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Assessment of seasonal soil moisture forecasts over Central Mediterranean toward groundwater management

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Abstract. It is highly likely that the Mediterranean region will experience increased aridity and hydrological droughts. Therefore, seasonal forecasts of soil moisture can be a valuable resource for groundwater management. However, their accuracy in this region has not been evaluated against observations. This paper presents an evaluation of soil moisture in the Central Mediterranean region during the period 2001-2021 using the seasonal forecast system SEAS5. Standardized anomalies of soil moisture are compared with observed values in ERA5 reanalysis. In terms of the average magnitude of the forecast error and the anomaly correlation coefficient, the forecasts demonstrate good performance only in certain regions of the domain for the deepest soil layer at 289 cm, the most interesting for groundwater management. No clear overlap with specific land features such as orography, land cover, or distance from the coast has been observed with respect to the forecast performance. Accordingly, seasonal forecasts can be used to detect wet and dry events for the deepest soil layer in certain regions, with lead-times of up to 6 months. In these regions, the area under the Relative Operating Characteristic (ROC) curve can reach values larger than 0.8. Dry events are generally better captured than wet events for all soil layers. We also analyzed the effectiveness of seasonal forecasts in predicting wet and dry events in Northern and Central Italy for the 2012-2013 period, with a lead-time of 6 months. We found that seasonal forecasting has great potential for groundwater management in certain areas of the Central Mediterranean. However, improvements are needed in observations, data assimilation methods, and the seasonal forecasting system to ensure reliable forecasts for upper soil layers and other regions.

1 Introduction

Soil moisture, starting from the soil surface to the deepest soil layers, represents an invaluable parameter which has a fundamental role in the dynamics of the earth system (McColl et al., 2017). Its variability results from the complex interaction between the atmosphere, vegetation and soil processes.

On the soil surface, soil moisture is an essential component of the Earth surface energy budget, influencing the surface heat

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fluxes and evapotranspiration from land to atmosphere (Seneviratne et al., 2010). From the climate point of view, Mueller and Seneviratne (2012) have shown that the number of hot days is largely determined by a precipitation deficit at the surface that implies small values of soil moisture. This soil-atmosphere coupling, where drier soils determine warmer atmospheres (soil moisture-temperature feedback, see also Seneviratne et al., 2010), could lead to an amplification of the global warming by changing the surface heat balance (Qiao et al., 2023). Apart from soil moisture-temperature feedbacks, most studies have focused on the soil moisture-precipitation feedback. Several processes can contribute to this feedback by acting both a synoptic scale, by changing synoptic settings and enhancing the advection of water vapour, and locally, by changing the boundary layer characteristics and influencing the organization of convection (Hohenegger et al., 2009; Hohenegger and Stevens, 2018; Taylor, 2008; Taylor et al., 2010). However, it is still difficult to determine an overall sign (positive or negative) for such a feedback. The soil moisture available in the root zone is essential for vegetation and agriculture. Its values can be used as indexes for detecting hydrological drought (Spennemann and Saulo, 2015). Through its impact on photosynthesis processes, the variability of soil moisture in climate model simulations drives the 90% of the inter-annual variability of the global land carbon uptake (Humphrey et al., 2021).

The deep soil moisture is fundamental with respect to aquifer recharge mechanisms, particularly for unconfined shallow aquifers. For example, Rodell et al. (2007) used the satellite observed terrestrial water storage from the Gravity Recovery and Climate Experiment (GRACE) to determine the groundwater storage. Later Getirana et al. (2020) demonstrated that the initialization of seasonal forecast with such data improves groundwater forecasts in the US. Also Li et al. (2021) evaluates groundwater recharge from different land surface models and found that, despite model improvements are needed to increase the recharge estimates accuracy, the seasonal cycle of simulated groundwater storage compared well with in situ groundwater observations.

Despite its fundamental role, in situ observations of soil moisture are scarce. Satellite and reanalysis products can provide a useful alternative to fill this gap. However, direct satellite observations are possible only for the first few centimeters below the surface (Dorigo et al., 2021). These surface observations can be propagated through the root zone by filtering operations, empirical models or by land surface models. Reanalysis offer a great alternative for studying soil moisture and they have shown significant correlations with in situ observations. Li et al. (2020) compares different reanalysis and found ERA5 to show the highest skill. Also Bongioannini Cerlini et al. (2017, 2021) shows the strong correlation between ERA5 fluxes and aquifer water table observations. The same was found by Spennemann and Saulo (2015) between GLDAS and multi-satellite soil moisture anomalies. The relevance of soil moisture data from land surface models regards especially not its absolute value, but their time variations, which are very well captured when compared to observations (Koster et al., 2009). By analyzing different reanalysis and land surface models with respect to observational data in Central Italy, Bongioannini Cerlini et al. (2023) found, on average, the best performances of the ERA5 reanalysis with respect to other well-established reanalysis. For these reasons, in this paper ERA5 reanalysis will be used as a reference soil moisture condition. ERA5 soil moisture comes from a particular land surface model that lack of a sophisticated representation of certain hydrological processes (e.g., subsaturated vertical flow, interflow, groundwater flow) (Koster et al., 2009). However, adding complexity to a land surface model does not ensure an

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improvement of soil moisture simulations (Beck et al., 2021).

There is high confidence that the Mediterranean region will suffer from an increased aridity and an increase in hydrological droughts (Ranasinghe et al., 2021). In this context of climate change, sub-seasonal to seasonal (S2S) forecasts are a fundamental tool for adaptation strategies, especially in the context of water resources management. The accuracy of S2S forecast system relies on the simulation of the response of the atmosphere to the slowly varying states of the ocean and land surface (Koster et al., 2004). On the scale of S2S forecasts, soil moisture is the most impactful land parameter and can contribute to the forecast skill (Koster et al., 2004, 2016; Merryfield et al., 2020; Dirmeyer et al., 2018). Esit et al. (2021) found that land initialization contributes to approximately a third of the total soil moisture predictability, while the remaining part is attributable to ocean conditions. Moreover, they found that the same initialization can provide limited skill in the precipitation forecast but enough skill in the soil moisture forecast. This result suggests that skillful seasonal prediction can be made on drought occurrence focusing on the soil state. This is traced back to reduced variability of soil moisture which is an order of magnitude smaller than that of rainfall. The study by Kumar et al. (2019) in North America suggested that this source of predictability is connected to the soil moisture reemergence process, in which moisture anomalies stored in the deep soil layer can "reemerge" to the surface, restoring the earlier root zone anomaly and providing a year-to-year soil moisture memory. Spennemann et al. (2017) found that seasonal forecast of Standardized Soil Moisture Anomalies (SSMA) perform better than forecast of precipitation by using the CFSv2 (Climate Forecast System) in South America. Moreover, the performance were found to be higher for austral winter than summer, and for dry events rather than wet episodes. This result shows the value of seasonal forecast of SSMA for their use for agricultural drought monitoring. A recent study by Boas et al. (2023) found that seasonal forecasts by the European Center for Medium-range Weather Forecast (ECMWF) system, the SEAS5 system, satisfactorily reproduces the inter-annual variation of crop yield and also the high- and low-yield seasons in Germany and Australia. However, a systematic bias of soil moisture was found when comparing with satellite observations.

