HIGH RESOLUTION MAPPING OF SOIL MOISTURE BY AMSR2 DATA DISAGGREGATION BASED ON SENTINEL-1 AND MACHINE LEARNING

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Abstract *– Thanks to the frequent revisiting, satellite microwave radiometers have great potential for surface Soil Moisture (SM) monitoring. However, their spatial resolution is not sufficient for hydrological studies in small catchments as well as applications to precision farming.*

In this study, a disaggregation technique based on machine learning is proposed: the technique combines Sentinel-1 SAR (S-1) data with SM generated from AMSR2 by the IFAC's HydroAlgo algorithm, with the aim of enhancing the SM spatial resolution from the original 10 km to about 30 m. To this scope, two machine learning techniques have been considered for the implementation, namely Artificial Neural Networks (ANN) and Random Forests (RF). Training is carried out by aggregating and coregistering S-1 data with the HydroAlgo SM at 10 km resolution. After training the ANN and RF algorithms are applied pixel by pixel to the Sentinel-1 images at full resolution for generating the enhanced SM maps.

The method has been implemented and validated in two agricultural areas located in Central Italy, where a series of experiments has been carried out between 2019 and 2020 for collecting the main soil and vegetation parameters at the same time of satellite overpasses.

To assess the actual resolution of the output SM, the validation against in-situ measurements has been carried out by aggregating data at 10, 30, 50 and 70m. The results confirmed the effectiveness of the proposed method: validation carried out at 30m obtained $R \simeq 0.82$ and $RMSE \simeq 0.05$ m^3/m^3 that represent a noticeable improvement with respect to the results obtained by HydroAlgo at 10 km ($R \simeq 0.56$ and RMSE >> 0.1 m^3/m^3). Validation results also pointed out superior performances of the ANN based with respect to the RF based disaggregation.

Index Terms— AMSR2, Sentinel-1, HydroAlgo, Soil Moisture, Artificial Neural Networks, Random Forest, disaggregation.

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I. INTRODUCTION

The availability of Soil Moisture (SM) products has greatly improved with the launch of satellite missions carrying onboard microwave radiometers operating at L- band, as the NASA's Soil Moisture Active and Passive (SMAP) [1] and the ESA's Soil Moisture and Ocean Salinity (SMOS) [2] and also at higher frequencies, as the JAXA Advanced Microwave Scanning Radiometer 2 (AMSR2) [3]. These instruments can revisit most of the earth surface daily, offering the possibility of frequent SM mapping at a global scale with the very high accuracy which is peculiar of this kind of technique. However, their spatial resolution in the order of dozens of kilometres, although still suitable for global scale monitoring, hampers the detection of hydrological patterns in small catchments and some potential applications as the precision farming, making in fact the SM products generated by satellite radiometers unable to meet the requirements of most users.

For this reason, large efforts are being carried out by the scientific community to improve the spatial resolution of SM products generated by these sensors. Studies on SMOS were based on deconvolution techniques taking advantage of the multi-angular observations that are a peculiarity of this instrument (e.g. [4]-[5]), while the possibility of improving the spatial resolution of the SMAP SM has been the subject of several studies, especially after the failure of the SMAP radar that prevented the generation of SM products at 3 Km resolution.

In [6], post processing of data has been implemented by applying deconvolution techniques, to obtain an enhanced SM product which has been posted at 9 Km resolution. Other techniques have been developed as well, as the routinely assimilation into land surface models, for generating SMAP Level-4 Soil Moisture product at 9 km resolution [7].

Significant research focused on disaggregating SM based on optical/multispectral data. In general, these methods exploit the relationship between LST and SM based on the evapotranspiration process (e.g. [8]-[9]): most of them disaggregate SMAP based on MODIS products (e.g. [10] - [11]). Some concerns have been however raised about the disaggregation techniques based on multispectral data, because of the lack of direct relationships between the optical measurements and the soil moisture. For this reason, the idea to replace the SMAP radar with another radar/SAR sensor, being more physically based, has gained interest in the community, and several studies addressing this possibility have been carried out. Among the others, the possibility of integrating SMAP with Sentinel-1 (S-1) for improving the spatial resolution of the SM retrievals has been exploited. Sentinel-1 is a constellation of two (S-1A and S-1B) satellites carrying onboard a C-band SAR: it is characterized by a revisiting frequency of 6 days, which is significantly higher than any other SAR, and it provides observations at 20m resolution. Unfortunately, Sentinel 1-B ceased operating at the end of 2021 by halving the temporal revisiting.

The possibility of combining SMAP and S-1 for mapping SM at 3 and 1 Km resolution respectively, has been proposed in [12]. This study demonstrated that the S-1 C band SAR, although operating at a frequency less sensitive to SM than L- band, is effective for improving the spatial resolution of the SM products. The SM products based on [12] have been recently updated and they are currently distributed by NSIDC [13].

Other efforts have been also made in improving the spatial resolution of AMSR2. AMSR2 is a microwave radiometer operating in 7 frequency bands between 6.8 and 89 GHz. The AMSR2 sampling rate in the first six bands is approximately 10 km, however the antenna footprint at the lower frequencies is significantly larger, by reaching ≃70 km x ≃40 km at C band, so that each acquisition is averaged over an area that is several times the nominal pixel size. The overlapping of acquisitions made it possible to apply an antenna pattern matching technique for obtaining brightness temperature measurements at a resolution comparable with the sampling rate, which are currently delivered by JAXA as operational product [14].

In this study, an algorithm for disaggregating the AMSR2 SM generated by the HydroAlgo Algorithm [15] by means of S-1 data acquired in Interferometric Wide Swath mode is proposed. HydroAlgo is an algorithm aimed at global mapping of SM, vegetation biomass (VWC) and Snow depth (SD) by taking advantage of the multifrequency AMSR2 observations, without involving auxiliary data. With respect to the model driven approaches for estimating SM from the microwave radiometric data, which are in general based on the inversion of zero-order approximation of the radiative transfer theory, as the τ-ω [16] for the SMAP single and dual channel algorithms [17], or the L-MEB [18] for SMOS, the HydroAlgo SM retrievals are based on Artificial Neural Networks (ANN) trained following an hybrid (model + data) driven approach that combines the representativeness of data driven retrievals with the physical basis of model driven methods [19].

