Francois Waldner

List of Publications by Year
in descending order

51 papers	3,382 citations	186265 28 h-index	189892 50 g-index
55 all docs	55 docs citations	55 times ranked	3605 citing authors

#	Article	IF	Citations
1	ResUNet-a: A deep learning framework for semantic segmentation of remotely sensed data. ISPRS Journal of Photogrammetry and Remote Sensing, 2020, 162, 94-114.	11.1	728
2	The academic, economic and societal impacts of Open Access: an evidence-based review. F1000Research, 2016, 5, 632.	1.6	284
3	A comparison of global agricultural monitoring systems and current gaps. Agricultural Systems, 2019, 168, 258-272.	6.1	183
4	Estimating wheat yields in Australia using climate records, satellite image time series and machine learning methods. ISPRS Journal of Photogrammetry and Remote Sensing, 2020, 160, 124-135.	11.1	157
5	The academic, economic and societal impacts of Open Access: an evidence-based review. F1000Research, 2016, 5, 632.	1.6	141
6	Automated annual cropland mapping using knowledge-based temporal features. ISPRS Journal of Photogrammetry and Remote Sensing, 2015, 110, 1-13.	11.1	135
7	Deep learning on edge: Extracting field boundaries from satellite images with a convolutional neural network. Remote Sensing of Environment, 2020, 245, 111741.	11.0	134
8	A multi-disciplinary perspective on emergent and future innovations in peer review. F1000Research, 2017, 6, 1151.	1.6	134
9	Sentinel-2â€™s Potential for Sub-Pixel Landscape Feature Detection. Remote Sensing, 2016, 8, 488.	4.0	132
10	An Automated Method for Annual Cropland Mapping along the Season for Various Globally-Distributed Agrosystems Using High Spatial and Temporal Resolution Time Series. Remote Sensing, 2015, 7, 13208-13232.	4.0	112
11	Towards a set of agrosystem-specific cropland mapping methods to address the global cropland diversity. International Journal of Remote Sensing, 2016, 37, 3196-3231.	2.9	92
12	Mapping Priorities to Focus Cropland Mapping Activities: Fitness Assessment of Existing Global, Regional and National Cropland Maps. Remote Sensing, 2015, 7, 7959-7986.	4.0	87
13	A Generic Algorithm to Estimate LAI, FAPAR and FCOVER Variables from SPOT4_HRVIR and Landsat Sensors: Evaluation of the Consistency and Comparison with Ground Measurements. Remote Sensing, 2015, 7, 15494-15516.	4.0	70
14	Mapping Cropland Abandonment in the Aral Sea Basin with MODIS Time Series. Remote Sensing, 2018, 10, 159.	4.0	68
15	A multi-disciplinary perspective on emergent and future innovations in peer review. F1000Research, 2017, 6, 1151.	1.6	62
16	Land Cover and Crop Type Classification along the Season Based on Biophysical Variables Retrieved from Multi-Sensor High-Resolution Time Series. Remote Sensing, 2015, 7, 10400-10424.	4.0	54
17	Maize Leaf Area Index Retrieval from Synthetic Quad Pol SAR Time Series Using the Water Cloud Model. Remote Sensing, 2015, 7, 16204-16225.	4.0	53
18	A Unified Cropland Layer at 250 m for Global Agriculture Monitoring. Data, 2016, 1, 3.	2.3	52