Most of the above results apply to large continental regions in North and South America. However, the same analysis could bring different results in regions with marked orographic impact and land-sea contrast such as the Mediterranean region. A recent study over the Mediterranean region by Calì Quaglia et al. (2022) found that individual seasonal forecasting systems outperform elementary forecasts of precipitation anomalies based on persistence or climatology. However, the added value is not uniform over the Mediterranean area. The same dis-homogeneity and potential usefulness of seasonal forecast in the Mediterranean was found also by Costa-Saura et al. (2022) for agriculture and forestry. In contrast to the above papers which focused on surface atmospheric variables, this work focuses on evaluating seasonal forecasts of soil moisture for water resources management and estimation of aquifer recharge, with particular attention for wet and dry events. The key question we try to address is: can we use seasonal forecast of soil moisture over Central Mediterranean for predicting the flow toward groundwater, for forecasting dry and wet periods, and then supporting water resources management?
Accordingly, the paper is structured as it follows. Section 2 describes the study area, the seasonal forecast system and the data used to validate the forecast (i.e., ERA5 reanalysis and water table observations). Section 3 provides a description of how

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seasonal forecasts and reanalysis data are processed and the scores used for evaluating the forecast performance. The results of the different scores are reported in Section 4 over the whole analyzed period and study domain. Section 5 examines some case studies of extreme dry and wet periods, showing a possible applications of seasonal forecasts to groundwater management. Finally, section 6 summarizes the main findings of this paper.

2 Study area and data

2.1 Study area

This study focuses on the Central part of the Mediterranean region (5^{o}E-25^{o}E, 35^{o}N-50^{o}N) as shown in Figure 1. Such an area represents a challenge for seasonal forecasts (Doblas-Reyes et al., 2013) for different reasons. First it is greatly influenced by climate change, sometimes recognized as a hot spot. As stated by the sixth IPCC report (Ranasinghe et al., 2021), in the Mediterranean region there is a strong agreement between regional climate models that precipitation will decrease and temperature will increase by mid- and end-century for the Representative Concentration Pathway (RCP-8.5) and the Shared Socioeconomic Pathways (SSP5-8.5) scenarios. Therefore, with high confidence, this area will suffer from an increased aridity and an increase in hydrological droughts. Second, the complex orography of such region (the Alps, the Apennines, the Dinaric Alps, and part of the Atlas mountains) complicates the precipitation forecasts. Finally, additional sources of uncertainties comes from land-sea contrast, atmosphere-sea interactions, and the complex dynamics of extra-tropical atmospheric circulation.

2.2 The seasonal forecasting system: SEAS5

Seasonal forecasts of monthly mean soil moisture were taken from the fifth generation seasonal forecasting system (SEAS5) of ECMWF (Johnson et al., 2019). In the following, we briefly provide a few details on SEAS5, but the reader is referred to Johnson et al. (2019) for further information.

SEAS5 is based on cycle 43r1 of the Integrated Forecast System (IFS) and consists of a coupled system of atmospheric, land surface, oceanic, and sea-ice components. The horizontal resolution of the atmospheric model physics is about 36 km (O320 grid) with 91 levels in the vertical. The ocean model is ORCA (0.25^o) with 75 levels in the vertical. Land surface is represented through the H-TESSEL model (Balsamo et al., 2009), while sea-ice is treated with the LIM2 model (Fichefet and Maqueda, 1997). The atmosphere and land surface are initialized using ECWMF operational analyses, while the ocean and sea-ice are initialized using OCEAN5 (Zuo et al., 2019), which combines the ORAS5 historical ocean reanalysis with the OCEAN5-RT daily ocean analysis.

In this paper, SEAS5 hindcasts, also indicated as reforecasts, that is forecasts produced for the past period between 2001-2016 and forecasts between 2016-2021, for a total period of twenty years (2001-2021), are used. There is no substantial difference between the system set up for hindcasts (reforecasts) and forecasts. Such a distinction is done since the SEAS5 system become operational in 2017 and the actual forecasts were started from that period. Hindcasts are performed in order to extend the

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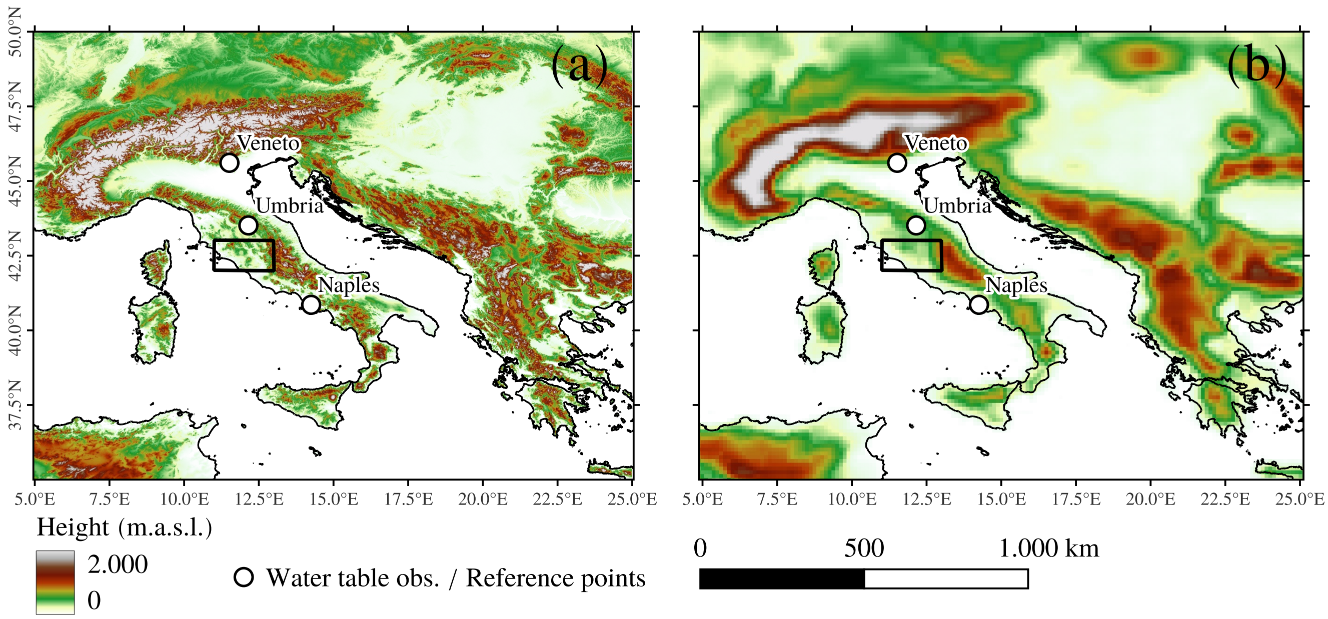

Figure 1. The study area and its orography as represented by: (a) Digital Elevation Model with 1 km resolution (Danielson et al., 2011, GMTED) and (b) ERA5 reanalysis with horizontal resolution of about 31 km (which can be taken as a reference also for SEAS5 system which has resolution of about 36 km). White dots represent water table observations (Veneto and Umbria) and additional reference points (Naples) used in the case studies analyzed in this work. The black rectangular area is used as a reference area for averaging anomaly correlation coefficients in Central Italy.

available time period of seasonal forecasts and allow a better calibration. Moreover, the period until 2016 is used as a reference period for calculating anomalies and the bias adjustment of forecasts with respect to observations. Each forecast consists of different members and lead-time months. The SEAS5 reforecasts have 25 members, while the forecasts have 51 members. To have a homogeneous number of members throughout all the analyzed period, only the first 25 forecast members are considered. Regarding the lead-times, each forecast consists of 7-month time steps and it is initialized at the beginning of each month. In our analysis, all lead-times spanning from 1 to 6 months are considered.

2.3 Soil moisture reanalysis ERA5

The deterministic high-resolution version of ERA5 reanalysis (Hersbach et al., 2020) is used here as a reference dataset for soil moisture, since it has been shown to have good performance in representing the observed soil moisture (Li et al., 2020), especially regarding its seasonal cycle.