HydroAlgo has been developed in the framework of the JAXA AMSR science team activities and validated in several studies (e.g. [20]-[21]). The disaggregation which reappraises and exploits the concepts preliminary presented in [22], has been developed and validated in two test areas located in central Italy, for which timeseries of satellite data and in-situ measurements from long term experiments and SM probes were available from January 2019 to October 2020.

The high-resolution SM is obtained in three steps:

1. as first, the low-resolution (LR) dataset is generated by aggregating and coregistering the S-1 data with the SM generated from AMSR2 by HydroAlgo at ≃ 10 km.
2. The machine-learning (ML) algorithms, namely Artificial Neural Networks (ANN) and Random Forests (RF), are trained and tested on the LR dataset by considering the aggregated backscattering as input and the HydroAlgo SM as target. The concept is that the algorithms learn the relationship between backscattering and SM from the LR data.
3. After training, the algorithms are applied to the full resolution S-1 data to generate the SM maps at S-1 resolution, which are then validated against the in-situ measurements. To assess the actual resolution of the maps, the validation has been carried out at four different resolutions, by aggregating data at 10m, 30m, 50m and 70m.

The paper is organized as follows: section II describes the test area, the data involved and their organization for implementing the algorithms and validating the results. The ANN and RF based retrieval concepts are described in section III, the results are described in section IV and discussed in section V.

II. Test Areas and Datasets

A. *Test Areas*

The two test areas are located in the Tuscany region, central Italy. The weather characteristics are typical of Mediterranean climates, with a strong seasonality characterized by dry conditions in summer and moist condition in spring and autumn (Fig. 1).

The first area extends for about 30 km x 30 km and is centred on a hydroelectric basin (Pontecosi) on the Serchio river. The central coordinates are 44°7’37” N; 10°23’34” E. The area is characterized by a heterogeneous landscape, including agricultural areas, forests and urban, that set important constraints to the AMSR2 observations for SM monitoring. For the scopes of this study, three SM probes have been installed in the surrounding of the hydrological basin. Each probe sampled an area of about least 50m x 50m, characterized by uniform vegetation cover and surface conditions, providing continuous recordings of SM and air temperature. In total, 125 SM samples have been collected in correspondence to the satellite overpasses. The second test area selected for the experimental activities is an agricultural area along the Elsa River, close to the Ponte a Elsa town.

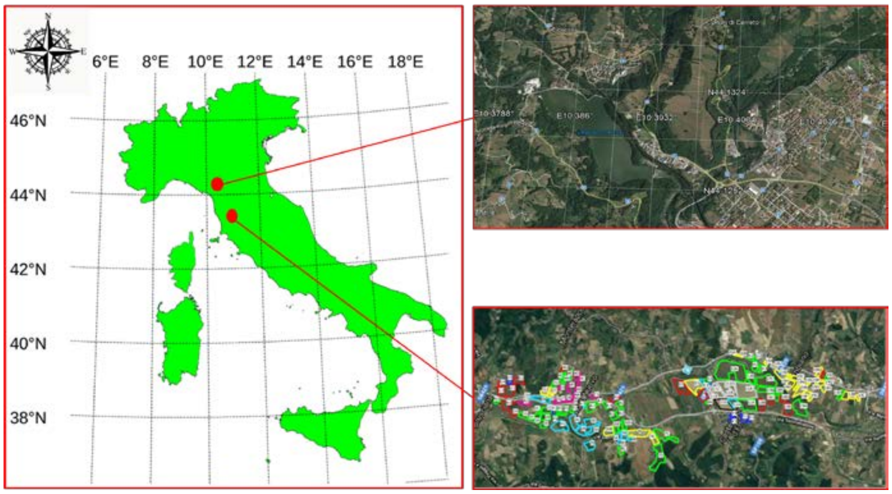

Fig. 1. The Pontecosi and Val D'Elsa test areas in Tuscany, central Italy.

The area extends for about 270 hectares, with centre coordinates 43°41′20.37″N and 10°53′42.38″E. It is characterized by rather large homogeneous fields with various crops, including wheat, corn, sorghum, alfalfa, colza, fava bean, pastures, vineyards, and olive- groves. Dedicated experiments have been carried out in correspondence with the S-1 overpasses to acquire the main parameters of soil (SM and soil roughness) and vegetation (plant density, geometry, and vegetation biomass). In detail, SM was sparsely sampled within each field of the area and each sample has been associated to the coordinates of the sampling point. In total, 175 SM measurements have been collected in correspondence to the satellite overpasses, by following the sampling strategy described in [23]. The SM values recorded in the area during the experiment ranged between ≃0.1 m^3/m^3 and ≃0.55 m^3/m^3, the corresponding vegetation biomass, expressed as Plant Water Content (PWC) was between 0 and ≃8 kg/m^2. The in-situ investigations included soil surfaces with roughness from smooth (Height Standard Deviation – HSTD ≃ 0.5 cm) to rough (HSTD ≃ 4 cm).

A. Sentinel-1 SAR data

Sentinel-1 (S-1) covered the two areas in the orbits 15 and 168: a total of 64 ground range detected (GRD) in interferometric wide swath mode (IW) images have been selected for which colocated AMSR-2 acquisitions were also available. The images have been downloaded from the Copernicus Open Access Hub in the time frame January 2019 - October 2020, calibrated radiometrically, multilooked and geocoded for obtaining the georeferenced and calibrated backscattering values (σ°) at 10m resolution. The σ° calibration accounted for the local incidence angle (LIA) obtained by terrain correction using a DEM of the area derived from SRTM. It should be mentioned that S-1 B was still operating at the time of the experiment, so that the revisiting was ensured every 6 days.

