{B11}$$

CD confidence level classification (2)

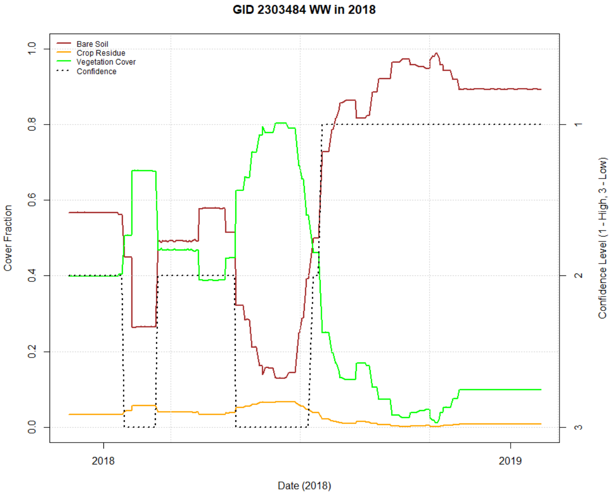
- Cover fractions established by spectral unmixing
- End member determination by scatter plot of all CAI/NDVI pairs at each site
- Confidence level assigned as below

Classification scheme

Class, *c*	Confidence Level	BS	NPV	PV	Logic
1	HIGH	> 0.6	< 0.2	< 0.3	AND
2	MEDIUM	> 0.4	< 0.2	< 0.5	AND
3	LOW	$\leqslant 0.4$	$\geqslant 0.2$	$\geqslant 0.5$	OR



Example: winter wheat field (2303484) at Fincham in 2018

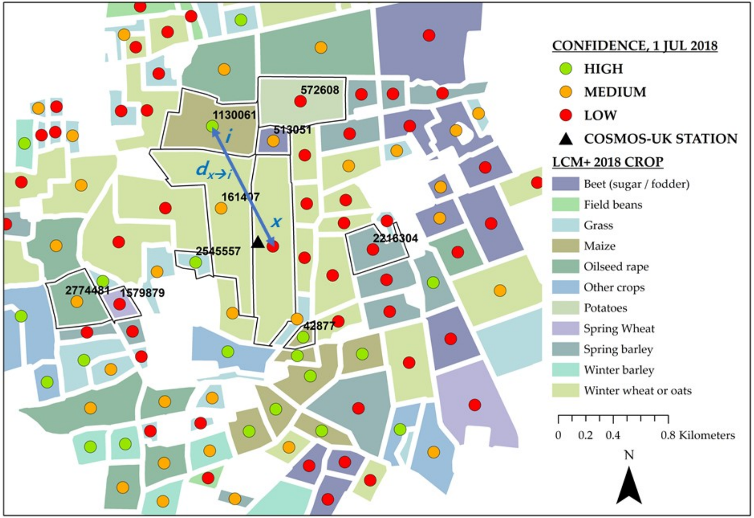


Spatial interpolation algorithm

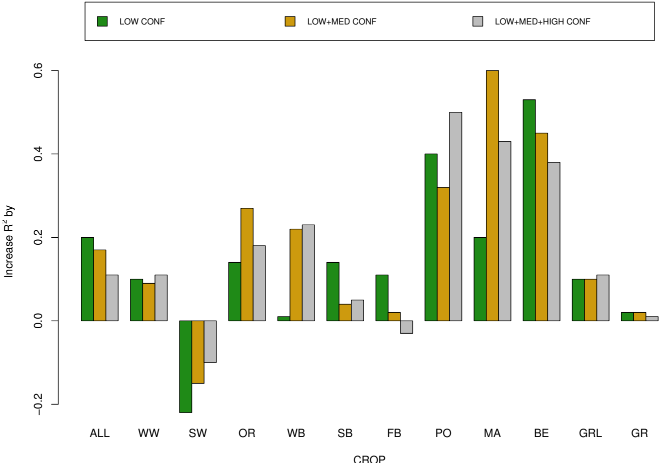
Inverse distance and confidence weighting (IDCW)

$$SM_x = \frac{\sum_{i=1}^{n} \frac{SM_i}{|d_{i\to x}|^{p} * c_i^{q}}}{\sum_{i=1}^{n} \frac{1}{|d_{i\to x}|^{p} * c_i^{q}}}$$