ERA5 is produced by using the Integrated Forecasting System (IFS) model version CY42R1. The land surface model is HT-ESSEL (Balsamo et al., 2009) which interacts directly with the atmosphere. Soil moisture is a prognostic variable and, for this reason, its initial value is needed to run the model. The high horizontal resolution of ERA5 ($0.28^o \approx 31$ km), together with an

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improved physics and data assimilation methods, make this reanalysis one of the most reliable and physically consistent dataset of global soil moisture. Seasonal forecasts products from SEAS5 come from a different model version, with different initial conditions, different data assimilation methods, and different horizontal resolution. In order to compare SEAS5 and ERA5 data, both dataset have been interpolated to a higher resolution grid of about 0.25^o.
Observations in ERA5 are assimilated each 12 hours through a 4d-variational (4d-Var) approach. A simplified Extended Kalman Filter (De Rosnay et al., 2013) is implemented in IFS to produce the initial condition for the soil moisture analysis. It is based on two different sources of observations (Albergel et al., 2012): the surface observations of temperature and relative humidity from synoptic stations (SYNOP) measured at 2 m above the ground level (the so-called screen level), and MetOp-A, MetOp-B Advanced Scatterometer (ASCAT) soil moisture data from satellites. Screen-level parameters are indirectly related to soil moisture, while satellites provide a more direct measurement of the surface soil moisture. Since the latter source is capable of describing only the top few centimeters of the soil (Albergel et al., 2012), the root-zone soil moisture is estimated by propagating downwards this information by means of the H-TESSEL hydrological model.

2.4 Water table observations

In this study, we use surface observations of water table as a direct proxy for dry and wet case study events. We select 2 piezometers in two different Italian regions, Umbria and Veneto, respectively located in the Central and Northern part of Italy (white dots in Figure 1). The piezometers monitor two different shallow alluvial and unconfined aquifers with a mean depth of water table below 10 m, whose evolution has been found to be representative of a large area surrounding the point observation. In fact, in such aquifers, a direct interaction between land and atmosphere occurs and the flux in the vadose zone is a significant aquifer recharge mechanism.
The measurements of the water table elevation are provided by the regional piezometric network of the Umbria region, managed by the Regional Environmental Protection Agency [Agenzia Regionale per la Protezione Ambientale (ARPA)] and by local water management services in Veneto. Daily water table data are collected for at least 10 years and have been subjected to preliminary quality control procedures (see Bongioannini Cerlini et al., 2021, for a detailed description of the quality controls), before calculating their monthly mean and the corresponding standardized anomalies.
The southernmost point in Figure 1 (Naples) lacks of a direct measurement of water table elevation, but it will be used later in Section 4 as a reference point to better show the different performances of seasonal forecast across the domain.

3 Methods

Monthly mean values of soil moisture from seasonal forecasts are validated against monthly mean values of soil moisture from ERA5 reanalysis. Both datasets are interpolated over a regular grid of 0.25^o of horizontal resolution. The number and the depth of soil layers in each column is the same in both SEAS5 and ERA5: 4 soil layers at a depth of 7, 28, 100, 289 cm, respectively. The evaluation of seasonal forecasts and also the discrimination of dry and wet periods is performed over the Standardized Soil

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Moisture Anomaly (SSMA). Following the approach by Spennemann et al. (2017), SSMA is calculated at each grid point (i,j) and soil layer (k) as:

$$SSMA_k(i,j,t) = \theta_k(i,j,t) - \overline{\theta_k(i,j,t_{month})}/\sigma_{\theta_k(i,j,t_{month})} \quad (1)$$

where $\bar{\cdot}$ = time average operator, σ = standard deviation operator, t_{month} indicates the month (from January to December) over which the statistics is computed. The time period considered for the forecast validation spans 20 years from 2001 to 2021, while the reference time period considered for evaluating the monthly climatology ranges from 2001 to 2016.

The same reference period is also considered for the bias adjustment of seasonal forecast. The method used in this work is the simple Mean and Variance Adjustment method as described by Manzanas et al. (2019). In our case, each member mean and variance over each grid point is bias-adjusted with respect to the ERA5 observation mean and variance over the period 2001-2016, in the following form:

$$\theta'_k(m,t) = (\theta_k(m,t) - \hat{\theta_k})\frac{\sigma_{obs}}{\sigma_f} + \hat{\theta_k^{obs}} \quad (2)$$

where m is the index representing each ensemble member, $\hat{\theta_k}$ is the ensemble average of the time mean $\overline{\theta_k(m,t)}$, σ_f is the standard deviation of the complete ensemble, $\hat{\theta_k^{obs}}$ is the average of all observation over the considered time period, and σ_{obs} is the standard deviation of all observations. The same operation is computed for each forecast lead-time (from 1 to 6 months). Although the most simple among different methods, Manzanas et al. (2019) demonstrated that MVA methods represent a good compromise between computational cost and performance. This is particularly relevant, since the final aim of this study is to develop real-time applications for climate services.

The performance of SSMA forecasts is evaluated through 3 different metrics. First, the average magnitude error of SSMA ensemble mean is evaluated trough the Root-Mean-Squared Error (RMSE). Successively, the Anomaly Correlation Coefficient (ACC) is used to measure the correspondence between forecasted and observed ensemble mean SSMA. Then the ability of SEAS5 system to discriminate between different event type is measured by the area under the Relative Operating Characteristic (ROC) curve. In particular, dry and wet events have been defined as those with the SSMA being smaller or larger than 1, respectively. Each metric has been evaluated for the different forecast lead-times. The first two metrics (RMSE and ACC) are evaluated by considering the ensemble mean SSMA values, while the latter (ROC) is evaluated by considering all the ensemble members. All metrics calculations rely on the xskillscore Python Package, https://github.com/xarray-contrib/xskillscore.

4 Results

In the following subsections, the results for the mentioned performance metrics are reported: RMSE, ACC and the area under the ROC curve.

4.1 Root-Mean-Squared Error (RMSE)

The RMSE of the seasonal forecasts ensemble mean SSMA over all soil layers is shown in Figure 2 for lead-times 1,3 and 6 months. The average magnitude error is always larger than one standard deviation of soil moisture (1 SSMA) over soil level 1 and soil level 2 (Figures 2a and 2d). This error remains almost constant over different forecast lead-times.

Going towards the deepest soil layers and considering lead-time 1 month, the RMSE decreases over certain regions (Provence in France, Central and North Italy, Hungary and Romania), with values below 0.75, while it largely increases in other regions like the Alps, South-eastern Sicily, Sardinia and Tunisia (Figure 2l). The same distribution of average errors characterizes also lead-times 3 and 6 months, even if with a slight increase of RMSE over all regions. As a result, it can be stated that the accuracy of seasonal forecasts increases for the deeper soil level layers. This can be reconduced to the slower dynamic of deep soil layers, that are less influenced by fast temporal oscillations due to rain and evaporation as for the upper layers.

4.2 Anomaly Correlation Coefficient (ACC)

Figure 3 shows the ACC between forecasted and observed SSMA. As found for the RMSE, the ACC reaches significant values (as indicated by black dots in Figure 3) above 0.8 (shaded contours in Figure 3) only on the deepest soil layer and over certain regions like Central and Northern Italy, some parts of France, Croatia and Hungary (Figure 3l). At lead-time 6 month, some regions like Central and Northern Italy and Bavaria, still exhibit high correlation values (Figure 3n). On the other hand, no correlation is found for the upper soil layers at 3 and 6-months lead-time (Figures 3b,c,e,f,h,i). This absence of correlation is also present at the deepest soil layer in the Alps, the Sardinia, the South-western coast of Italy, and in Tunisia, where correlation coefficient become negative (Figure 3n). At 6-month lead-times, the correlation disappears also for all the Western coast of Balkan peninsula (Figure 3n), where positive values are present at 1 and 3 lead-time month (Figure 3l and 3m, respectively).

