Evaluation of Remotely Sensed Soil Moisture Products using Crowdsourced Measurements

Luca Zappa[a], Mel Woods*[b], Drew Hemment[c], Angelika Xaver[a], Wouter Dorigo[a]
[a]Department of Geodesy and Geoinformation, TU Wien, Vienna, Austria; [b]DJCAD, University of Dundee, Dundee, UK; [c] Edinburgh Futures Institute, University of Edinburgh, Edinburgh, UK

ABSTRACT

Global soil moisture products retrieved from various sensors onboard satellites are becoming readily available. However, validation of such products is a crucial step to ensure their reliability. In-situ measurements, which provide the most accurate soil moisture estimates, are often used as reference dataset, but they are limited in number. The GROW Observatory (GROW) was initiated to demonstrate that a 'Citizens' Observatory' (CO) can provide and utilise unprecedented amounts of data. We present GROW as a case study and demonstrate, for the first time, the use of crowdsourced observations to assess the temporal and spatial consistency of various satellite-derived soil moisture products. In particular, we provide evidence of the added value to Earth Observation, thanks to (i) the high number of sensors deployed, covering a wide range of land use, environmental, and climatic conditions, and (ii) the unique spatial density in GROW. Our results confirmed that SMAP and ESA CCI SM can better capture the temporal dynamics compared to the other products investigated. We found high uncertainties due to the spatial mismatch between in-situ and satellite observations, not only for coarse scale but also for high-resolution soil moisture products. This finding highlights the importance of crowdsourced observations, which have the potential to reduce representativeness errors. Finally, a preliminary analysis of the spatial consistency of Sentinel-1 soil moisture showed a poor agreement against GROW data. We conclude presenting the challenges and the steps that will follow this preliminary analysis, as well as design guidelines for COs to meaningfully contribute to Earth Observation.

Keywords: Citizens' Observatory, Crowdsourcing, Remote Sensing, Soil Moisture, Satellite Validation, In-situ, Citizen Science, Design

*m.j.woods@dundee.ac.uk; phone +44 1382 540455; dundee.ac.uk

1. INTRODUCTION

Soil moisture is a key variable regulating the water, energy, and carbon fluxes between the soil-plant-atmosphere continuum[1]. For instance, soil moisture affects the partitioning of water between runoff and groundwater recharge, controls the ratio between sensible and latent heat fluxes, and governs the water available to vegetation for photosynthesis[2–4]. Therefore, accurate knowledge of spatial and temporal patterns of soil moisture is essential to deepen our understanding of hydrologic processes, vegetation productivity, and the climate system. This, in turn, can benefit society as a whole, by e.g., enhancing resilience to extreme climate events such as floods, drought, and wildfires.

Remote sensing is a very efficient means of monitoring soil moisture conditions globally. Since the last two decades, microwave sensors on-board satellites have been used to retrieve soil moisture either from backscatter (active sensors, i.e. radars) or from brightness temperature (passive sensors, i.e. radiometers). Soil moisture has been successfully estimated because of the high contrast between the dielectric properties of water and dry soil[5]. Several satellite-derived soil moisture products are currently available, with a varying range of spatial and temporal resolutions. Widely used soil moisture products are based, among others, on the SMAP (Soil Moisture Active Passive) mission[6] launched by NASA (National Aeronautics and Space Administration), the ASCAT (Advanced Scatterometer) sensor[7] on board the Metop satellites, and the recently launched Sentinel-1 mission by ESA (European Space Agency). Furthermore, efforts have been directed to develop algorithms for merging various products, in order to improve either the observation period, the spatial/temporal resolution, or both. For instance, the ESA CCI (Climate Change Initiative) SM product is obtained by blending several active and passive products[8].

In order to exploit such remotely sensed data, validation is a crucial step to ensure their reliability. In-situ (i.e. ground) measurements collected by soil moisture sensors are commonly used as reference, i.e. the so-called ground truth. However, validation of soil moisture products is difficult because of two main factors[9]. The first is the spatial mismatch between the satellite footprint and the volume of soil sampled by a sensor. The second, which further amplifies the previous issue, is the high spatial variability of soil moisture. Therefore, a large number of in-situ sensors would be necessary to thoroughly validate soil moisture products. Unfortunately, the setup of such a network is not feasible because of the high costs associated with the installation and maintenance of ground sensors[10].

An appealing solution to fill this gap is offered by Citizens' Observatories (COs), which have gained great attention in the last decade[11]. COs are community-based environmental monitoring and information systems bringing together stakeholders from policy and science with individuals and communities to share and use data and observations. Many of these initiatives make use of accessible sensing technologies for data gathering and also create learning resources and protocols for participants to ensure data quality. COs frequently adopt participatory approaches with the aim of empowering people to make sense of the data, and use the data to address both scientific and community challenges. These measures have the potential to overcome barriers such as motivation and retention of citizens, data quality and accuracy, and improved decision-making.

In particular, the GROW Observatory (GROW), one of four H2020 CO Innovation Actions funded by the European Commission (EC) in 2016, had the ambition to monitor soil moisture continuously over an extended period and at an unmatched spatial density[12]. GROW provided the means for farmers and land managers to contribute to validation of satellite soil moisture products, and address their own local environmental issues relating to soil condition and climate variability. In its support for growing communities, GROW moved beyond the provision of information and knowledge, to give communities access to open data in order to stimulate social innovation. GROW generates crowdsourced data at high temporal and spatial density, verifies quality and validity, integrates the data in global monitoring systems, and creates information services built on that data. GROW data has been integrated in the International Soil Moisture Network (ISMN)[13]and has potential to extend the in-situ segment of the Global Earth Observation System of Systems (GEOSS).

The objective of this study was to employ for the first-time crowdsourced soil moisture observations for evaluating the accuracy of various remotely sensed soil moisture products. Both coarse scale (ASCAT, SMAP, and ESA CCI SM) and high-resolution (Sentinel-1) products have been evaluated against in-situ measurements collected within GROW. Thanks to the spatial density and coverage of crowdsourced measurements we were able to (i) analyse the performance of satellite products over different climatic and environmental conditions, (ii) analyse the within-pixel variability for highly represented pixels, and finally (iii) carry out an evaluation of the spatial consistency of the Sentinel-1 high-resolution product.