Based on IDW [15]



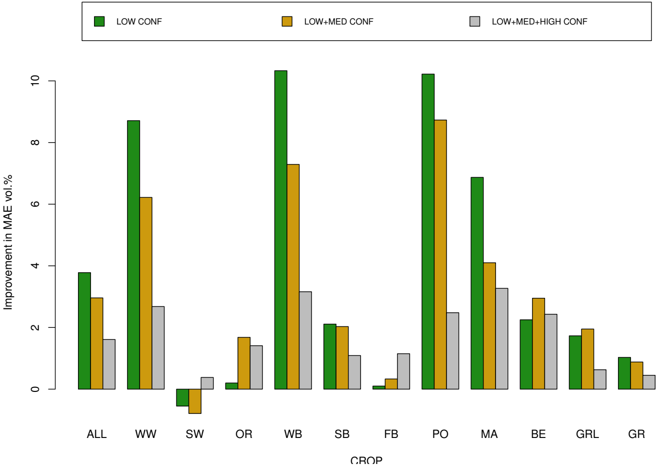
Results (1)
Increase in coefficient of determination, R^2



Key to crop types

ALL	all crops
WW	winter wheat
SW	spring wheat
OR	oil-seed rape
WB	winter barley
SB	spring barley
FB	field beans
PO	potatoes
BE	beet
GRL	ley grass
GR	grass (not ley)

Results (2)
Reduction of mean absolute error, *MAE*



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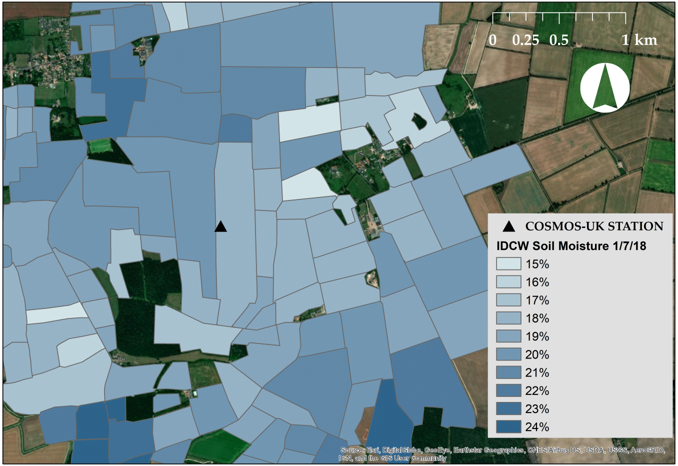
Results (3) - Benefits of IDCW to the accuracy of field-scale, SAR-derived surface SM

Crop	Period of confidence level: All Year	Low	Low/Medium	Headline
All	▲	▲	▲	
Oil-Seed Rape	▲	□	▲	*MAE* down from 7.42 vol.% to 6.01 vol.% over the whole year
Winter Wheat	▲	▲▲	▲▲	For LOW confidence *MAE* down from 16.1 vol.% to 7.39 vol.%
Spring Wheat	□	▽	▽	Reduction in R^2
Winter Barley	▲	▲▲	▲▲	*MAE* down from 20.5 vol.% to 10 vol.% in low conf.
Spring Barley	▲	▲	▲	R^2 up from 0.39 to 0.53 in low conf.
Field Beans	□	□	□	No benefit
Potatoes	▲▲	▲▲	▲▲	*MAE* down from 15 vol.% to 4.7 vol.% in low conf.
Maize	▲▲	▲▲	▲▲	*MAE* down from 11.5 vol.% to 4.5 vol.% in low conf.
Beet	▲	▲	▲▲	R^2 up from 0.09 to 0.62 in low conf.
Ley Grass	□	▲	▲	*MAE* down from 10 vol.% to 8 vol.% in low conf.
Grass	□	□	□	No benefit

▲▲ = Large benefit, ▲ = Small benefit, □ = No benefit, ▽ = Small disbenefit.