Figure 4 shows the average ACC for all forecast months and lead-times. The first column shows values averaged over all domain, while the second column shows values averaged over Central Italy (black squared shown in Figure 1). Either averaging over all the domain or only over Central Italy, no correlation is evident until the deepest soil layer (SSMA4) is considered. With regard to the correlation of SSMA4 forecasts with observations, the domain-average ACC is always below 0.6, while it increases above 0.8 over Central Italy. In general, the highest correlations are found over the Autumn (SON) season, while the lowest are during the winter (DJF) season. In areas with a high correlation, like Central Italy, the most correlated target-months are between April and October, with a minimum in December and January.

4.3 Relative Operating Characteristic (ROC)

The ability of the seasonal forecasts to discriminate between dry and wet events is examined trough the area under the ROC curve. Here, a wet and dry event is considered as the one in which the SSMA is above or below 1, respectively. A ROC area larger than 0.5 means that forecasts can give more information than climatology alone, thereby indicating the potential usefulness of the forecasts. Figure 5 shows the ROC area for dry events for the first three soil layers at lead-time 1, 3, and 6 months. As also found for RMSE and ACC, it is evident that the forecast becomes more effective going towards the deepest

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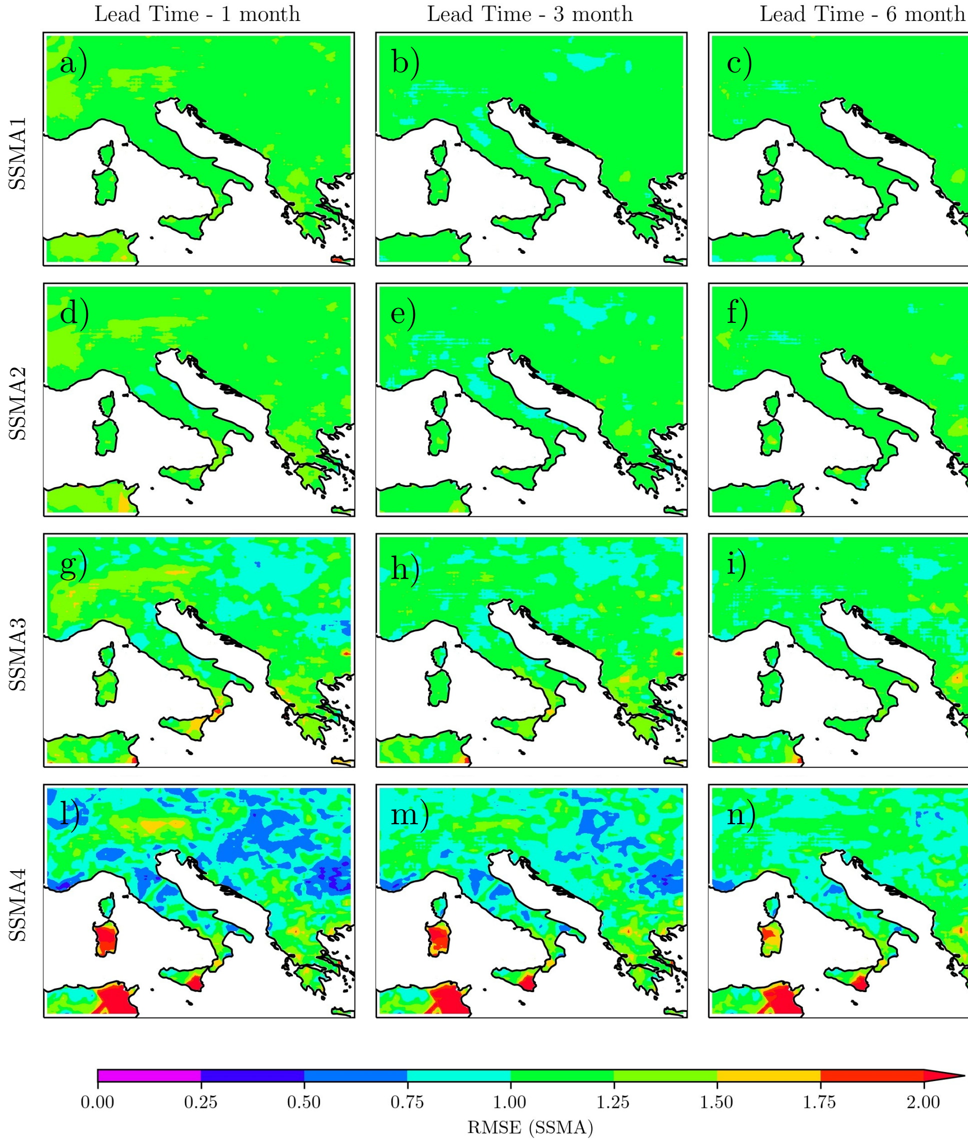

Figure 2. RMSE of Standardized Soil Moisture Anomalies (SSMA) averaged over the whole analyzed period (2001-2021). Rows show different soil layer from the top layer (SSMA1, 7 cm depth) to the bottom layer (SSMA4, 289 cm depth). Columns show the same statistics at for the forecast values at different forecast lead-times 1, 3, and 6 months).

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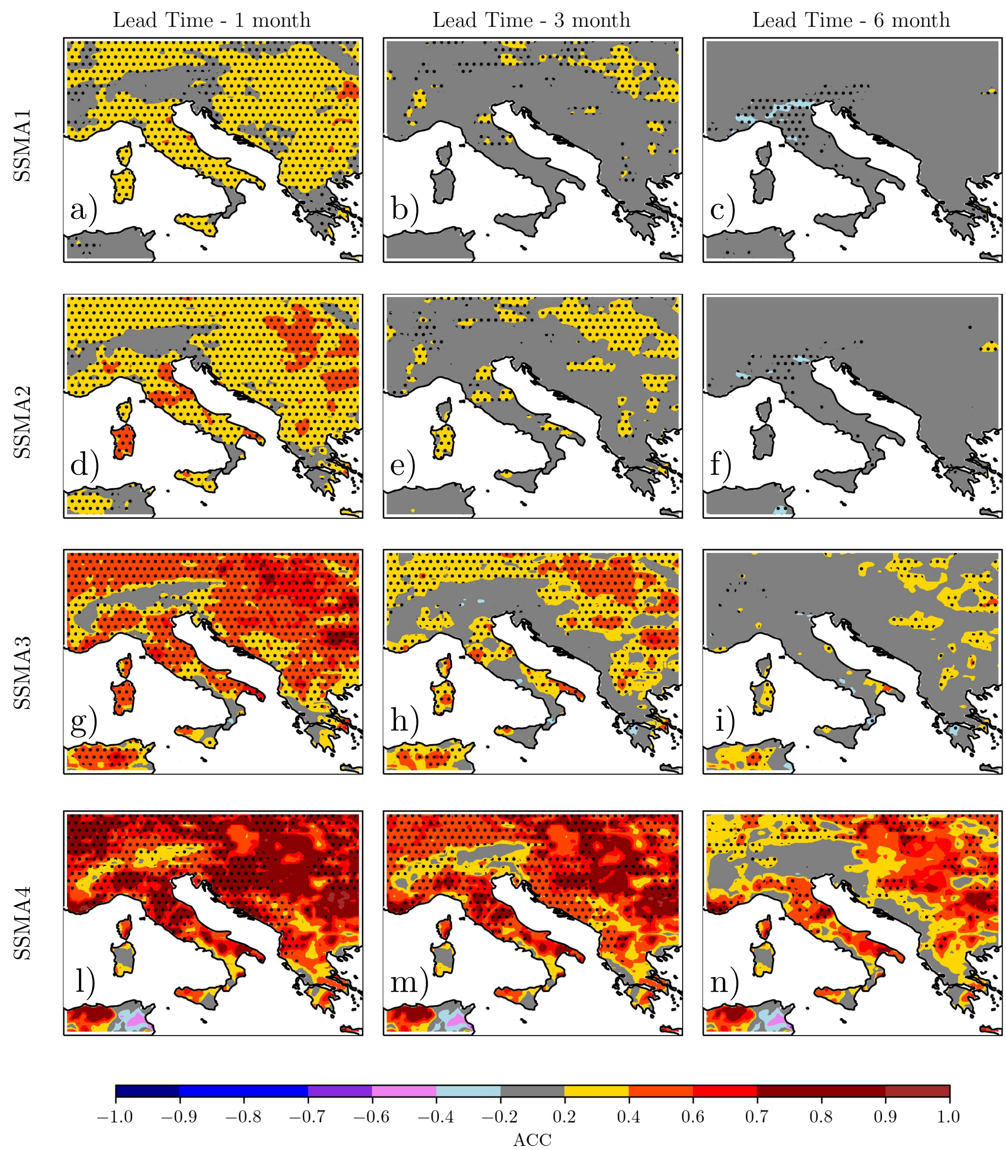