B. AMSR2 and SMAP data

The AMSR2 L1R V2.1 brightness temperatures [14] acquired on both areas have been downloaded from the JAXA's GCOM data portal. AMSR2 overpasses the area at approximately 2:00 PM (local time) in Ascending orbit and 2:00 AM in Descending orbit. Only the AMSR2 overpasses covering entirely the areas and acquired within the same day of S-1 acquisitions have been considered, to prevent any problem due to partial coverage and excessive temporal distance between S-1 and AMSR2 data. This dataset served as input to generate the SM data at 10 km resolution by using the IFAC's HydroAlgo algorithm for AMSR2 [15].To assess the HydroAlgo SM, the SMAP radiometer enhanced 9km SM product [6] has been also downloaded from the NSIDC data portal for the same dates of AMSR2 acquisitions.

C. Data Organization

Two datasets at different spatial resolution have been generated from the 64 combined S-1 and AMSR2 acquisitions: a low resolution (LR - ≃10 km) dataset, which served for training and testing the ML algorithms, and a High resolution (HR ≃ 10m) HR dataset, which served to generate the disaggregated SM which is then validated against in-situ measurements.

The LR dataset is composed of temporally and spatially co-located AMSR2 Tb and SM data, SMAP SM, and S-1 σ° downscaled and aggregated at the same resolution of AMSR2 SM and reprojected on the AMSR2 SM grid. To address the not easy task of aggregating at AMSR2 resolution the S-1 data having an original resolution of 10 m each, S-1 image has been low-passed and resampled at half resolution until the 10 km resolution is reached. This was done since the single-pass aggregation initially attempted was found causing artifacts and anomalies in the nonuniform areas of the aggregated images, mainly because of the anomalous propagation of the not valid values, either zeros or NaN, through the aggregation process.

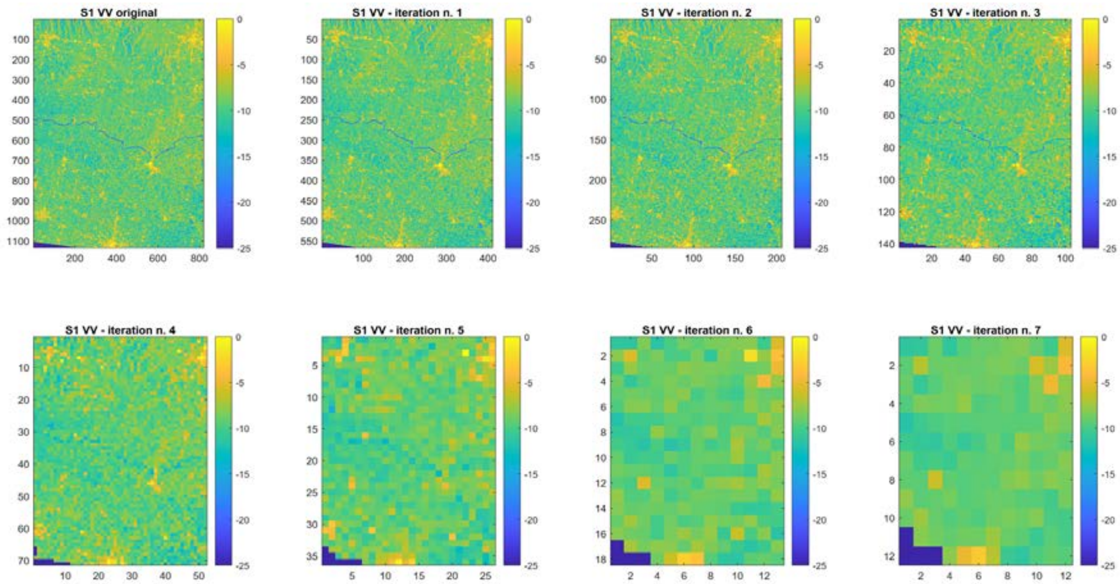

Fig. 2. Example of the iterative aggregation of S-1 data at 10 km resolution. Axes values are the number of pixels.

An example of the iterative S-1 aggregation is shown in Fig. 2 for one of the 64 images involved in this study, the example refers to VV polarization, an identical processing has been applied to the VH polarization. As a final step, each S-1 image aggregated at 10km is reprojected on the AMSR2 SM grid. The LR dataset output of this processing is composed of 66000 coregistered values of S-1 σ°, LIA, and SM.

The HR dataset is composed of the S-1 calibrated and coregistered σ° at VV and VH polarization and LIA at original (10m) resolution. The HR dataset also contains the in-situ SM measurements that have been georeferenced with Sentinel-1 and aggregated at pixel scale. The total amount of coregistered and aggregated SM samples was ≃300 samples, including 175 samples collected in the Ponte ad Elsa test area and 125 samples collected in Pontecosi. These measurements served for validating the ANN and RF algorithm outputs.

III. Methods

The SM disaggregation proposed in this study is based on ML techniques that, with respect to model based methods, have a well proven ability in modelling highly dimensional datasets with non-linear relationships and missing values [24]. The disaggregation is composed of three steps: generation of the LR dataset, ML algorithms implementation, training and test, and generation of HR SM: Fig. 3 shows the flowchart of the entire process.

A. LR dataset generation

In the first step, the LR SM dataset (10 km resolution) is generated by combining the 10 Km aggregated σ° from S-1 with SM estimated at the same resolution by the IFAC's HydroAlgo for AMSR2. HydroAlgo is an algorithm based on multifrequency AMSR2 data that attempts simultaneously the retrieval of SM, VWC and SD. It is based on pre-trained ANNs, and it does not make use of any other data than AMSR2 brightness temperature at C, X, Ku, and Ka bands. HydroAlgo also includes a spatial resolution enhancement algorithm based on the Smoothing Filter Based Intensity Modulation (SFIM - [25]) that allows estimating SM at 10 km spatial resolution. Although HydroAlgo has been largely validated in previous publications (e.g. [26]-[27]), a further verification of the HydroAlgo SM used in this study has been carried out against the SMAP enhanced SM product.