Prototype field-scale soil moisture map

A selection of fields around the Fincham COSMOS-UK site, on 1st July 2018
SM values derived from Sentinel-1 C-band SAR by field-scale CD followed by IDCW



Conclusions

- Field-scale arable crop performance of CD for SM estimation from Sentinel-1 SAR data is a function of crop canopy development and tillage state
- SM estimation errors of up 20 vol.% were found during the peak growth period
- The proposed automated process based on spectral vegetation indices is effective at identifying these periods of poor performance
- The proposed IDCW is effective for arable crops at all times of year, reducing errors to 5 vol.% as required for agricultural use [16]
- IDCW benefit is greatest for autumn-sown cereal crops
- These methods require no model training or *a-priori* knowledge of land use and crop type

The output from this study is a step towards providing a useful and reliable field-scale soil moisture product that works as well on arable fields as it does for other land uses

Recommendations

The proposed method is capable of further refinement and enhancements

- Extension to consider landscape heterogeneity/topography
- Modify interpolation according to soil maps and rainfall radar
- Use SAR data to identify periods of poor performance
- Find a solution to differentiate between grazed grass fields and ley grass

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References I

[1] F. Mattia, A. Balenzano, G. Satalino, F. Lovergine, J. Peng, U. Wegmuller, O. Cartus, M. W.J. Davidson, S. Kim, J. Johnson, J. Walker, X. Wu, V. R.N. Pauwels, H. McNairn, T. Caldwell, M. Cosh, and T. Jackson. Sentinel-1 & Sentinel-2 for soil moisture retrieval at field scale. *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2018-July(1):6143–6146, 2018. doi: 10.1109/IGARSS.2018.8518170.

[2] Michael Hornacek, Wolfgang Wagner, Daniel Sabel, Hong-Linh Truong, Paul Snoeij, Thomas Hahmann, Erhard Diedrich, and Marcela Doubkova. Potential for High Resolution Systematic Global Surface Soil Moisture Retrieval via Change Detection Using Sentinel-1. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 5(4):1303–1311, 2012. ISSN 1939-1404. doi: 10.1109/JSTARS.2012.2190136.

[3] Bernhard Bauer-Marschallinger and Christoph Paulik. Product User Manual, Surface Soil Moisture, Collection 1km, Version 1, 4 2019. URL https://land.copernicus.eu/global/sites/cgls.vito.be/files/products/CGLOPS1_PUM_SSM1km-V1_I1.30.pdf.

[4] Bernhard Bauer-Marschallinger, Vahid Freeman, Senmao Cao, Christoph Paulik, Stefan Schaufler, Tobias Stachl, Sara Modanesi, Christian Massari, Luca Ciabatta, Luca Brocca, and Wolfgang Wagner. Toward Global Soil Moisture Monitoring With Sentinel-1: Harnessing Assets and Overcoming Obstacles. *IEEE Transactions on Geoscience and Remote Sensing*, 57(1):520–539, 1 2019. ISSN 0196-2892. doi: 10.1109/TGRS.2018.2858004. URL https://ieeexplore.ieee.org/document/8444430/.

[5] Houda Ouled Benbrahim, Amine Merzouki, and Khalid Minaoui. Quantification of soil moisture variability over agriculture fields using Sentinel imagery. In *2020 International Conference on Intelligent Systems and Computer Vision (ISCV)*, pages 1–4. IEEE, 6 2020. ISBN 978-1-7281-8041-0. doi: 10.1109/ISCV49265.2020.9204120. URL https://ieeexplore.ieee.org/document/9204120/.

[6] Francesco Mattia, Anna Balenzano, Giuseppe Satalino, Davide Palmisano, Annarita D'Addabbo, and Francesco Lovergine. Field Scale Soil Moisture From Time Series Of Sentinel-1 & Sentinel-2. In *2020 Mediterranean and Middle-East Geoscience and Remote Sensing Symposium (M2GARSS)*, pages 176–179. IEEE, 3 2020. ISBN 978-1-7281-2190-1. doi: 10.1109/M2GARSS47143.2020.9105290. URL https://ieeexplore.ieee.org/document/9105290/.