Figure 3. ACC of Standardized Soil Moisture Anomalies (SSMA) averaged over the whole analyzed period (2001-2021). Rows show different soil layer from the top layer (SSMA1, 7 cm depth) to the bottom layer (SSMA4, 289 cm depth). Columns show the same statistics at different forecast lead-times (1, 3 and 6 months). Significant correlation (p-value < 0.05) are marked with black dots.

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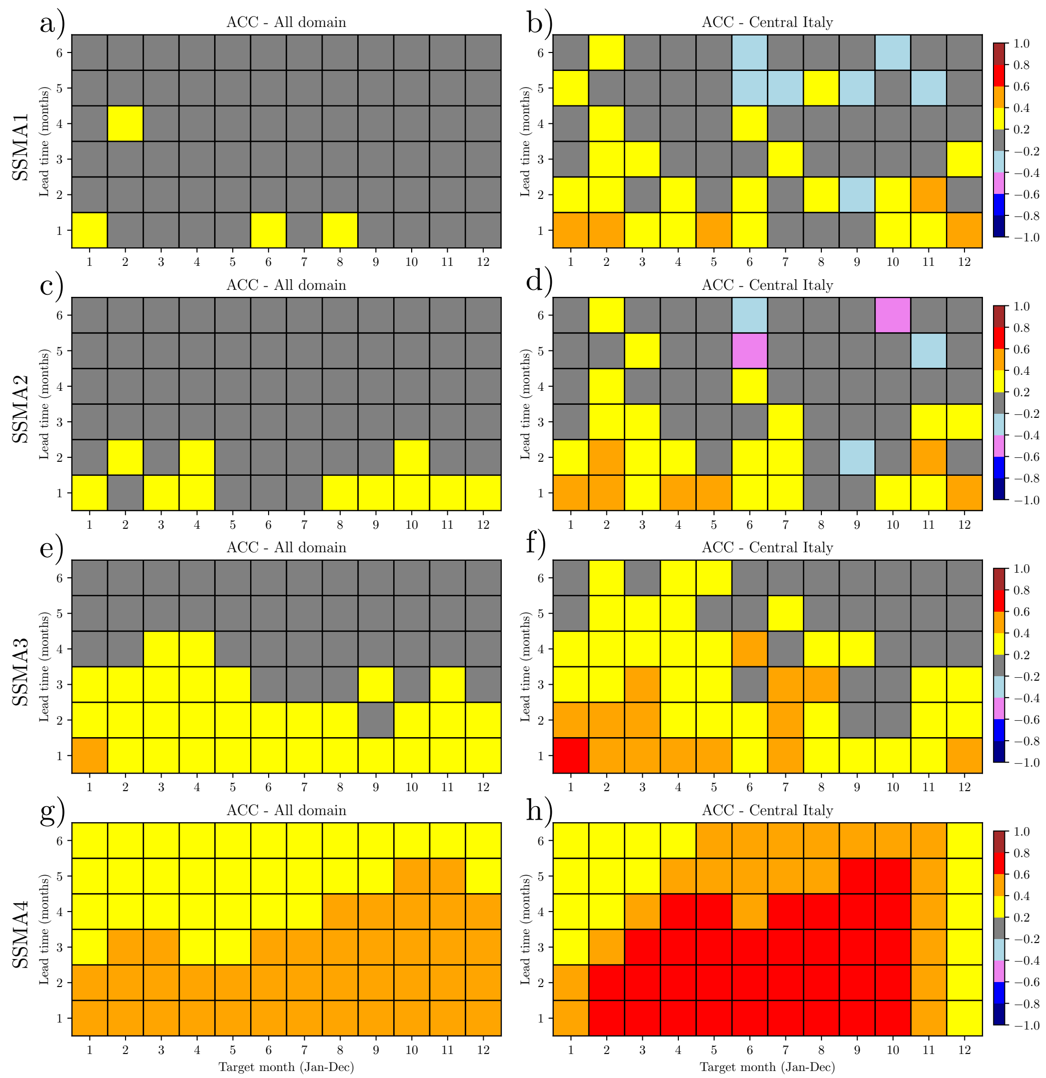

Figure 4. Area averaged ACC coefficient for each target month (x axis) and for different lead-times (y axis). Average values are computed over all domain (a,c,e,g) and Central Italy (b,d,f,h, black squared areas reported in Figure 1a). Rows show different soil layer from the top layer (SSMA1, 7 cm depth) to the bottom layer (SSMA4, 289 cm depth).

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soil layers. Values larger than 0.8 concern only SSMA2 and SSMA3 and some regions (i.e., Central and Northern Italy, internal areas of Hungary). Such values decrease with increasing forecast lead-time, until we get no skill everywhere in the domain for all soil layer levels at lead-time six months. The same behavior is observed for wet events, but with smaller values of ROC area, indicating that wet events are less predictable than dry events. From Figure 5 it is evident that seasonal forecast for the upper three layers is useful only in certain regions like the Central and Northern part of Italy and some internal area of Hungary, and only for few lead-time months. There are also some areas which exhibit no skill at all, neither at different levels or different lead-time months: the South-western coast of Italy, the Southern part of the Balkan peninsula, and the Alps.

The picture changes for the deepest soil layer as shown in Figure 6. At lead-time 1 month, dry and wet periods show similar spatial distribution of ROC area, but with dry events (Figure 6a) having larger values than wet events (Figure 6b). Areas with no skill are still present and they are very similar to those listed above for the other soil levels: South-western coast of Italy, the Alps, Tunisia, the Alps and the Southern portion of Balkan Peninsula. There are also regions, like Sicily and Sardinia, where the ROC area is larger than 0.5 for dry events, but it turns into values smaller than 0.5 for wet events.