2. DATA AND METHODS

2.1 The GROW approach

GROW developed and evaluated a challenge-based, design-led approach to scope issues, build cross-disciplinary partnerships, develop scientific protocols, collect and integrate data, and stimulate innovation and advocacy built on data[14,15]. A sensor distribution plan was defined according to both scientific needs and social variables to meet the requirement for a large scale, high density network of soil sensors across Europe**.** Priority areas called GROW Places were designed and specified as a model for minimum viable high-density clusters, based on geographical, climatic, social and scientific criteria. At each GROW Place, a Community Champion was tasked in distributing that site’s allocation of sensors to community participants, maintenance of the sensing network, and trained to cascade information on ideal installation and sensing practices to the participants.
The selection of GROW places was defined by the following scientific and social criteria:

- Meaningful geographic coverage (across a breadth of climate, soil, and land-use types, and agro-technology approaches)
- An area of approximately 50x50 km can be described with a distribution density of about 1000 sensors

- Soil, terrain and land-use variability, with relatively homogenous characteristics around each sensor (20-30 meter radius)
- Good quality of environmental data (terrain, soil, and land-use)
- Having a scientific institution capable of supervising the process
- A local organization with established connections to maintain and extend the network
- An identified Community Champion with competencies for leadership, education and ability test the engagement, awareness-raising strategies, and toolsets

In order to maintain scientific rigor for the placement of sensors to provide robust data quality a high degree of training along with a participatory strategy was initiated. GROW built on previous research in the development of training resources and validation of participatory strategy methods, tools and resources for citizen sensing[16] . An intensive social peer-to-peer education and training programme using digital tools such as Massive Open Online Courses (MOOCs), was developed and delivered over three years. These included basic education on soils, sensors, data awareness as well as specific training with physical resources such as field guides and handbooks to support the scientific protocols. This innovation widened participation beyond the geographical areas that were engaged in distributing sensors to empower a more participatory, inclusive society.

Over the course of three years, GROW iteratively built both community and scientific momentum. Year 1 focused on aligning community and science challenges, validation of scientific methods and low-cost sensor technology, protocols and the criteria for geographic distribution, as well as training citizen scientists through massive online open courses (MOOCs) and the participatory approach. Year 2 implemented sensor distribution and enlisted Community Champions in nine communities who tested protocols and sensor placement. Finally, Year 3 implemented rapid scaling using the strategies of amplification to extend the activities of existing communities, and replication to enlist new communities that met the scientific, geographic and social criteria.

In all, twenty-four GROW Places were selected as communities who met the scientific and social criteria, across thirteen European member-states (Figure 1). The Community Champions and community members became a community of practice, placing and connecting more than 6,500 low-cost sensors to the platform.

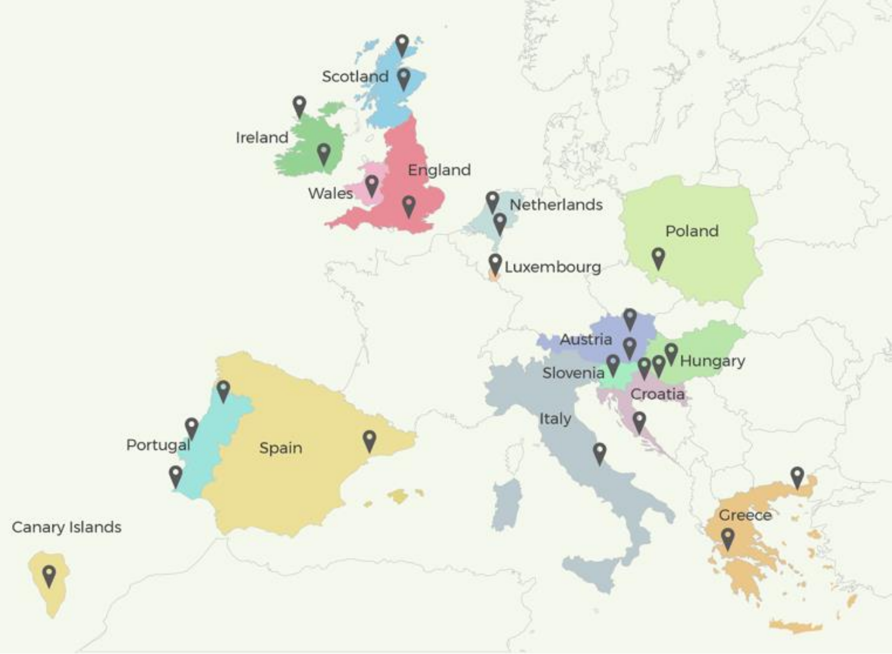


Figure 1. The twenty-four GROW Places in year 3, with a total of 6,500 low-cost sensors deployed and connected to the platform.

2.2 In-situ soil moisture measurements

The aim of GROW was to generate a vast in-situ soil moisture network across Europe maintained by citizens using the commercial sensor Flower Power, produced by the French company Parrot SA. A thorough evaluation of the accuracy of such sensors has been carried out both in the lab and in the field[17]. The authors found strong agreement between soil moisture observed by the low-cost sensors and gravimetric samples in the lab, as well as against professional sensors in the field. Furthermore, the inter-sensor variability was negligible. Overall, the low-cost sensors were found suitable for environmental monitoring and scientific applications.

The crowdsourced dataset generated within GROW was employed for further analysis if meeting certain requirements. In particular, we disregarded measurements from sensors located in proximity (< 10 km) of water bodies or in urban areas according to the ESA CCI Land Cover[18]. The hourly measurements taken with simultaneous air temperature below 4 °C were also neglected. Following previous studies[19], only observations flagged as good based on the ISMN quality control procedure[20] were selected for further analysis. Finally, the temporal analysis has been carried out against sensors with at least one year of measurements, in order to ensure both a wide range of soil moisture conditions being covered and a robust overlap with satellite observations. As a result, 154 sensors were employed as reference dataset for the temporal evaluation (Figure 2 top), while 761 sensors located in the Danube region formed the reference for the spatial consistency analysis (Figure 2 bottom).

