The iCOLT climate service: Seasonal predictions of irrigation for Emilia-Romagna, Italy

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Abstract
Emilia-Romagna is a region of Northern Italy whose land use is mainly devoted to agriculture, especially over the plain area. Since the region is characterized by summer water shortages and recurrent drought conditions, a summer irrigation water demand forecast system has been developed, operating both at regional and Land Reclamation and Irrigation Board levels. Remote sensing crop detection is used in combination with a soil water balance model as a monitoring tool in support to water management and to optimize the use of available water resources. These instruments are also integrated with operational calibrated probabilistic seasonal forecast products currently based on Copernicus Climate Services, in order to evaluate summer irrigation water needs in advance in support to decision-making by water managers. Results obtained using this prediction system are characterized by a significant forecast skill. The sources of the predictability of this system are specifically evaluated, showing that the correct representation of crop geographical distribution is crucial for the ability of the system to capture spatial variability in irrigation demand. Furthermore, the system forecast skill is mostly due to the use of an empirical model to assess the hypodermic water table depth initialized by means of the observed meteorological data of the months before the beginning of the summer season. Finally, calibrated probabilistic seasonal predictions also contribute to a minor extent to the good performance of the system as a whole.

KEYWORDS
crop development model, early crop map, hypodermic water table, irrigation planning, probabilistic seasonal forecasts, remote sensing detection, soil water balance model

1 | INTRODUCTION
Climate services are progressively becoming a common product of the scientific community addressed to the society (European Commission, 2015). Many definitions of climate services have been proposed by different organizations (Brasseur & Gallardo, 2016) but the common baseline is the focus on supporting decision-making.
driven by climate data, through an alliance between providers and users (Lourenço et al., 2016). Therefore the innovative feature of climate services is the connection between research and development and actual exploitation of climate services, which is still representing a critical issue, called “Valley of Death” (Brasseur & Gallardo, 2016).

This connection has been specifically called for in 2009, by the World Climate Conference-3, which launched a Global Framework for Climate Services (GFCS), implemented later on in 2012, in order to “strengthen the production, availability, delivery and application of science-based climate prediction and services” and to coordinate existing initiatives and develop new infrastructures to meet society’s climate-related challenges (Hewitt et al., 2012).

As the increase of climate variability is one of the most relevant impacts of climate change, the mission of GFCS is to cope with risks and exploit opportunities to reduce climate impacts, with a focus for those who are most vulnerable to climate-related hazards.

GFCS is organized into priority areas, including agriculture and food security, disaster risk reduction, energy, health and water. This structure testifies the climate services wide-ranging domain through the society sectors affected by weather (Larosa & Mysiak, 2019). At European level, climate services are defined as the intelligence behind the transition to a climate-resilient and low-carbon society, priorities pursued by the EU Green Deal, as they provide support to increasing resilience and enhance adaptive capacities by means of informed decisions (European Commission, 2015). The commitment of European Commission to unlocking the potential of climate services is substantiated by the initiative Copernicus Climate Change service (C3S), a new system for climate services in the framework of the Copernicus initiative (www.copernicus.eu). The system provides on the one hand a comprehensive set of observational data and analyses datasets that can be used to monitor current and past land use and meteorological conditions (Noone et al., 2020), and on the other hand ensemble climate predictions and projections, which can be used as input to impact models so as to produce probabilistic predictions and climate services applied in several fields (Hewitt & Lowe, 2018).

As the impacts of climate variability on agricultural systems is well known and documented (Hansen, 2002), several applications and studies have been carried out in order to develop climate services for agriculture at different spatial scales and with different purposes (Sivakumar, 2006).

In the context of climate services for agriculture, seasonal predictions are one of the most suitable tools to be adopted by crop and livestock producers as their decisions can be guided, among others, with respect to agronomical operations (i.e., irrigation, planting, and harvest timing, selection of crop type and/or crop variety), to crop storage and purchase of crop insurance (Klemm & McPherson, 2017).

A consolidated service of seasonal forecasts addressed to agriculture is the seasonal climate outlook (SCO produced by Department of Primary Industries and Regional Development’s (DPIRD) Statistical Seasonal Forecast (SSF) system specifically for the Western Australian grainbelt and by the Australian Bureau of Meteorology; SCO is a monthly newsletter that summarizes climate outlooks for the next 3 months, incorporated into on-farm decision-support systems (https://www.agric.wa.gov.au/newsletters/sco).

Furthermore, the Famine Early System Network (www.fews.net) is an operational service that provides early warnings of the main factors contributing to famine and food insecurity (Ross et al., 2009), obtained by means of seasonal forecasts, applied on 28 countries (FEWS NET, 2018).

With regard to seasonal irrigation demand predictions, services on specific crops have been already developed (An-Vo et al., 2019).

The novelty of the present study is the integration of different data types in order to set up an operational climate service able to predict seasonal crop water needs applied on a regional domain, conceived as water resource planning tool devoted to water managers. The presented climate service is obtained by means of the integration of different data sources from remote sensing, agrometeorological modelling and climatology.

In more details, this work presents the operational system iCOLT (Irrigazione delle COLture in atto classificate con il Telerilevamento, i.e., irrigation of crops classified with remote sensing) implemented by ARPAE and applied in Emilia-Romagna (Italy) over the years 2011–2019 in order to predict summer irrigation demand at regional and Land Reclamation and Irrigation Board scales, and evaluates its performance, trying to identify the bases for its predictability capacity. In more detail, the results of iCOLT are described in two study areas to demonstrate the service: the Land Reclamation and Irrigation Boards of Burana and Romagna (Consorzio della Bonifica Burana and Consorzio di Bonifica della Romagna).