#	Article	IF	Citations
19	Cropland Mapping over Sahelian and Sudanian Agrosystems: A Knowledge-Based Approach Using PROBA-V Time Series at 100-m. Remote Sensing, 2016, 8, 232.	4.0	49
20	A global reference database of crowdsourced cropland data collected using the Geo-Wiki platform. Scientific Data, 2017, 4, 170136.	5.3	46
21	Looking for Change? Roll the Dice and Demand Attention. Remote Sensing, 2021, 13, 3707.	4.0	44
22	A Dynamic Vegetation Senescence Indicator for Near-Real-Time Desert Locust Habitat Monitoring with MODIS. Remote Sensing, 2015, 7, 7545-7570.	4.0	43
23	National-scale cropland mapping based on spectral-temporal features and outdated land cover information. PLoS ONE, 2017, 12, e0181911.	2.5	42
24	Operational Monitoring of the Desert Locust Habitat with Earth Observation: An Assessment. ISPRS International Journal of Geo-Information, 2015, 4, 2379-2400.	2.9	39
25	Regional-scale monitoring of cropland intensity and productivity with multi-source satellite image time series. GIScience and Remote Sensing, 2018, 55, 539-567.	5.9	38
26	Needle in a haystack: Mapping rare and infrequent crops using satellite imagery and data balancing methods. Remote Sensing of Environment, 2019, 233, 111375.	11.0	37
27	High temporal resolution of leaf area data improves empirical estimation of grain yield. Scientific Reports, 2019, 9, 15714.	3.3	35
28	Detect, Consolidate, Delineate: Scalable Mapping of Field Boundaries Using Satellite Images. Remote Sensing, 2021, 13, 2197.	4.0	32
29	Yield forecasting with machine learning and small data: What gains for grains?. Agricultural and Forest Meteorology, 2021, 308-309, 108555.	4.8	28
30	Where can pixel counting area estimates meet user-defined accuracy requirements?. International Journal of Applied Earth Observation and Geoinformation, 2017, 60, 1-10.	2.8	25
31	Conflation of expert and crowd reference data to validate global binary thematic maps. Remote Sensing of Environment, 2019, 221, 235-246.	11.0	24
32	Roadside collection of training data for cropland mapping is viable when environmental and management gradients are surveyed. International Journal of Applied Earth Observation and Geoinformation, 2019, 80, 82-93.	2.8	22
33	Nationwide crop yield estimation based on photosynthesis and meteorological stress indices. Agricultural and Forest Meteorology, 2020, 284, 107872.	4.8	22
34	Timely monitoring of Asian Migratory locust habitats in the Amudarya delta, Uzbekistan using time series of satellite remote sensing vegetation index. Journal of Environmental Management, 2016, 183, 562-575.	7.8	19
35	The impact of training class proportions on binary cropland classification. Remote Sensing Letters, 2017, 8, 1122-1131.	1.4	18
36	The academic, economic and societal impacts of Open Access: an evidence-based review. F1000Research, 0, 5, 632.	1.6	17

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37	A multi-disciplinary perspective on emergent and future innovations in peer review. F1000Research, 0, 6, 1151.	1.6	14
38	Socio-psychological and management drivers explain farm level wheat yield gaps in Australia. Agronomy for Sustainable Development, 2019, 39, 1.	5.3	12
39	All pixels are useful, but some are more useful: Efficient in situ data collection for crop-type mapping using sequential exploration methods. International Journal of Applied Earth Observation and Geoinformation, 2020, 91, 102114.	2.8	11
40	Simplicity on the far side of complexity: optimizing nitrogen for wheat in increasingly variable rainfall environments. Environmental Research Letters, 2020, 15, 114060.	5.2	11
41	Modelling seasonal pasture growth and botanical composition at the paddock scale with satellite imagery. In Silico Plants, 2021, 3, .	1.9	11
42	An information-based criterion to measure pixel-level thematic uncertainty in land cover classifications. Stochastic Environmental Research and Risk Assessment, 2017, 31, 2297-2312.	4.0	9
43	Social capital and transaction costs in millet markets. Heliyon, 2018, 4, e00505.	3.2	9
44	Local adjustments of image spatial resolution to optimize large-area mapping in the era of big data. International Journal of Applied Earth Observation and Geoinformation, 2018, 73, 374-385.	2.8	9
45	To Blend or Not to Blend? A Framework for Nationwide Landsatâ€"MODIS Data Selection for Crop Yield Prediction. Remote Sensing, 2020, 12, 1653.	4.0	6
46	How Response Designs and Class Proportions Affect the Accuracy of Validation Data. Remote Sensing, 2020, 12, 257.	4.0	6
47	Combining Fractional Cover Images with One-Class Classifiers Enables Near Real-Time Monitoring of Fallows in the Northern Grains Region of Australia. Remote Sensing, 2020, 12, 1337.	4.0	5
48	Graincastâ„¢: monitoring crop production across the Australian grainbelt. Crop and Pasture Science, 2023, 74, 509-523.	1.5	5
49	Data fusion using climatology and seasonal climate forecasts improves estimates of Australian national wheat yields. Agricultural and Forest Meteorology, 2022, 320, 108932.	4.8	5
50	The T Index: Measuring the Reliability of Accuracy Estimates Obtained from Non-Probability Samples. Remote Sensing, 2020, 12, 2483.	4.0	4
51	Climate drivers provide valuable insights into late season prediction of Australian wheat yield. Agricultural and Forest Meteorology, 2020, 295, 108202.	4.8	3