B. Algorithms' implementation, training and test

In the second step, two different ML algorithms, are implemented, trained, and tested by considering the 10 Km aggregated S-1 σ° in both VV and VH polarizations and the LIA as algorithm inputs and the HydroAlgo SM as output. The assumption behind the proposed implementation is that the algorithms can learn from the LR dataset the mechanism driving the backscattering from vegetated surfaces, which is supposed not to change when passing from low to high resolution, thus keeping the σ° relationship with SM, soil roughness, vegetation parameters and observation geometry.

For better matching the daily SM dynamics, depending on the temporal changes in vegetation biomass and surface features other than SM affecting the scattering mechanism, the training is repeated for each couple of Sentinel and AMSR2 images thus obtaining a different ML implementation for each day available in the dataset.

The two ML algorithms are based on ANN and RF, respectively. Feed-forward artificial neural networks (FF-ANN, hereafter ANN) have been considered in this study because of their well proven capability of solving nonlinear problems [28]-[29].

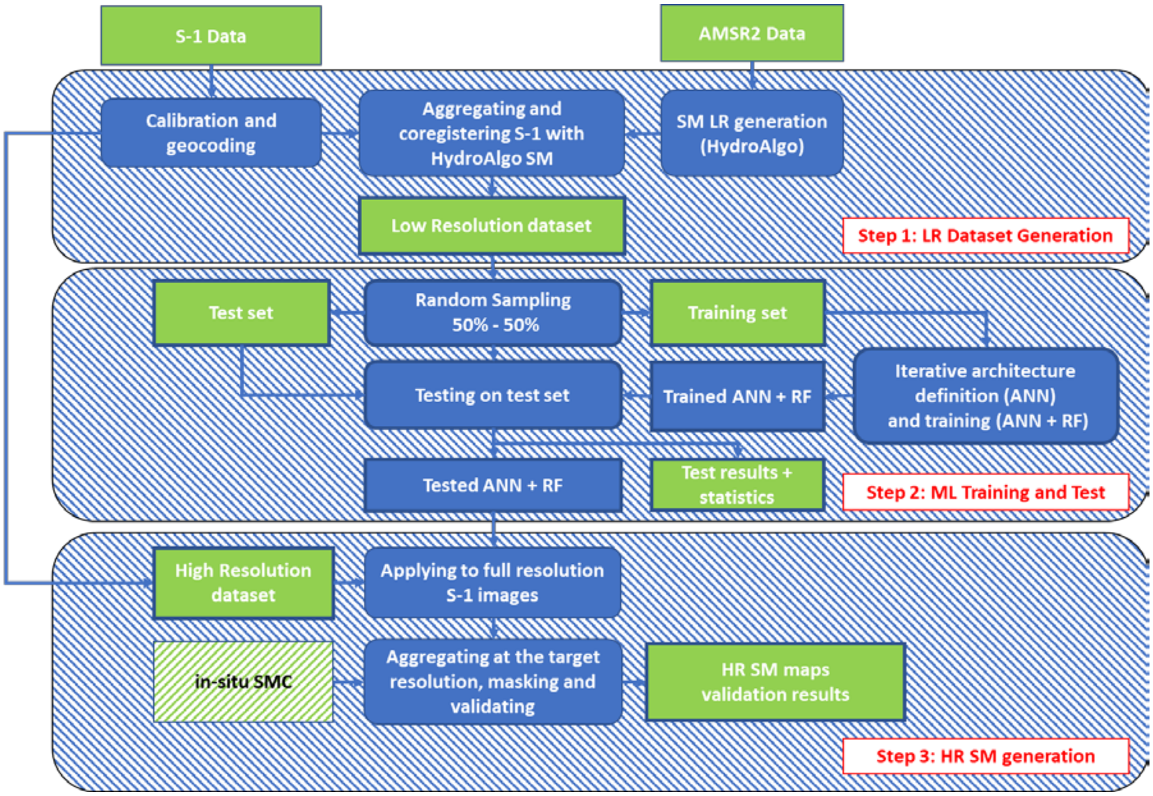

Fig. 3 – Flowchart of the proposed algorithm for estimating SM at high resolution by integrating AMSR2 and S-1 data.

ANN are composed of one or more hidden layers with a given number of fully interconnected perceptrons [30], an input and an output layer. ANN training is based on the back propagation learning rule (BP), and an iterative process derived from the one proposed in [31] is applied to systematic search for the "optimal" number of neurons and hidden layers and for the most appropriate transfer function, with the aim of minimizing underfitting and overfitting problems. For the same scope, the so called "early stopping" rule is also applied [32].

The architecture resulting from the iterative optimization and training was composed of two hidden layers with 8 neurons each and a transfer function of type tangent sigmoid (tansig [28]). Another SM disaggregation algorithm based on RF has been implemented in this study. RF belong to the ensemble learning methods [33], which base the prediction on an average of the results from several predictors called decision trees. Each decision tree is trained by a subset of data created by random sampling with replacement (bagging) of the training set. The number of decision trees is a parameter to be defined when implementing the RF model [34]: in this study, the number of trees was set to 50 after some iterations, this value was shown as the best trade-off between training accuracy and computational cost. For training and testing the ML algorithms, the LR dataset has been divided by sequential sampling in two subsets composed of 50% of data each. Training is carried out by considering aggregated S-1 σ° at both polarizations and LIA as inputs and the HydroAlgo SM as a target. It is worthy noticing that, in the ANN training process, the training set is further subsampled for applying the early stopping rule. The trained ANN and RF are then tested on the remaining 50% of the LR dataset that have not been involved in the training process, to keep training and test as independent as possible.

C. Generation of SM HR Maps

In the third step, after training and testing on the LR dataset, the ANN and RF algorithms are finally applied to the 10 m HR Sentinel-1 dual polarization data to generate the HR SM maps representing the final output of the processing. The SM HR maps at 10m are then masked for open water, dense forests and urban areas based on cartography, aggregated at 30, 50 and 70 m resolution, and validated against in-situ SM.