When examining lead-time 6 months, there are some areas where the seasonal forecasts are still very useful and exhibit large ROC area: Provence, South eastern coast of Italy, Central and Northern Italy, internal areas of Balkan peninsula. Instead, other areas loose their predictability, such as the Adriatic coast of Balkan peninsula or the Alps. A ROC area larger than 0.8 for both dry and wet events in many regions of the Central Mediterranean for lead-time of 6 months is a clear indication of the potential usefulness of seasonal forecast of soil moisture in these regions.

5 Case study: The 2012-2013 dry and wet periods

Figure 7a shows the water table level observations (expressed as a standardized anomalies with respect to their mean and standard deviation) in two different locations of Italy, Umbria and Veneto, in the Central and Northern part of Italy, respectively (Figure 1). The monitored aquifers are selected to be shallow (depth smaller than 10 m) and unconfined in order to be directly influenced by atmospheric conditions rather than other groundwater processes (Bongioannini Cerlini et al., 2021). From such observations we detect only three dry periods where the standardized anomalies of water table level were less than -1 for both regions: 2007, 2012 and 2017. On the other hand, wet periods in the water table observations, where values larger than 1 are observed, seem to happen more frequently.

The water shortage of 2007, 2012 and 2017 in different parts of Italy is an indication of the synoptic scale character of such drought periods. The variability of water table level is well captured by the variability of deep soil moisture as extracted from ERA5 reanalysis, as reported in Figure 7b. The 2007 and 2012 are negative anomalies also for SSMA4 in both the analyzed piezometers, while the 2017 dry period is detected only in the time series extracted in Veneto. Such a correspondence between water level observations and soil moisture reanalysis further highlights the large potential usefulness of seasonal forecasts of soil moisture.

In the below analysis, we focus on the 2012 dry period and the following wet period in order to test the ability of seasonal

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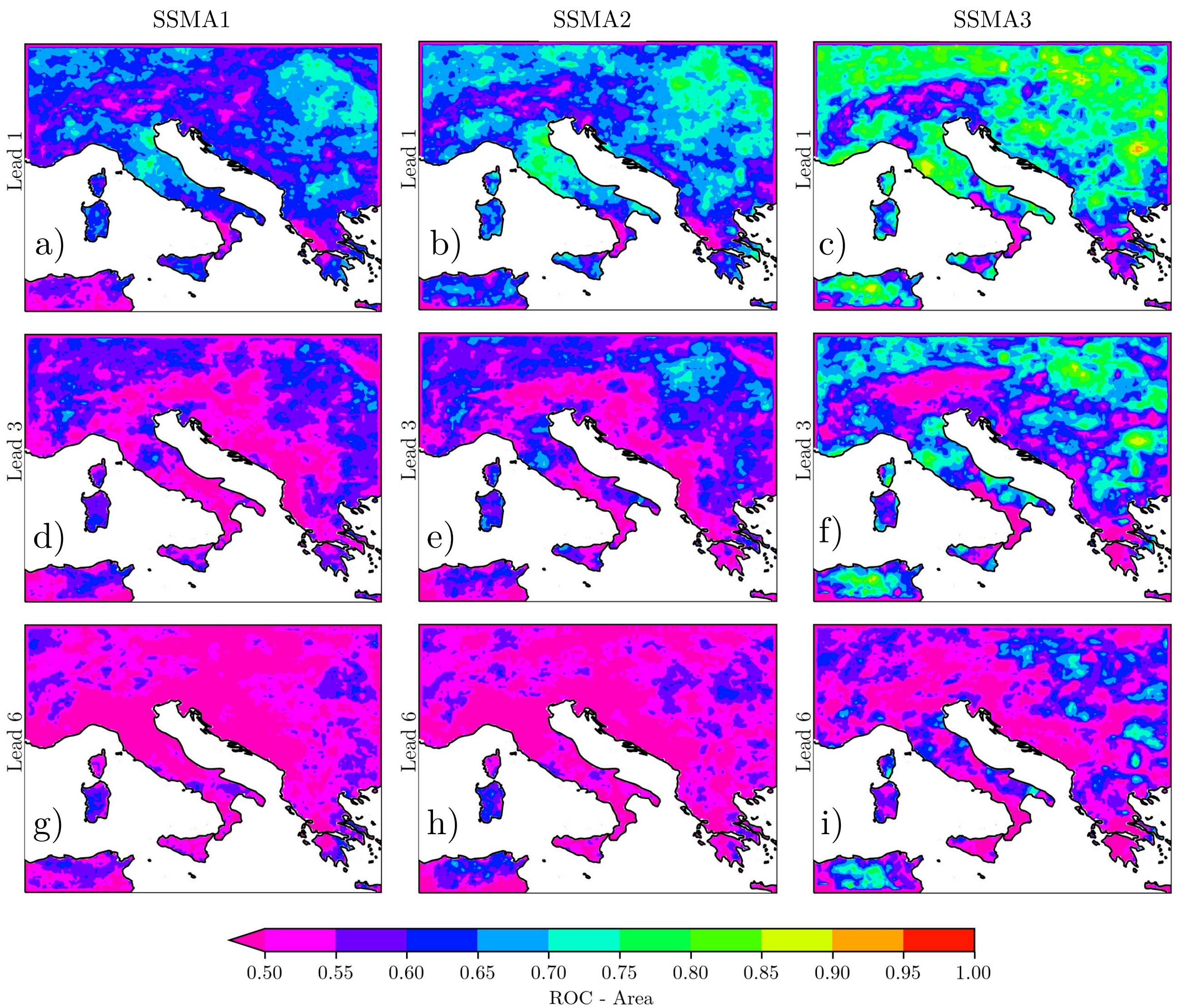

Figure 5. Area under the ROC curve averaged over all dry events during 2001-2021 for the first soil layer SSMA1 (a,d,g), the second soil layer SSMA2 (b,e,h) and the third soil layer SSMA3 (c,f,i). Different rows concern different lead-times.

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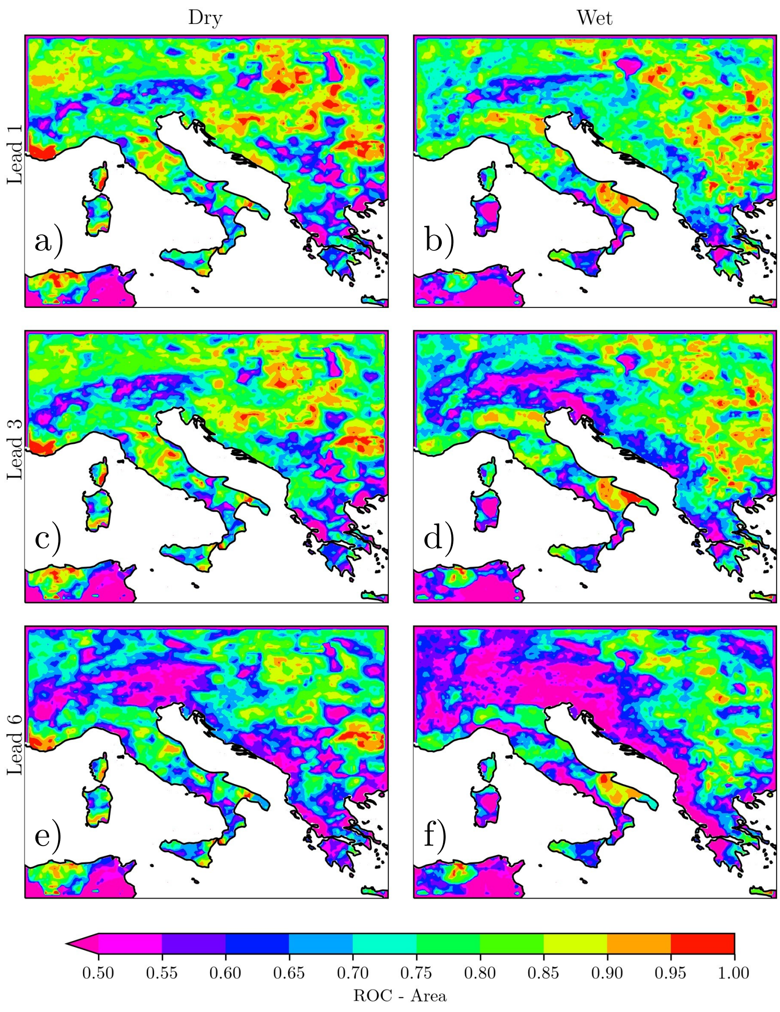

Figure 6. Area under the ROC curve averaged over all dry (a,c,d) and wet (b,d,g) events during 2001-2021 for the bottom soil layer SSMA4. Different rows concern different lead-times.