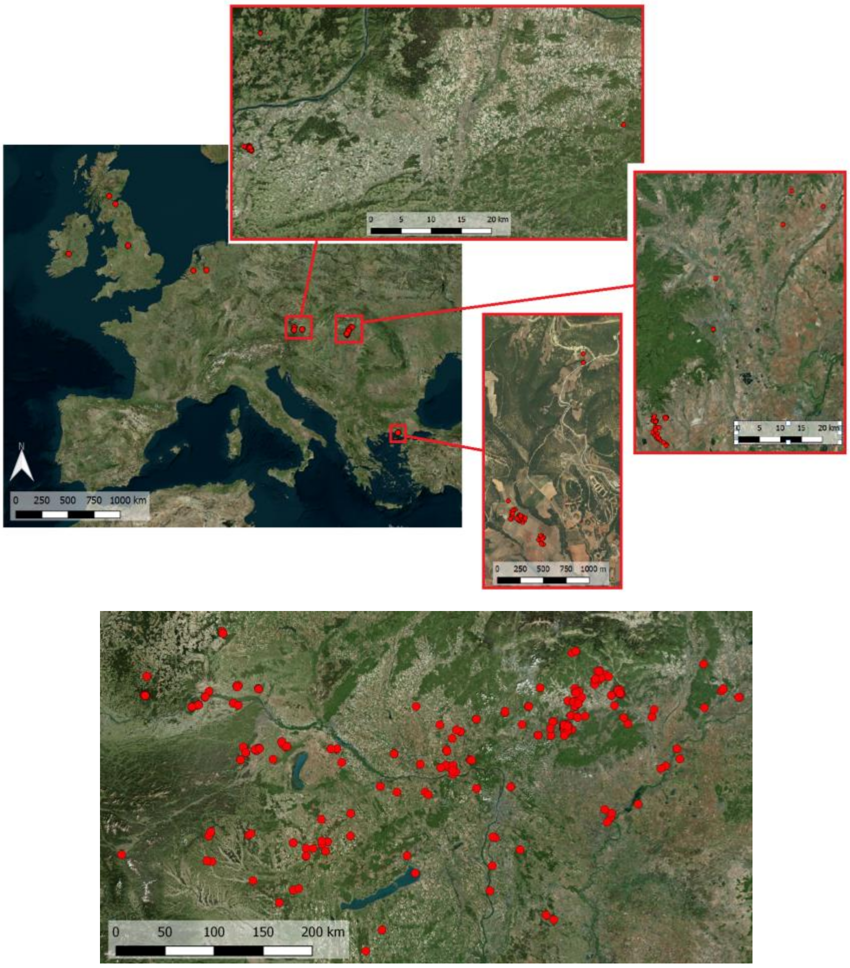


Figure 2. Distribution of the in-situ sensors employed for: the temporal analysis, with a zoom in the high-density clusters (top), and the spatial analysis carried out over the Danube region (bottom)

2.3 Satellite soil moisture products

Table 1 provides an overview of the satellite-derived soil moisture products investigated in this study.

Table 1. Overview of the satellite soil moisture products characteristics

	Spatial resolution	Revisit time	Unit
SMAP	36 km	1-2 days	$m^3 m^{-3}$
ASCAT	25 km	1 day	% saturation
ESA CCI SM	0.25°	1 day	$m^3 m^{-3}$
Sentinel-1	1 km	2-5 days	% saturation

2.3.1 SMAP

The Soil Moisture Active Passive (SMAP) is a mission specifically devoted to monitor soil moisture and freeze/thaw state, launched in 2015. SMAP follows a sun-synchronous orbit, with the overpass time at 6:00 a.m. and 6:00 p.m. for the descending and ascending orbits, respectively. SMAP carries a radiometer (1.41 GHz) and a radar (1.26 GHz) operating at L-band[6]. The radar instrument, however, stopped working after about three months of operation. The brightness temperature retrieved by SMAP is converted to volumetric soil moisture using the V-pol single channel algorithm (SCA-V)[21]. Technical details on the soil moisture retrieval via the SCA-V algorithm can be found in [22]. The SMAP product is gridded on the 36 km Equal-Area Scalable Earth grid version 2 (EASEv2). Here, we employed observations from the morning overpasses (06:00 a.m.) because of the better thermal equilibrium conditions[23].

2.3.2 ASCAT

The Advanced SCATterometer (ASCAT) is a real aperture radar sensor carried on board the Metop satellites. The first satellite, Metop-A, was launched in 2006, followed by Metop-B and Metop-C, launched in 2012 and 2019, respectively. The Metop satellites follow a sun-synchronous near-polar orbit, with the morning (descending) overpass at 9:30 a.m. and the evening (ascending) overpass at 9.30 p.m. on average. The ASCAT sensor measures the backscatter at C-band (5.255 GHz) in VV polarization. Soil moisture is retrieved from backscatter using the TU Wien change detection algorithm[24]. In short, a linear relationship between backscatter and soil moisture is expected, vegetation is accounted for using seasonal parameters, while surface roughness is assumed constant during the retrieval period[25]. The historically lowest and highest values of backscatter are assigned to the driest and wettest soil moisture references, which are used to derive relative soil moisture content (from 0% to 100%). This procedure is computed for each pixel individually. The ASCAT soil moisture product is retrieved at a resolution of 25 km. Building on the results of [26], we employed observations collected during the descending (a.m.) orbit.

2.3.3 ESA CCI SM

The ESA CCI combined SM is a merged product obtained from the retrieval of both active and passive sensors[8]. In particular, the CCI product combines in a synergistic way the soil moisture products from SMMR, SSM/I, TMI, AMSR-E, ERS AMI, and ASCAT. These various datasets are scaled to the climatology obtained from the Global Land Data Assimilation System[27] (GLDAS) Noah Land Surface Model[28] using a cumulative distribution function (CDF) matching method. Then, the signal to noise ratio (SNR) of each dataset is used to derive a product-specific weight, necessary for the subsequent merging process. The CCI SM is provided in volumetric unit ($m^3 m^{-3}$) and with a daily time stamp centred at 0:00 UTC, even though the actual observation time varies among the different input products[29]. The CCI product is generated starting from 1979 and has a spatial resolution of 0.25°.

2.3.4 Sentinel-1

The Sentinel-1 mission consists of two identical satellites carrying a C-band (5.405 GHz) synthetic aperture radar (SAR) system. Sentinel-1A was launched in 2014, followed by Sentinel-1B in 2016. A revisit of up to 1.5-4 days can be obtained over Europe when both satellites are in orbit. Both satellites follow a near-polar sun-synchronous orbit, with acquisition time at 6:00 a.m. and 6:00 p.m. for the descending and ascending nodes, respectively. In the Interferometric Wide (IW) swath mode, the SAR sensor allows to retrieve backscatter at 20 x 22 m. Because of the high signal complexity, backscatter observations are upscaled to 500 m sampling, featuring spatial resolution of 1 km. Soil moisture is then obtained after adapting the TU Wien model to SAR sensors, thus is expressed as percentage of saturation[30]. Sentinel-1 soil moisture was obtained through the Copernicus Global Land Service[31], where it is provided with a timestamp centered at 0:00 UTC.