IV. Results

A. HydroAlgo SM Assessment

As previously stated, HydroAlgo has been largely validated against SMAP and other SM products in previous studies. Anyway, the reliability of HydroAlgo SM on the selected test areas has been verified in comparison with the corresponding SM enhanced data product generated by SMAP. The comparison has been carried out by re-gridding the SMAP

SM on the AMSR2 grid: the results are shown in the density plot of Fig. 4, which represents HydroAlgo SM as a function of SMAP SM.

The two SM products appear highly correlated, as pointed out by the correlation coefficient R = 0.91, although the HydroAlgo SM shows a slight underestimation of the higher SM values, which can be attributed to the intrinsic sensitivity limitations of the C- band onboard AMSR2 when compared to the L- band onboard SMAP.

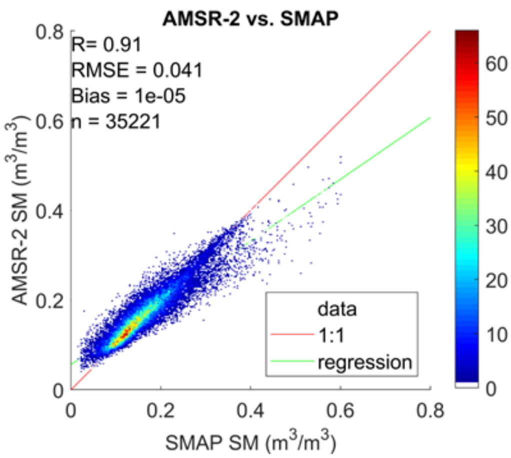

Fig. 4. AMSR2 SM as a function of SMAP SM.

B. S-1 SENSITIVITY TO SM

The S-1 sensitivity to SM has been verified on LR data by plotting the aggregated S-1 σ° as a function of the HydroAlgo SM. The results are shown in Fig. 5, where both VV (magenta) and VH (cyan) are plotted against the SM values generated by HydroAlgo. The logarithmic regressions are also shown in the figures along with the correlation coefficients that are R≃0.4 for VV and R≃0.35 for VH polarization.

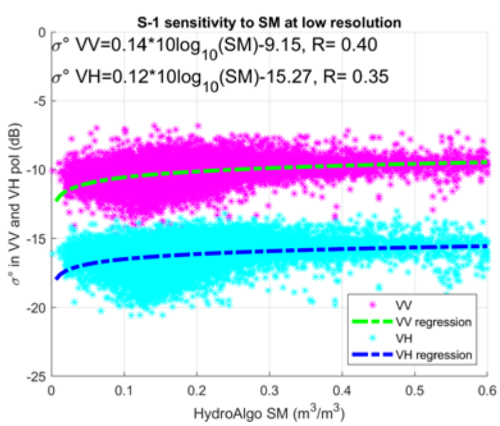

Fig. 5. Aggregated S-1 backscattering at both VV and VH polarization as a function of SM generated by HydroAlgo.

Despite the coarse resolution and the heterogeneity of the surface features in the areas, the increasing trend of σ° when SM increases is confirmed, with a dynamic range of ≃2.5 dB in VV pol. and ≃2.2 in VH pol for SM ranging between 0.01 and 0.6 m^3/m^3. Such relatively small dynamic and the evident saturation for SM higher than 0.3 – 0.4 m^3/m^3 can be explained by considering the effect of vegetation, which is not negligible at C- band. In fact, the growing vegetation increasingly attenuated the measured signal, reaching a maximum during the rainy season in spring, when also the higher SM values have been recorded.

C. ANN AND RF ALGORITHMS TEST (LR DATASET)

The results obtained by applying both ANN and RF to the LR S-1 dual pol + LIA test dataset, composed of the 50% data not involved in the training, are represented in Fig. 6 a) for ANN and Fig. 6 b) for RF.

Fig. 6 show the density plots of the SM estimated by the algorithms as a function of the reference SM derived from AMSR2.

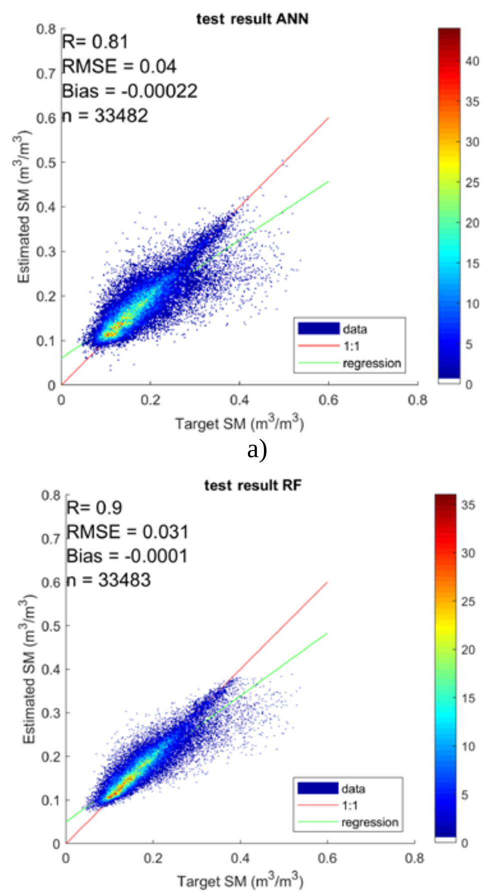

Fig. 6. Test of the ANN on the test set (50% of the entire LR dataset not involved in training), b) the same for RF.