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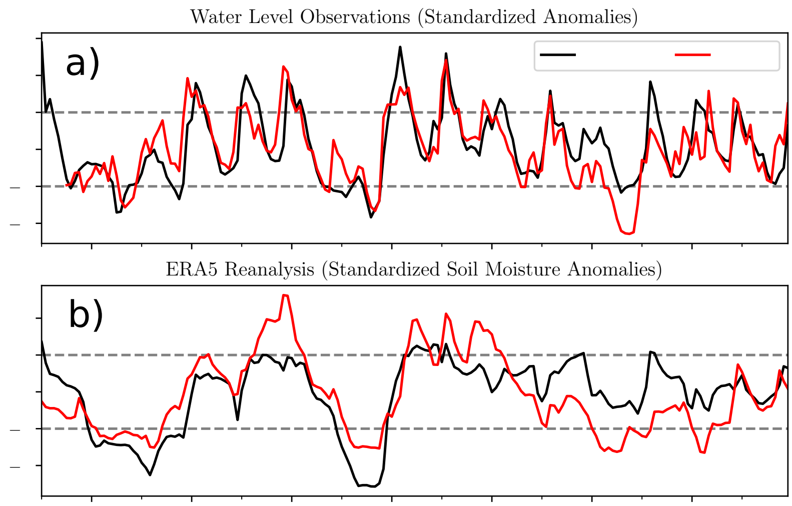

Figure 7. The correspondence between standardized anomalies of the water table elevations from a piezometric network (a) and SSMA4 from ERA5 reanalysis (b) in two points of the Mediterranean region (Umbria and Veneto, as shown in Figure 1).

forecasts to predict such events. Figures 8a, 8b and 8c show the spatial distribution of SSMA4 over the Central Mediterranean on June 2012, December 2012, and June 2013, respectively. These periods are taken as a reference for the start of the dry period, the end of the dry period and the start of the wet period, as observed in Figure 7b for North-Central Italy.

June 2012 is characterized by a large negative anomaly over all the domain expect for the Alps, Sicily, Tunisia and the Adriatic coast of the Balkan Peninsula. Seasonal forecasts for lead-time 1 month predict smaller negative anomalies over Central Italy and the Balkan peninsula, while largely underestimating the positive anomalies over the Alps (Figure 8d).The forecast slightly improves in Northern Italy and Balkan peninsula going to lead-time 3 and 6 months (Figure 8g and 8l), while it gets worse for Sicily and Tunisia.

December 2012 shows a similar spatial distribution of SSMA4 except for larger positive anomalies on the Alps, the South-western coast of Italy, and the South-western coast of the Balkan Peninsula (Figure 8b). Also the amplitude of negative anomalies of SSMA4 decreases in Central and Northern Italy. The seasonal forecasts perform well in Central and North Italy, in the South-eastern coast of Italy, in Sicily and in Provence for all lead-times (Figure 8e-h-m). However, it was not able to detect the large increase in positive anomalies over the Alps, the Western coast of Balkan peninsula, and the Tyrrhenian coast of Italy. Also the larger negative SSMA4 in the internal regions of the Balkan peninsula was not detected.

The wet period of June 2013 involved especially the Northern part of the domain with large positive anomalies of SSMA4 (Figure 8c). Seasonal forecasts show in general a good performance especially in Central and North Italy at lead-time 1-month

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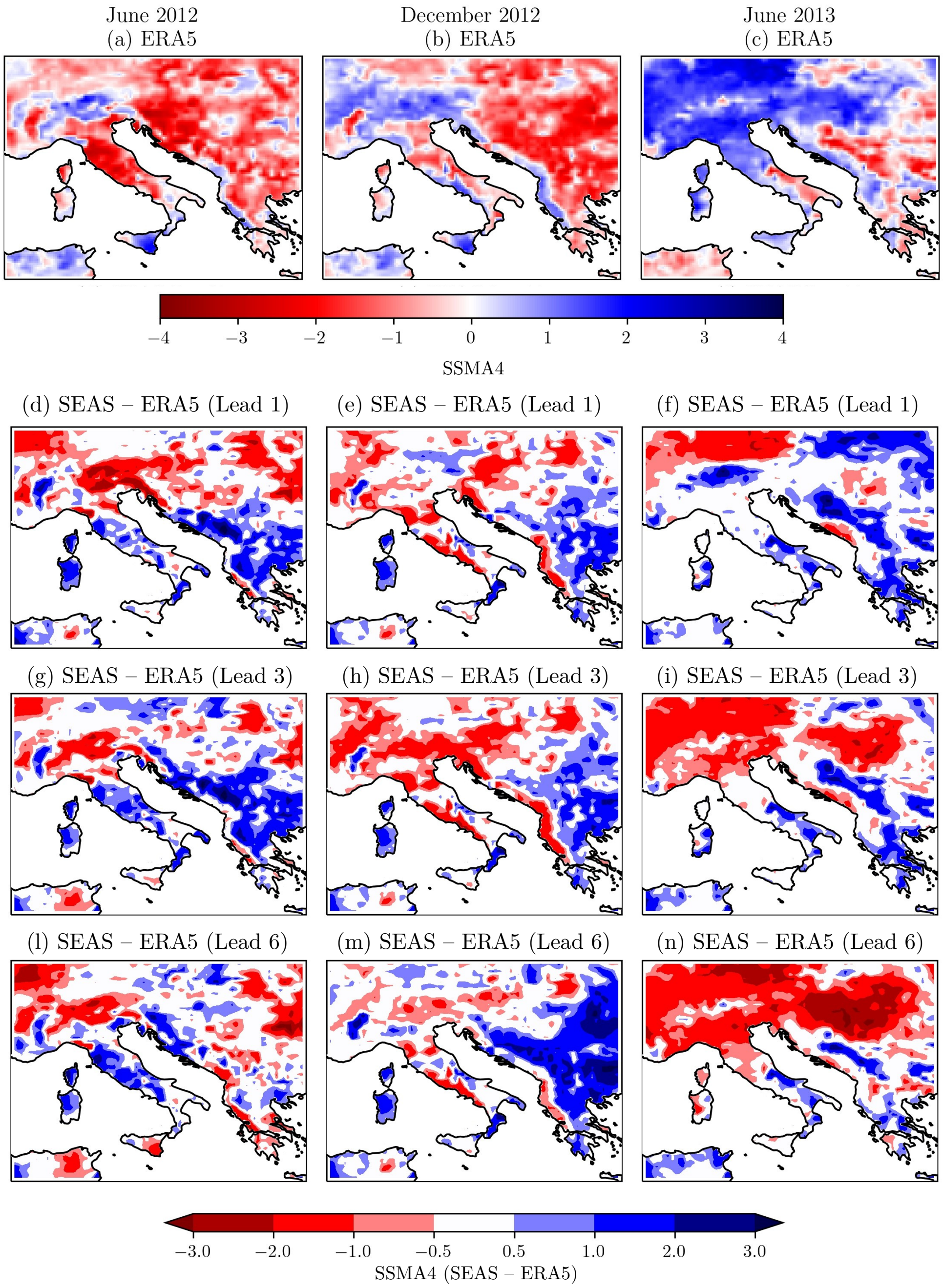

Figure 8. Spatial distribution of observed (a,b,c) and forecasted SSMA4 anomalies (d-n) during the analyzed case studies: first column for the dry period of June 2012, second column for the dry period of December 2012, and last column for the wet period of June 2013. Figures (d,e,f) concern forecast lead-time 1 month, (g,h,i) lead-time 3 months and (l,m,n) lead-time 6 month.