2.4 Preprocessing and analysis

2.4.1 Temporal matching

The remotely sensed soil moisture products used in this study cover slightly different periods. All coarse-scale products (ASCAT, CCI, SMAP) were available until December 2018, while the high-resolution product (Sentinel-1) was available until May 2019. The instantaneous ground measurements closest to the satellite observation time were considered. Given the higher temporal resolution of in-situ measurements, the difference between satellite overpasses and ground observations was always equal to or less than one hour.

2.4.2 Scaling

Because of the spatial mismatch between satellite soil moisture products and in-situ measurements, a direct comparison between these two sources will be strongly affected by representativeness error[10]. Therefore, remotely sensed datasets have been rescaled to match the temporal mean and standard deviation of the in-situ references. Applying a statistical rescaling allows to account for (i) systematic representativeness error, (ii) the specific depth sensed by each satellite product and the in-situ sensor, as well as (iii) the different measurement units.

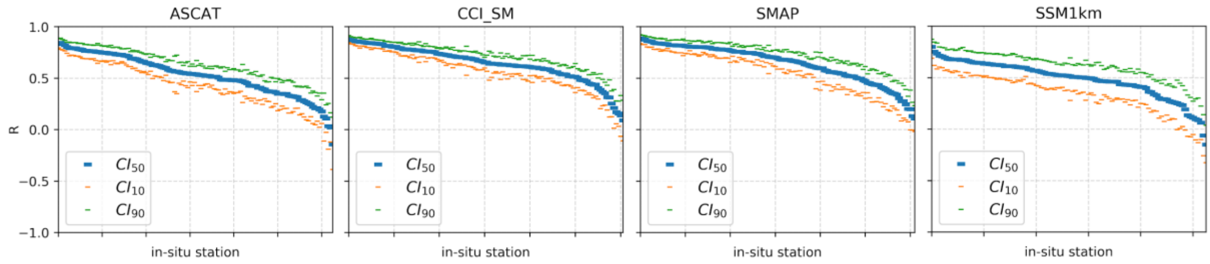
2.4.3 Statistical metrics

The Pearson correlation (R) and the unbiased root mean square deviation (ubRMSD) have been calculated to assess the satellite soil moisture accuracy with respect to the ground observations, both for the temporal and spatial evaluation. Please note that bias was not included because systematic differences between the reference dataset and satellite products have been intentionally removed with rescaling.

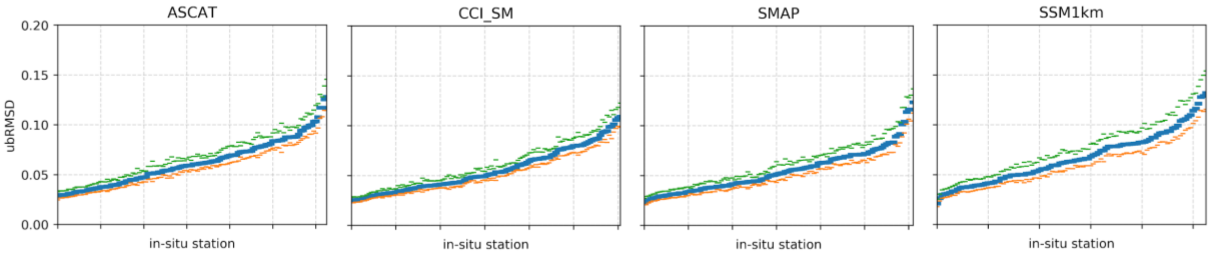
3. RESULTS AND DISCUSSION

3.1 Temporal analysis

Figure 3 shows Pearson correlation and ubRMSD between soil moisture timeseries obtained from crowdsourced measurements and satellite observations, for each of the 154 in-situ sensors employed for the temporal evaluation. Please note that the number of temporal matches (n) is not identical because of the revisit time specific to each remotely sensed product (Table 1). For instance, Sentinel-1 is characterized by less frequent overpasses compared to other products, resulting in a lower number of pairs (n=106) regardless the data availability over a longer period. Notwithstanding the slightly different time interval covered by the various satellite products, we found that the highest correlation (median R = 0.67) was achieved by SMAP, followed by CCI (R = 0.63). On the other hand, CCI and SMAP obtained the lowest ubRMSD (0.054 and 0.056 m^3 m^{-3}, respectively). The ASCAT product showed modest accuracy (R = 0.52 and ubRMSD = 0.062 m^3 m^{-3}), and slightly worse results are attained by Sentinel-1 (R = 0.49 and ubRMSD = 0.069 m^3 m^{-3}). Overall results of each remotely sensed product are reported in Table 2.



(a) Pearson R



(b) ubRMSD (m^3 m^{-3})

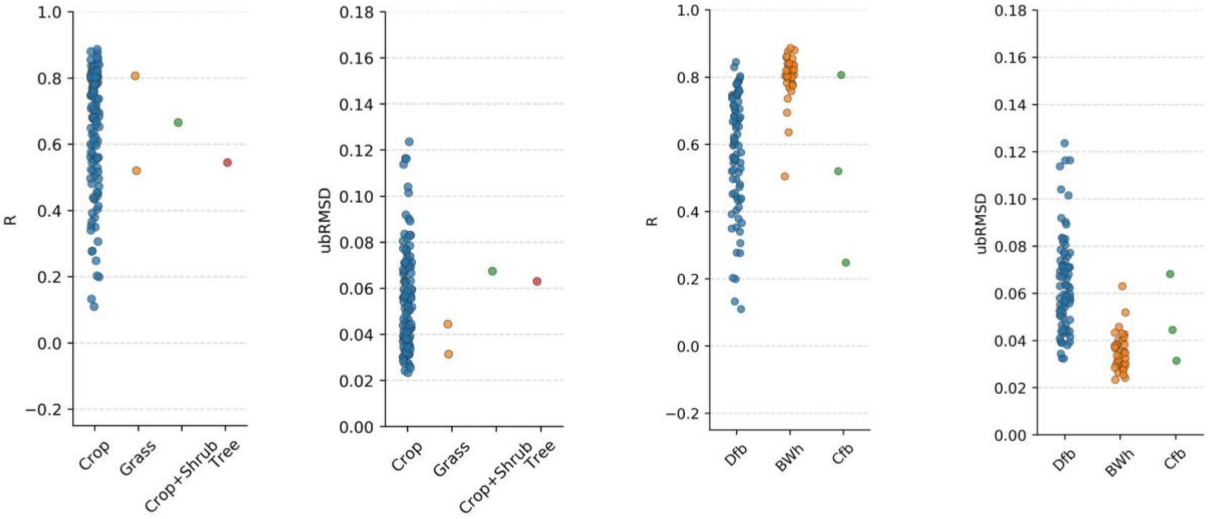
Figure 3. Evaluation metrics for all satellite products compared to GROW in-situ measurements. The median value (blue dots) and the associated confidence interval (10th and 90th percentiles) against each in-situ sensor are depicted.