The obtained statistics, also reported in the diagram, are correlation coefficient R=0.81 and RMSE=0.04 m^3/m^3 for

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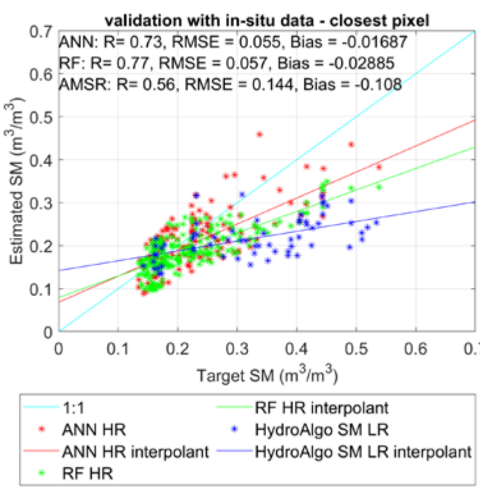
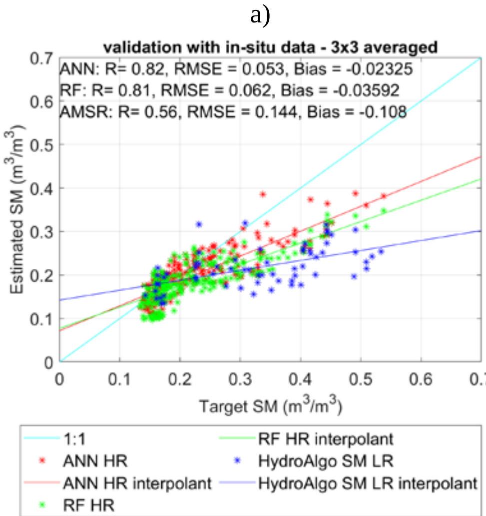
ANN and R = 0.9 and RMSE = 0.03 for RF. Bias is negligible in both cases. From this comparison, the RF algorithm seems outperforming the ANN; however, the validation at high resolution against in-situ measurements reverted these results, by pointing out some limits in the generalization capabilities of RF.

D. ANN and RF Algorithms Validation (HR Dataset)

The validation has been obtained by comparing the HR SM output with the in-situ SM collected in the January 2019 – October 2020 timespan in both Pontecosi and Ponte ad Elsa areas. SM measurements in the two areas ranged from ≃ 0.1 m^3/m^3 to ≃0.55 m^3/m^3, PWC was in the 0-8 kg/m^2 range and HSTD was in the 0.5-4 cm range. Four different validation attempts have been carried out at different spatial resolutions: at 10m, by associating the in-situ SM with the closest in space and time SM derived from the HR maps and at 30, 50 and 70m, by averaging the data over a window increasing from 3x3 to 5x5 and 7x7 pixels, respectively. The result obtained at 10m is shown in Fig. 7 a), while the results obtained at 30, 50 and 70m are shown in Fig. 7 b) – d).



a)



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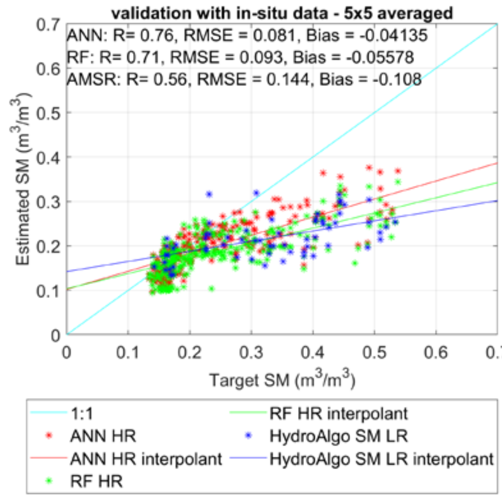
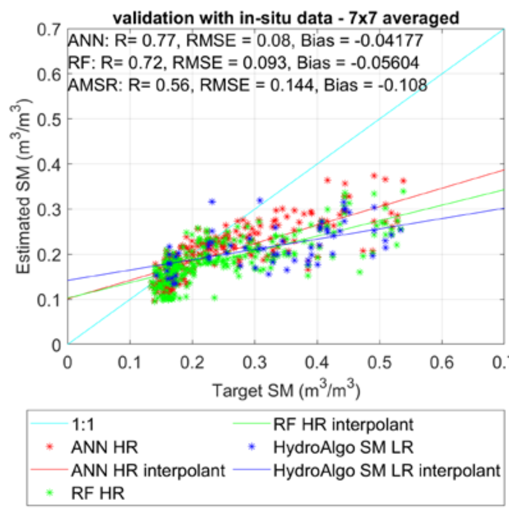


c)



d)

Fig. 7. Algorithm validation vs in-situ data: a) closest pixel at 10m, b) 30m average, c) 50m average, d) 70m average. In all plots, red dots indicate the ANN SM and green dots indicate the RF SM. The HydroAlgo validation at 10 km is also shown.

The comparison between HydroAlgo outputs at 10 km and in-situ measurements aggregated at AMSR resolution is also shown in all plots as a reference.

The results shown in Fig. 7 point out the effectiveness of the disaggregation technique: the results at 10, 30, 50 and 70m are all improved with respect to the HydroAlgo validation at 10 km.

The validation at 10m (Fig. 7 a) is characterized by a larger data dispersion, that can be attributed to the speckle affecting the input S-1 data. The comparison at 30m (data averaged over a 3x3 window) shows the better performances, with R= 0.82 and RMSE = 0.053 m^3/m^3 for ANN and R=0.81 and RMSE=0.062 m^3/m^3 for RF. Increasing the averaging window size to 5x5 and 7x7 pixels does cause a worsening of the results, and a more pronounced underestimation of the highest SM, thus suggesting that the 30m resolution is the one actually reached by the proposed method.