[7] Mohammad El Hajj, Nicolas Baghdadi, Hassan Bazzi, and Mehrez Zribi. Penetration Analysis of SAR Signals in the C and L Bands for Wheat, Maize, and Grasslands. *Remote Sensing*, 11(1):31, 12 2018. ISSN 2072-4292. doi: 10.3390/rs11010031. URL http://www.mdpi.com/2072-4292/11/1/31.

References II

[8] John Beale, Toby Waine, Ronald Corstanje, and Jonathan Evans. A performance assessment method for SAR satellite derived surface soil moisture data using a soil water balance model, meteorological observations, and soil pedotransfer functions. In *EGU General Assembly 2020*. Copernicus GmbH, 3 2020. doi: 10.5194/egusphere-egu2020-3387. URL https://meetingorganizer.copernicus.org/EGU2020/EGU2020-3387.html.

[9] John Beale, Toby Waine, Ron Corstanje, and Jonathan Evans. A Method to Assess the Performance of SAR-derived Surface Soil Moisture Products. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, In press, 2021.

[10] Jonathan G. Evans, H. C. Ward, J. R. Blake, E. J. Hewitt, R. Morrison, M. Fry, L. A. Ball, L. C. Doughty, J. W. Libre, O. E. Hitt, D. Rylett, R. J. Ellis, A. C. Warwick, M. Brooks, M. A. Parkes, G. M.H. Wright, A. C. Singer, D. B. Boorman, and A. Jenkins. Soil water content in southern England derived from a cosmic-ray soil moisture observing system – COSMOS-UK. *Hydrological Processes*, 30(26):4987–4999, 2016. ISSN 10991085. doi: 10.1002/hyp.10929.

[11] R.D. Morton, C.G. Marston, A.W. O'Neil, and C.S. Rowland. Land Cover Map 2018 (land parcels, GB), 2020. URL https://doi.org/10.5285/9f7f7f70-5137-4bfc-a6a3-f91783d5a6a6.

[12] Jibo Yue and Qingjiu Tian. Estimating fractional cover of crop, crop residue, and soil in cropland using broadband remote sensing data and machine learning. *International Journal of Applied Earth Observation and Geoinformation*, 89(September 2019):102089, 2020. ISSN 03032434. doi: 10.1016/j.jag.2020.102089. URL https://doi.org/10.1016/j.jag.2020.102089.

[13] Juan Pablo Guerschman, Michael J Hill, Luigi J Renzullo, Damian J Barrett, Alan S Marks, and Elizabeth J Botha. Estimating fractional cover of photosynthetic vegetation, non-photosynthetic vegetation and bare soil in the Australian tropical savanna region upscaling the EO-1 Hyperion and MODIS sensors. *Remote Sensing of Environment*, 113(5):928–945, 5 2009. ISSN 00344257. doi: 10.1016/j.rse.2009.01.006. URL http://dx.doi.org/10.1016/j.rse.2009.01.006https://linkinghub.elsevier.com/retrieve/pii/S0034425709000121.

[14] Yady T. Solano-Correa, Daniel Carcereri, Francesca Bovolo, and Lorenzo Bruzzone. Identification of non-photosynthetic vegetation areas in Sentinel-2 satellite image time series. In Lorenzo Bruzzone, Francesca Bovolo, and Jon Atli Benediktsson, editors, *Image and Signal Processing for Remote Sensing XXV*, number October 2019, page 32. SPIE, 10 2019. ISBN 9781510630130. doi: 10.1117/12.2533761. URL https://www.spiedigitallibrary.org/conference-proceedings-of-spie/11155/2533761/Identification-of-non-photosynthetic-vegetation-areas-in-Sentinel-2-satellite/10.1117/12.2533761.full.

[15] Donald Shepard. A two-dimensional interpolation function for irregularly-spaced data. In *Proceedings of the 1968 23rd ACM national conference on -*, pages 517–524, New York, New York, USA, 1968. ACM Press. doi: 10.1145/800186.810616. URL http://portal.acm.org/citation.cfm?doid=800186.810616.

[16] M. Susan Moran. New imaging sensor technologies suitable for agricultural management. *Aspects of Applied Biology*, 6(1998):1–10, 2000.

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