Table 2. Median values of evaluation metrics obtained between satellite products and GROW in-situ measurements

	Pearson R	**ubRMSD (m^3 m^{-3})**
ASCAT	0.52	0.062
ESA CCI SM	0.63	0.054
SMAP	0.67	0.056
Sentinel-1	0.49	0.069

We further investigated the remotely sensed products' skill in relation to static properties associated to each in-situ sensor location, namely the land cover type (Figure 4a) and climate class (Figure 4b). Figure 4 shows results obtained for SMAP only, because very similar patterns were observed for the other satellite products investigated. According to the ESA CCI Land Cover map 2010, which provides information with a spatial resolution of 300 m, most of the sensors (150) are located in "cropland" pixels. Of the remaining sensors, two are situated in grassland, one sensor belongs to a mixed pixel consisting of cropland, shrubs and trees, and one sensor to deciduous broadleaf forest. Due to this unbalanced ratio, a comparison among land cover classes was not possible. However, the "cropland" class shows that a wide range of accuracy, both in terms of Pearson R and ubRMSD, can be found within the same land cover type. For instance, Pearson R ranges from 0.11 up to 0.89 and the ubRMSD varies between 0.023 and 0.12 m^3 m^{-3} for the SMAP soil moisture product. Notwithstanding the very limited number of samples belonging to other land cover classes, we can infer that SMAP, and other satellite products, has higher agreement with sensors located in grassland and shrubs rather than in forested sites. This result confirms that the soil moisture retrieval is more challenging over densely vegetated areas[19].

According to the Koeppen-Geiger classification[32], sensors used for the temporal analysis belong to three climate classes. Most of the sensors (114) are located in a continental climate without dry season and with warm summer (Dfb), 37 sensors are located in arid hot climate (BWh), and the remaining 3 sensors in temperate climate without dry season and with warm summer (Cfb). Even if the distribution among climate classes is not well balanced, an overall trend can be observed (Figure 4b). Higher accuracy is found against sensors situated in the arid climate (BWh), regardless the satellite product considered. Commonly, vegetation is less vigorous and/or sparser in arid climates compared to temperate and continental regions, thus allowing a better retrieval of soil moisture. In-situ sensors located in the arid climate have been installed in vineyards, which are characterized by a considerably lower vegetation cover and density compared to forest and agricultural crops. The latter, i.e. crops, are the most represented land use type among the sensors installed in Austria and Hungary.



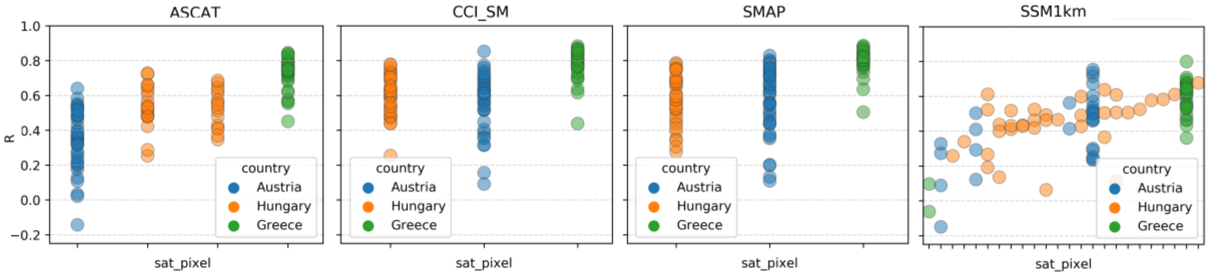
(a) Land Cover

(b) Climate class

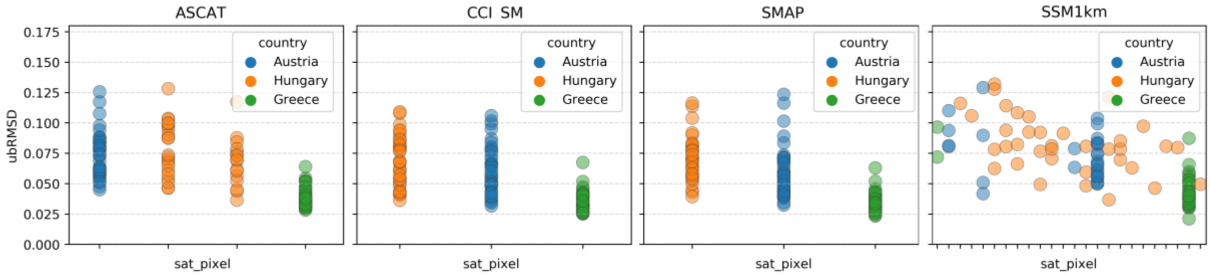
Figure 4. SMAP evaluation metrics grouped by land cover (a) and climate class (b). Note that similar results were found for the other satellite products

Figure 5 shows the accuracy of the satellite soil moisture products against in-situ measurements grouped by pixel. Note that only pixels covering Austria, Hungary and Greece are shown, because of the high number of sensors available in these GROW Places. A marked difference in the number of pixels observing the same in-situ sensors is evident, especially between coarse scale and high-resolution products because of the distinct pixel sizes (from 36 km to 1 km). Our results show that even within the same pixel, various degrees of agreement between remotely sensed and in-situ soil moisture can be found. For instance, the correlation obtained between SMAP observations and ground measurements ranges from 0.11 to 0.83 for the same pixel. The highest (median) correlation for a SMAP pixel is 0.81, obtained for the satellite pixel covering the sensors in Greece. Furthermore, the same pixel shows a smaller variability of both Pearson R and ubRMSD compared to other highly represented pixels, i.e. in Austria and Hungary. As explained above, the sensors in Greece are located in vineyards, which can explain the higher skill (because of lower vegetation density and cover). Additionally, the homogeneous vegetation type explains the lower intra-pixel variability observed. On the other hand, both SMAP pixels observing Austria and Hungary are compared to sensors located in agricultural fields where various crop types, i.e. summer and winter crops, are grown. Hence, a much larger variability in the statistical metrics between remotely sensed soil moisture and in-situ measurements is found. Both ASCAT and CCI SM products show a similar pattern.