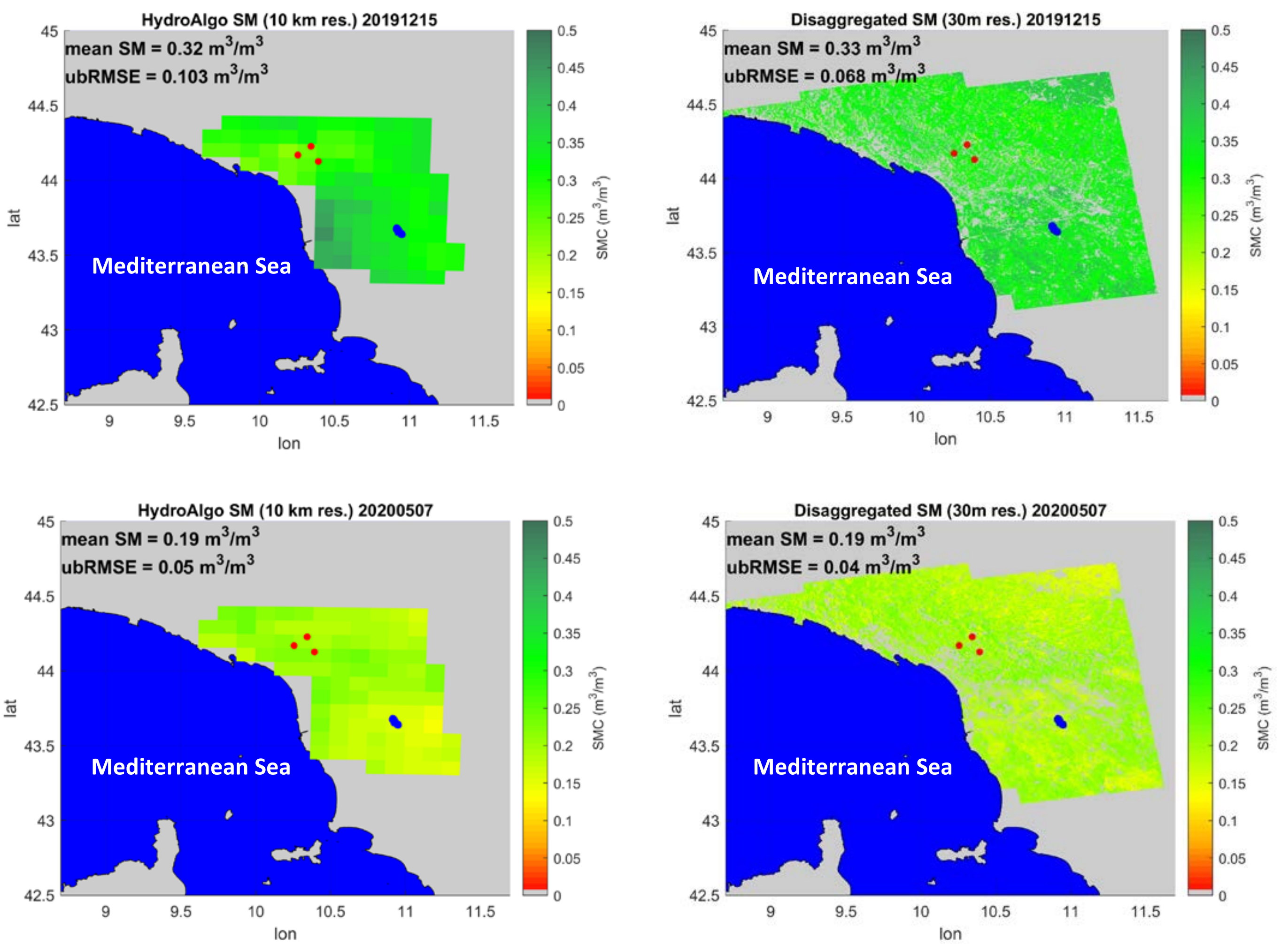
The comparison also reverses the test results: the ANN algorithm shows better generalization capabilities by slightly outperforming the RF that, in turn, showed better results in training and test.

ANN also compensated the higher computational cost for training with a faster application to HR data, while RF is faster in training but takes more time to be applied to the full resolution S-1 images. In both cases anyway, the SM computation from an S-1 image at full resolution takes only few minutes.

A. SM MAPS

After the validation against in-situ SM, the algorithms have been applied to the entire S-1 frame for generating the SM maps. Examples of maps generated by the ANN are shown in Fig. 8 for some dates chosen as representative of the seasonal cycle in December, May, and September. The HR maps at 30 m resolution are shown in the right panels while the LR maps at 10 km resolution generated by HydroAlgo are shown for comparison in the left panels. Some coverage of the LR SM is missing along the coast because the pixels are contaminated by the sea and they have been therefore removed, based on the land/ocean flag delivered with AMSR2 data.

The HR maps are masked (grey colour) for open water and urban areas, which conversely are not detectable in the LR images. The location of the in-situ measurements is also shown in the maps as red dots for Pontecosi and blue dots for Ponte ad Elsa. The qualitative comparison between LR and HR maps points out some agreement between the coarse scale SM patterns identified by HydroAlgo and those appearing in the disaggregated maps, which in addition show small-scale patterns not detectable in the LR SM maps because of the coarse resolution. Notably, the proposed disaggregation keeps the average, as it is confirmed by the almost coincident SM averaged values over the entire image in the LR and HR maps shown in Fig. 8.



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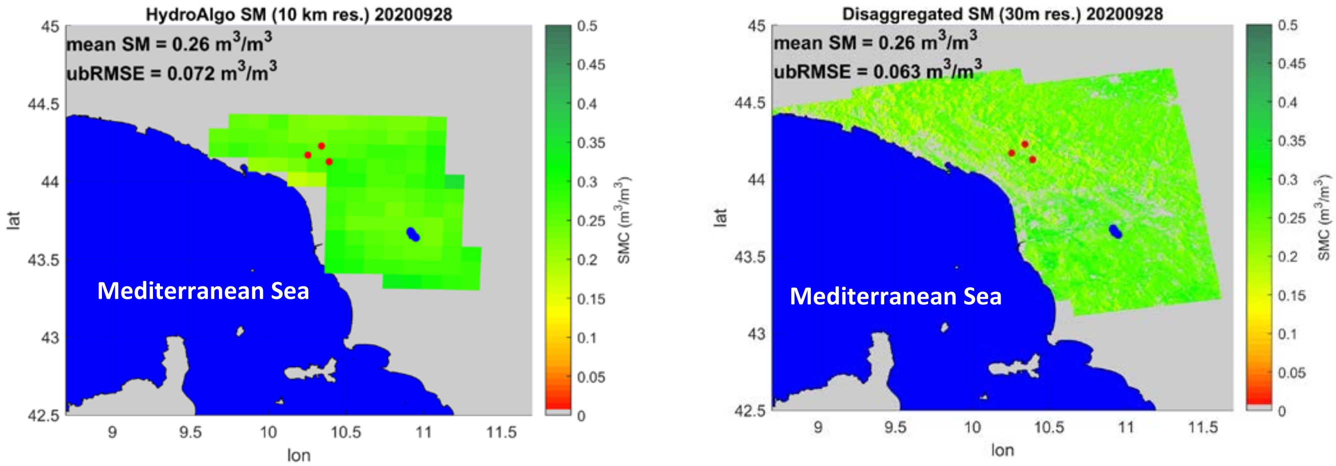