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(Figure 8f), while they tend to underestimate such positive anomaly at larger lead-times, especially over Hungary (Figure 8i-n).

Figure 9a and 9b show how the ensemble members follow quite well the observations for Umbria (Central Italy) and Veneto (Northern Italy). On the other hand, this is not true for Naples, which is taken here as a reference point for the South-western coast of Italy (Figure 1). By looking at December 2013, the increase of SSMA4 in this region is not captured by the ensemble mean. Only few members detect such an increase and only one member reaches values of SSMA4 larger than 1. As highlighted also by the analysis of the ROC curve in Figure 6, Figure 9c confirms the fact that seasonal forecasts have no sufficient skill to be used in the South-western coast of Italy neither for dry or wet events prediction.

6 Conclusions

This paper provides a first assessment of seasonal forecast of soil moisture for the Central Mediterranean Region. The seasonal model is SEAS5 from the ECMWF and the ERA5 reanalysis is considered as a reference for soil moisture observations. 25 member forecasts with lead-times from 1 to 6 months have been analyzed from 2001 to 2021, by considering the hindcast period 2001-2016 as climatology. By considering such a climatological period, the standardized soil moisture anomaly (SSMA) has been evaluated and the forecast values bias-adjusted trough the mean-variance adjustment method. Then the RMSE, the ACC have been evaluated for the SSMA for all soil layers. To test the ability of the forecast to discriminate between dry and wet events, we calculate the ROC area. Finally, a case study of the dry and wet periods during 2012-2013 has been studied in detail, to show the potential usefulness of the seasonal model. The outcomes of the paper can be summarized in the following key points:

- the average magnitude of the forecast errors, as indicated by the RMSE, decreases as we go deeper into the soil. Only in the deepest soil layer at 289 cm depth, the RMSE can reach values below 0.5 even for lead-time 6 months. However, this is valid only over certain region like Central and Northern Italy, some internal regions of the Balkan Peninsula and the Provence region. The RMSE remains too large in other regions, even by considering only the deepest layer;
- significant values of the anomaly correlation coefficient (ACC), with values larger than 0.8, can be found over some region even at lead-time of 6 months;
- in areas with large correlation coefficient the larger correlations are found between April and October, while a minimum correlation is found in December and January;
- the ability of seasonal forecast to detect wet and dry events exhibit a large variability within the domain. However, a ROC larger than 0.8 can be found in certain region for the deepest soil layer also for lead-time 6 months. This means that in those regions, like Provence, Central and North Italy, the South-eastern coast of Italy and the internal regions of Balkan peninsula, we can use seasonal forecast to detect such events in advance;

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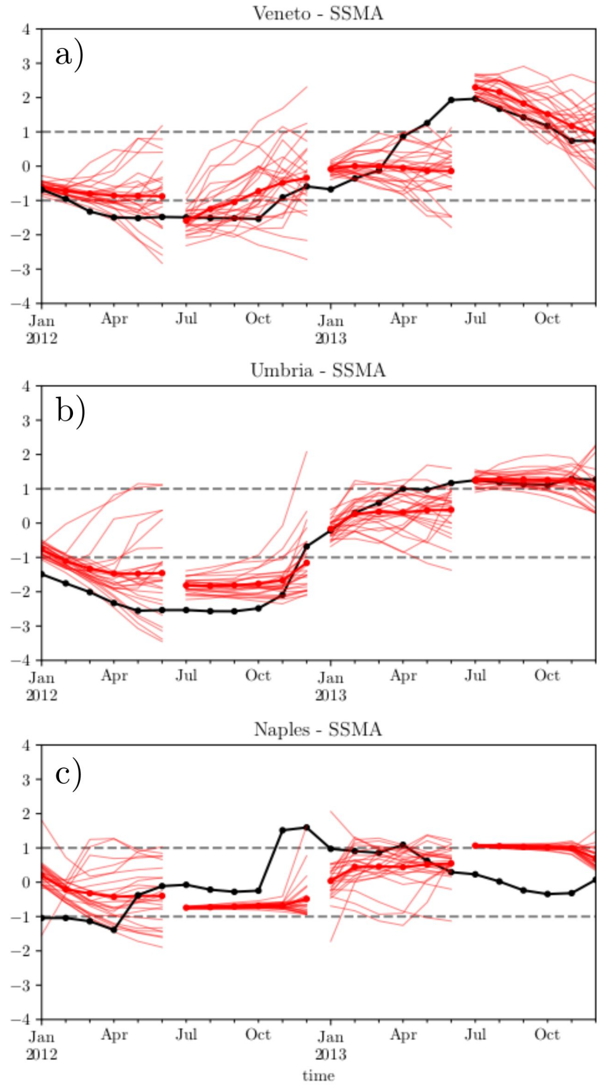

Figure 9. Time evolution of seasonal forecasts of SSMA4 over the period 2012-2013 and different points: a) Veneto, b) Umbria and c) Naples as reported in Figure 1. Thin red lines show each ensemble member with different lead-times and different forecasting starting periods. Black lines show the correspondent ERA5 reanalysis observation of SSMA4.

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- the ROC area for dry and wet events in the two uppermost soil layers is always smaller than 0.5 when lead-times larger than 3 months are considered;
- a small ROC area for dry and wet events is found at lead-time 6 months especially in coastal regions (South-western coast of Italy and Balkan peninsula, Sicily and Sardinia, Tunisia) and mountainous regions (Alps and Dinaric Alps);
- in general, for all soil layers, dry events are better captured than wet events.

As an example, the case study of 2012 drought period shows how the SEAS5 model is able to predict such an event for Central and Northern Italy 6 months before. Moreover, the strict connection between the deepest soil moisture and the water table of shallow unconfined aquifer in Italy, demonstrates the potential use of seasonal forecast for water management purposes. Using multiple seasonal models, more advanced bias-adjustment methods and a larger ensemble could definitely improve the proposed analysis, as well as improving deep soil moisture observations in order to verify both reanalysis and forecasts.

Code availability. The python packages xarray and xskillscore have been used extensively in this work and they are freely available at https://docs.xarray.dev/en/stable/ and https://xskillscore.readthedocs.io/en/stable/

Data availability. ERA5 reanalysis data and Seasonal forecasts data are available on the Copernicus Climate Data Store. The water table data of Umbria that support the findings of this study are available upon request from https://apps.arpa.umbria.it/acqua/contenuto/Livelli-Di-Falda..

Author contributions. All authors contributed to the conceptualization of the research. L.S. carried out the data analysis. All authors contributed to the investigation of the results. L.S. wrote the original draft. P.B.C. supervised all the research group work. All authors reviewed and edited the manuscript.

Competing interests. The authors declare that they have no conflict of interest

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