Interestingly, also two Sentinel-1 pixels compared against a large number of in-situ sensors follow the same trend, however, the smaller pixel size and the lower number of sensors lying within each pixel reduce this effect. For instance, the one pixel observing Austria shows Pearson correlation ranging between 0.23 and 0.75, and ubRMSD varying from 0.049 to 0.10 $m^3 m^{-3}$. Such outcome is related to the presence of various land cover and vegetation types within this pixel, which includes summer and winter crops, grassland and forest[33]. The similar behavior, even though less prominent, found for the pixel observing Greece can be explained by the high inter-rows soil moisture variability in vineyards. Overall, our results suggest that the use of one or very few sensors to monitor the pixel-scale soil moisture dynamics (even for high-resolution products) might be inadequate. The spatial representativeness of in-situ measurements is strongly related to the complexity of the landscape observed, and especially the presence of different vegetation types with distinct growing cycles leads to high soil moisture variability.



(a) Pearson R

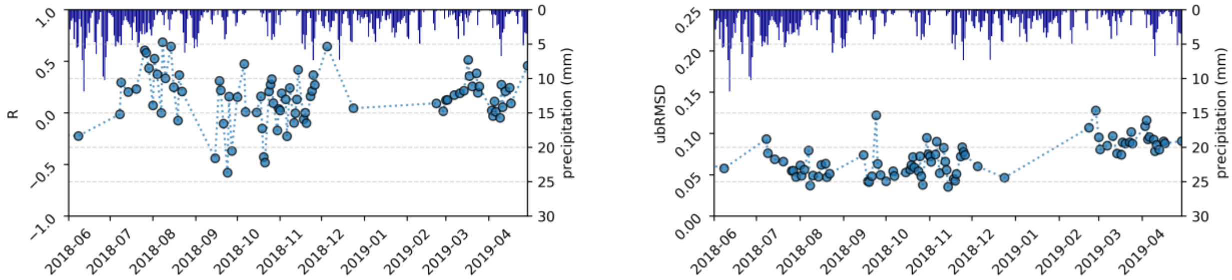


(b) ubRMSD (m^3 m^{-3})

Figure 5. Evaluation metrics for all satellite products compared to in-situ measurements grouped by GROW Place. Note that only results for Austria, Hungary, and Greece are depicted because of the high spatial density of the sensors.

3.2 Spatial analysis

Spatial statistical metrics (Pearson R and ubRMSD) for the Danube region were calculated only for the Sentinel-1 soil moisture product (Figure 6), because of its high spatial resolution. Large data gaps in the timeseries exist due to the relatively poor temporal resolution of approximately 2-5 days characterizing the Sentinel-1 mission. Furthermore, numerous observations during winter (from December 2018 until mid-February 2019) have been masked because of temperature below 4°C, leading to inaccurate measurements for both the in-situ sensors and the satellite observations. The spatial correlation is generally positive, but several values below 0.5 were found. Furthermore, no clear seasonal trend can be observed. On the other hand, the ubRMSD increases during spring 2019 compared to autumn/winter 2018. This finding suggests that with the beginning of the vegetative season, and the consequent increase of vegetation water content in the leaves, stems, and shoots, the backscatter signal is mixed and the retrieval of soil moisture becomes more challenging. The fluctuating evolution of both metrics is likely an artifact due to incidence angle effects, and could be bypassed considering only measurements from either the ascending or descending orbit. Overall, a poor spatial agreement was found between in-situ measurements and Sentinel-1 soil moisture, however it must be noted that the in-situ sensors used for the calculation of spatial metrics were not fixed but changed over time. An additional source of uncertainty derives from the availability of only one or very few sensors serving as reference for each satellite pixel (as discussed above). Clearly, both factors have a negative impact on the accuracy assessment, and potentially underestimate the metrics computed.



(a) Spatial Pearson R

(b) Spatial ubRMSD ($m^3 m^{-3}$)

Figure 6. Evaluation metrics showing the spatial consistency of soil moisture derived from Sentinel-1 against GROW in-situ measurements over the Danube region.

4. CONCLUSION AND OUTLOOK

In this study we evaluated the accuracy of various remotely sensed soil moisture products against crowdsourced in-situ measurements generated within the GROW Observatory. Specifically, we analyzed and inter-compared the temporal consistency of ASCAT, SMAP, ESA CCI SM, and Sentinel-1 products employing data from 154 ground sensors covering different climatic and environmental conditions across Europe. Our results confirmed that SMAP and ESA CCI SM performances are comparable and they are generally able to better capture the soil moisture dynamics of soil moisture compared to other products. Furthermore, for well-represented satellite pixels, i.e. monitored with a high number of in-situ sensors, we found a wide range of satellite products' accuracy depending on the individual sensor used as a reference. This finding is more prominent for coarse scale products, however, the same behavior was observed also for high-resolution soil moisture product (Sentinel-1). As already reported in literature[29,34], employing a single point location as a reference to evaluate coarse-scale products (20-40 km) generates high uncertainties in the results because it is extremely difficult to estimate the representativeness of an in-situ measurement for such satellite footprints. Our results suggest that even at the kilometric scale one single in-situ sensor might not be representative of the overall soil moisture dynamics. This is especially valid for highly fragmented landscapes, where the presence of various land cover types, e.g. summer and winter crops, broadleaf and evergreen forest, leads to a great variability of soil moisture spatio-temporal patterns. The use of crowdsourced observations, such as those from GROW, is of utmost importance because it allows to monitor soil moisture intensively at the sub-pixel scale, reducing the representativeness errors and uncertainties generally associated to conventional networks. Finally, we evaluated the ability of Sentinel-1 to represent spatial patterns of soil moisture over the Danube region using measurements from 761 in-situ sensors. The spatial consistency of Sentinel-1 was only sufficient, however we discussed the sources of uncertainty and error that can explain this result. In particular, the change over time of the in-situ sensors used as reference, the representativeness of such measurements (generally only one or few sensors were available for each satellite pixel) as discussed above, as well as the period investigated (duration and climatic conditions) were identified as the main causes of underestimation. Hence, more robust analysis must be carried out when more data, both in terms of spatial and temporal coverage, will be available.