Fig. 8 left column: HydroAlgo SM at 10km resolution for 4 dates chosen as example, right column: corresponding disaggregated SM (≃30m) generated by the ANN algorithm. The average SM value and the ubRMSE from the comparison with in-situ SM are indicated in each map.

An attempt to quantify these results has been carried out by computing the unbiased RMSE (ubRMSE) of the comparison between SM estimated by the algorithms and corresponding in-situ values at the locations highlighted in the maps. The obtained results, are summarized in Tab. 1: although limited to the areas covered by the experimental campaigns, they seem confirming the improvement when moving from LR (HydroAlgo vs. in-situ aggregated at 10 km) to HR (ANN vs. in-situ aggregated at 30m).

Tab. 1. ubRMSE from the comparison with in-situ for the three maps shown in Fig. 8.

date	ubRMSE LR (m^3/m^3)	ubRMSE HR (m^3/m^3)
15/12/2019	0.103	0.068
07/05/2020	0.050	0.040
28/09/2020	0.072	0.063

Similar results have been obtained for the other maps not shown here with an average ubRMSE ≃ 0.049 m^3/m^3 for HydroAlgo LR SM and ubRMSE ≃ 0.037 for HR disaggregated SM. Further assessment of the maps outside the areas covered by the experimental campaigns was not possible since no other source of distributed SM data covering the S-1 frame with comparable resolution was available.

V. DISCUSSION

The validation results shown in the previous section demonstrate, in the limits of the relatively small test areas, a promising potential of the proposed disaggregation in increasing the spatial resolution from dozens of kilometres to ≃ 30m. The need of having temporally and spatially co-located SAR and radiometric data certainly represents the main constraint of this technique. The satellite microwave radiometers as the AMSR2, thanks to the acquisition geometry and the sun synchronous orbit, are capable of daily revisiting about 80% of the Earth surface, while Sentinel-1 temporal frequency is more limited, especially after the abovementioned failure of Sentinel-1B. The revisiting frequency is therefore mainly dependent on the availability of SAR acquisitions: combining different SAR sensors might therefore represent a suitable strategy for improving revisiting and coverage. In this respect, although it has been tested with S-1 and AMSR2, the proposed disaggregation can be applied to other combinations of radiometric and SAR data (e.g. ALOS PALSAR2 or SAOCOM in combination with AMSR2 or SMAP or SMOS). The incoming satellite missions (e.g. BIOMASS, NISAR, Rose-L, CIMR) could further enhance the coverage and revisiting possibilities. Given the ML algorithms characteristics, changing I/O data to other sensors' combinations is straightforward and the computational cost related to retraining is not an issue if using recent machines.

Of course, the accuracy will depend on the sensors involved: for instance, better results are expected if using L-band sensors (both SAR and radiometer) than sensors operating at higher frequencies.

Some improvement in coverage could also be achieved by extending the application of the algorithms outside the area in which they have been trained, i.e. areas in which S-1 data are available but AMSR2 data are not, although this eventuality is less likely, given that AMSR2 coverage and revisit are superior to those of S-1.

Regarding the accuracy, it is important to highlight that the achieved results are based on S-1 data and observation geometry only. Some further improvement could be obtained if considering auxiliary data as for instance NDVI from multispectral sensors (e.g. S-2) or X- band backscattering from SAR (e.g. ASI's Cosmo SkyMed [22]). As counterpart, including more EO data from other sources could add further constraints to the revisiting and coverage.

The disadvantages of the proposed disaggregation can be related to the general shortcomings of ML applications [24] and above all to the need of avoiding outliers, i.e. values in the data outside the training range, which could cause large errors in the predictions. In this sense, the proposed strategy of training over 50% data and testing over the remaining 50% not involved in training, should ensure some generalization capabilities and robustness to outliers, thus mitigating this problem.

As a final remark about the limitations, the applicability should be better assessed in case of very inhomogeneous surfaces, characterized by mixed targets and large SM variability. In such case, important differences in range and statistics could occur between LR and HR data, affecting unpredictably the ML algorithms.

VI. Conclusions

The ML algorithms proposed in this study aimed at increasing the spatial resolution of the AMSR2 SM product generated by the IFAC's HydroAlgo algorithm from the original 10 Km up to ≃30 m. To achieve this result, the S-1 data at VV and VH were first aggregated and resampled at the AMSR2 resolution and combined with the HydroAlgo SM for training the ML algorithms, based on ANN and RF, respectively. After training, both ANN and RF were applied to the full resolution S1 images to estimate SMC at improved spatial resolution. Validation results suggested 30m as the actual resolution of the disaggregation outputs.

Although the validation was so far limited to relatively small areas, the obtained results were encouraging, pointing out the algorithm capability in improving the correlation between estimated and in-situ SM from R≃0.5 of the original LR SM at 10 km up to R= 0.83 of the disaggregated SM at 30 m with a decrease in the corresponding error from RMSE=0.15 m^3/m^3 to RMSE= 0.053 m^3/m^3. These results will be better exploited in the prosecution of the work, by spatially and temporally extending the validation to other test areas and datasets.

The obtained results emphasize the potential of the SAR and radiometer synergy for operational applications at regional scale, particularly in heterogeneous environments as the Italian territory.

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