In conclusion, GROW has demonstrated for the first time that COs can contribute to and have potential to improve the validation of remotely sensed soil moisture products. Our results show that future technology for sensors along with the social aspects of any CO endeavor will play an important role in creating opportunities with the remote sensing community for environmental monitoring. They also show that success, when coupled with the need for continuous monitoring, should be determined over an extended period of time (e.g. months or years). Therefore, our findings highlight the need for longitudinal studies to better explore the impact of all facets of sensing that are validated, robust, and environmentally sound. Whilst the results are highly encouraging, they have implications for the design of COs and the integration of CO data in Earth Observation activities in the future. The requirement for temporal continuity underscores the ongoing need for strategic approaches both to the development of scientific protocols and criteria, and to promoting and resourcing the engagement of resilient communities of practice and place. In addition, new and ongoing CO initiatives will benefit from finding a balance between, on the one hand, scientific requirements and representation through the selection of sites, and, on the other hand, the interests and locations of citizen scientists, with some flexibility needed to accommodate varying technical and social competencies and needs for training and support. Therefore, education and resources are essential to sustain participation, and this can boost intrinsic motivation for individuals to continue to participate and for renewal of membership as natural participation cycles change. The offer of training does help to overcome common issues; to achieve scale, and mass training initiatives are necessary. Peer to peer platforms can also enable new communities to form, and knowledge to be exchanged, communities can learn from each other as well as from interactions with scientists. There are requirements for the technologies employed, with larger reference datasets requiring more robust sensors, this has implications, not only for the sensor instrument but also components such as batteries. The design of sensor housing can also pose a challenge where environmental conditions in which sensors are placed cause damage, such as water ingress and extremes in temperature. This is a common issue, particularly as continuous sensing through the seasons is a requirement. The unit cost of sensors creates a barrier to achieving high density clusters, and initiatives need to allow for a replacement strategy when technology fails. Ongoing refinement of protocols is necessary to address hyper-local needs, in land management and seasonal adjustments to those practices. In GROW, both the offer of access to open raw data, as well as an introduction to data awareness activities and tools helped to demonstrate the value of soil moisture at a local level for water resource management. GROW highlights the benefits of participation of all stakeholders in social innovation activity and outcomes. Finally, Citizens often cite policy as an area they do not feel they have any agency in, consequently we learn that engagement with policy through science should be implemented throughout all stages of the activity to enable the uptake of crowdsourced data at the highest level.

REFERENCES

[1] Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., Orlowsky, B. and Teuling, A. J., "Investigating soil moisture–climate interactions in a changing climate: A review," Earth-Science Reviews **99**(3–4), 125–161 (2010).

[2] Chen, T., McVicar, T., Wang, G., Chen, X., de Jeu, R., Liu, Y., Shen, H., Zhang, F. and Dolman, A., "Advantages of Using Microwave Satellite Soil Moisture over Gridded Precipitation Products and Land Surface Model Output in Assessing Regional Vegetation Water Availability and Growth Dynamics for a Lateral Inflow Receiving Landscape," Remote Sensing **8**(5), 428 (2016).

[3] Jung, M., Reichstein, M., Schwalm, C. R., Huntingford, C., Sitch, S., Ahlström, A., Arneth, A., Camps-Valls, G., Ciais, P., Friedlingstein, P., Gans, F., Ichii, K., Jain, A. K., Kato, E., Papale, D., Poulter, B., Raduly, B., Rödenbeck, C., Tramontana, G., et al., "Compensatory water effects link yearly global land CO2 sink changes to temperature," Nature **541**(7638), 516–520 (2017).

[4] Miralles, D. G., Teuling, A. J., van Heerwaarden, C. C. and Vilà-Guerau de Arellano, J., "Mega-heatwave temperatures due to combined soil desiccation and atmospheric heat accumulation," Nature Geosci **7**(5), 345–349 (2014).

[5] Ulaby, F. T., Moore, R. K. and Fung, A. K., "Radar remote sensing and surface scattering and emission theory," [Microwave remote sensing: Active and passive], United States, 624 (1982).

[6] Entekhabi, D., Njoku, E. G., O'Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., Entin, J. K., Goodman, S. D., Jackson, T. J., Johnson, J., Kimball, J., Piepmeier, J. R., Koster, R. D., Martin, N., McDonald, K. C., Moghaddam, M., Moran, S., Reichle, R., Shi, J. C., et al., "The Soil Moisture Active Passive (SMAP) Mission," Proc. IEEE **98**(5), 704–716 (2010).

[7] Wagner, W., Hahn, S., Kidd, R., Melzer, T., Bartalis, Z., Hasenauer, S., Figa-Saldaña, J., de Rosnay, P., Jann, A., Schneider, S., Komma, J., Kubu, G., Brugger, K., Aubrecht, C., Züger, J., Gangkofner, U., Kienberger, S., Brocca, L., Wang, Y., et al., "The ASCAT Soil Moisture Product: A Review of its Specifications, Validation Results, and Emerging Applications," metz **22**(1), 5–33 (2013).

[8] Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., Chung, D., Ertl, M., Forkel, M., Gruber, A., Haas, E., Hamer, P. D., Hirschi, M., Ikonen, J., de Jeu, R., Kidd, R., Lahoz, W., Liu, Y. Y., Miralles, D., et al., "ESA CCI Soil Moisture for improved Earth system understanding: State-of-the art and future directions," Remote Sensing of Environment **203**, 185–215 (2017).

[9] Cosh, M., "Watershed scale temporal and spatial stability of soil moisture and its role in validating satellite estimates," Remote Sensing of Environment **92**(4), 427–435 (2004).

[10] Gruber, A., Dorigo, W. A., Zwieback, S., Xaver, A. and Wagner, W., "Characterizing Coarse-Scale Representativeness of in situ Soil Moisture Measurements from the International Soil Moisture Network," Vadose Zone Journal **12**(2), 0 (2013).

[11] Hemment, D., Amditis, A., Fritz, S. and Wehn, U., "The Next Generation of Citizen Observatories," presented at The First International ECSA Citizen Science Conference, 19 May 2016, Berlin, Germany.

[12] Kovács, K. Z., Hemment, D., Woods, M., van der Velden, N. K., Xaver, A., Giesen, R. H., Burton, V. J., Garrett, N. L., Zappa, L., Long, D., Dobos, E. and Skalsky, R., "Citizen observatory based soil moisture monitoring – the GROW example," HunGeoBull 68(2), 119–139 (2019).

[13] Dorigo, W. A., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Xaver, A., Gruber, A., Drusch, M., Mecklenburg, S., van Oevelen, P., Robock, A. and Jackson, T., "The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements," Hydrol. Earth Syst. Sci. **15**(5), 1675–1698 (2011).

[14] Woods, M., Ajates, R., Gulari, N., Burton, V. J., van der Velden, N. K., & Hemment, D. "GROW Observatory: Mission Outcomes," (2019) University of Dundee.

[15] Woods, M., Hemment, D., Gonzalez, R. A., Cobley, A., Xaver, A. and Konstantakopoulos, G., "GROW Citizens' Observatory: Leveraging the power of citizens, open data and technology to generate engagement, and action on soil policy and soil moisture monitoring," presented at Digital Earth, 2019, Florence, 3.

[16] Woods, M., Balestrini, M., Bejtullahu, S., Bocconi, S., Boerwinkel, G., Boonstra, M., Boschman, D-S., Camprodon, G., Coulson, S., Diez, T., Fazey, I., Hemment, D., van den Horn, C., Ilazi, T., Jansen-Dings, I., Kresin, F., McQuillan, D., Nascimento, S., Pareschi, E., Polvora, A., Salaj, R., Scott, M and Seiz, G., "Citizen Sensing: A Toolkit". Making Sense (2018)

[17] Xaver, A., Zappa, L., Rab, G., Pfeil, I., Vreugdenhil, M., Hemment, D. and Dorigo, W., "Evaluating the suitability of the consumer low-cost Parrot Flower Power soil moisture sensor for scientific environmental applications," Geosci. Instrum. Method. Data Syst. (in press).

[18] Li, W., MacBean, N., Ciais, P., Defourny, P., Lamarche, C., Bontemps, S., Houghton, R. A. and Peng, S., "Gross and net land cover changes in the main plant functional types derived from the annual ESA CCI land cover maps (1992–2015)," Earth Syst. Sci. Data **10**(1), 219–234 (2018).

[19] Al-Yaari, A., Wigneron, J.-P., Dorigo, W., Colliander, A., Pellarin, T., Hahn, S., Mialon, A., Richaume, P., Fernandez-Moran, R., Fan, L., Kerr, Y. H. and De Lannoy, G., "Assessment and inter-comparison of recently developed/reprocessed microwave satellite soil moisture products using ISMN ground-based measurements," Remote Sensing of Environment **224**, 289–303 (2019).

[20] Dorigo, W. A., Xaver, A., Vreugdenhil, M., Gruber, A., Hegyiová, A., Sanchis-Dufau, A. D., Zamojski, D., Cordes, C., Wagner, W. and Drusch, M., "Global Automated Quality Control of In Situ Soil Moisture Data from the International Soil Moisture Network," Vadose Zone Journal **12**(3), 0 (2013).

[21] Zeng, J., Chen, K.-S., Bi, H. and Chen, Q., "A Preliminary Evaluation of the SMAP Radiometer Soil Moisture Product Over United States and Europe Using Ground-Based Measurements," IEEE Trans. Geosci. Remote Sensing **54**(8), 4929–4940 (2016).

[22] O'Neill, P. E., Chan, S., Njoku, E. G., Jackson, T. and Bindlish, R., "SMAP L3 Radiometer Global Daily 36 km EASE-Grid Soil Moisture, Version 5," Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center.

[23] Ma, H., Zeng, J., Chen, N., Zhang, X., Cosh, M. H. and Wang, W., "Satellite surface soil moisture from SMAP, SMOS, AMSR2 and ESA CCI: A comprehensive assessment using global ground-based observations," Remote Sensing of Environment **231**, 111215 (2019).

[24] Wagner, W., Lemoine, G. and Rott, H., "A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data," Remote Sensing of Environment **70**(2), 191–207 (1999).

[25] Naeimi, V., Scipal, K., Bartalis, Z., Hasenauer, S. and Wagner, W., "An Improved Soil Moisture Retrieval Algorithm for ERS and METOP Scatterometer Observations," IEEE Trans. Geosci. Remote Sensing **47**(7), 1999–2013 (2009).

[26] Albergel, C., "An evaluation of ASCAT surface soil moisture products with in-situ observations in Southwestern France," Hydrol. Earth Syst. Sci., 10 (2009).

[27] Rodell, M., Houser, P. R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin, J. K., Walker, J. P., Lohmann, D. and Toll, D., "The Global Land Data Assimilation System," Bull. Amer. Meteor. Soc. **85**(3), 381–394 (2004).

[28] "GLDAS.", .

[29] Dorigo, W. A., Gruber, A., De Jeu, R. A. M., Wagner, W., Stacke, T., Loew, A., Albergel, C., Brocca, L., Chung, D., Parinussa, R. M. and Kidd, R., "Evaluation of the ESA CCI soil moisture product using ground-based observations," Remote Sensing of Environment **162**, 380–395 (2015).

[30] Bauer-Marschallinger, B., Freeman, V., Cao, S., Paulik, C., Schaufler, S., Stachl, T., Modanesi, S., Massari, C., Ciabatta, L., Brocca, L. and Wagner, W., "Toward Global Soil Moisture Monitoring With Sentinel-1: Harnessing Assets and Overcoming Obstacles," IEEE Trans. Geosci. Remote Sensing **57**(1), 520–539 (2019).

[31] "Copernicus Global Land Service (CGLS).", .

[32] Kottek, M., Grieser, J., Beck, C., Rudolf, B. and Rubel, F., "World Map of the Köppen-Geiger climate classification updated," metz **15**(3), 259–263 (2006).

[33] Zappa, L., Forkel, M., Xaver, A. and Dorigo, W., "Deriving Field Scale Soil Moisture from Satellite Observations and Ground Measurements in a Hilly Agricultural Region," Remote Sensing **11**(22), 2596 (2019).

[34] Brocca, L., Melone, F., Moramarco, T. and Morbidelli, R., "Spatial-temporal variability of soil moisture and its estimation across scales: SOIL MOISTURE SPATIOTEMPORAL VARIABILITY," Water Resour. Res. **46**(2) (2010).