As Emilia-Romagna is characterized by drought periods and strongly negative values of the local climatic water balance (CWB) during summer, agriculture is mostly carried out by means of irrigation.

Current observational climate trends (Antolini et al., 2016) and climate change projections (Emilia-
Romagna Region, 2019) indicate that summer water shortage may recur more frequently in the future due to highly probable temperature increases and possible reductions of summer precipitation. For these reasons, water management becomes a crucial issue and a climate service like iCOLT can play a role in supporting to water procurement and allocation decision-making, to cope with the climate variability during the most critical season for crop yield.

The development of iCOLT is also framed in the context of a more sustainable approach to water resource management to mitigate a competing use of water from all different sectors during water shortage crisis and to satisfy the environmental requirements (Environmental European Agency, 2009).

The structure of the article is as follows: in Section 2.1, the selected study areas on which iCOLT is applied and tested are described; from Section 2.2 to 2.9, the iCOLT system is then presented, providing details on each work stage that comprises remote sensing analysis, calibrated probabilistic seasonal predictions, soil water balance modelling and its components. Finally, the iCOLT summer irrigation forecasts produced over the period 2011–2019 are described and validated by means of statistical indices in Sections 3.1 and 3.2. Discussion of results and remarks for further developments conclude the work in Sections 4 and 5.

2 | MATERIALS AND METHODS

2.1 | Study areas

Emilia-Romagna is a region located in Northern Italy, in the southern part of the Po river valley, and in the plain area its land use is mostly devoted to intensive agriculture with strong connections with the food sector. Within the total regional area of 22,447 km², the plain is about 47.1%, corresponding to about 10,573 km² located in the northern part of the region, where intensive agriculture is concentrated (Emilia-Romagna Region, 2015). Apennines mountains are present in the southern part of the region, which contribute to the regional production by means of low input agriculture, pasture and forest areas.

Concerning agricultural production, the crop distribution is linked to the specialized agriculture developed through the territory, due to pedo-climate conditions and food sector connections (Ghisellini et al., 2014). On the whole region, the autumn–winter and summer herbaceous crops cover most of the regional cropped area (78% of the utilized agricultural area [UAA]) with intensive tomato cropping systems in the western plain. 10% of UAA is dedicated to the forage (alfalfa, meadows and permanent grasslands) cropping for livestock, linked to the production of Parmigiano-Reggiano cheese. Tree crops cover the 12% of UAA: orchards and vineyards are widespread in the region, with concentrated cropping systems in areas where quality products are located (Emilia-Romagna Region, 2010).

With regard to irrigation management, the authorities in charge of water management for agriculture (water storage, transportation and distribution) are Land Reclamation and Irrigation Boards (Consorzi di Bonifica in Italian) (Pérez-Blanco et al., 2016). These entities are the main stakeholders of the summer operational seasonal predictions of irrigation presented here.

iCOLT irrigation water need predictions are operationally provided for the whole plain area, and for each of the eight Land Reclamation and Irrigation Boards. In the current study, results of the reforecasts obtained with the current operational set-up are described for two study areas: the Land Reclamation and Irrigation Board of Romagna (Consorzio di bonifica della Romagna—CBR) and the Land Reclamation and Irrigation Board of Burana (Consorzio della bonifica Burana—CBB), shown in Figure 1.

It is worth mentioning that observed data of water volumes applied for crop irrigation for both the study areas are unavailable due to the lack of measuring equipment on the whole water network distribution systems. Therefore, as better described in Section 2.8, the irrigation water needs obtained by forcing the water balance model with observed weather data are used as reference values.

CBR is located in the eastern part of Emilia-Romagna, on the Adriatic coast, characterized by Mediterranean climate. The domain of Land Reclamation and Irrigation Board of Romagna covers 352.456 ha. The cropping systems are specialized on tree crops (kiwi, fruit, peach) and vineyards for the production of Protected Designation of Origin wines.

CBB is in the central part of the region, just south of the Po river, characterized by continental climate. Its total area is 242.521 ha. The prevailing crops are linked with food sector (alfalfa, meadows and permanent grasslands) in connection with the Parmigiano-Reggiano supply chain, but the production include also orchards (notably pears) and vineyards representing a local excellence (Emilia-Romagna Region, 2010).

These study areas were selected because of the different geographical characteristics that determine different climate features mainly due to the different distance from the sea (Corinaldesi et al., 2020) and agricultural production.
2.2 | iCOLT prediction system

The iCOLT system integrates satellite data, calibrated probabilistic seasonal weather forecasts, observed weather data and a soil water balance (SWB) model so as to produce, by the end of May, an ensemble of irrigation predictions for the summer, intended as June–July–August. The timeline of the operational chain (Figure 2) starts from the previous winter and spring months in which an early crop map is produced by means of remote sensing analysis.

During May, calibrated probabilistic seasonal predictions are issued. The early crop map, the seasonal predictions and observed weather data are the input of CRITERIA soil water balance model to produce at the beginning of summer the probabilistic predictions of June–July–August irrigation. In the following autumn, the observed daily weather data are used as input of the soil water balance model so as to validate the predictions. The first version of this system was proposed within the European ENSEMBLES project (Tomei et al., 2009).

The different components integrated in the iCOLT operational system are described in the following.

2.3 | Early crop map

The early crop map is one of the crucial inputs for iCOLT because it provides an agricultural herbaceous crop classification at the beginning of the irrigation season to

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FIGURE 1 Emilia-Romagna map and study areas of CBR and CBB

FIGURE 2 The iCOLT system workflow
discriminate potentially non-irrigated from irrigated areas. The classification subdivides the agricultural areas into three classes, according to crop season: winter, multi-annual and spring–summer herbaceous crops. The classification of agricultural crops in macro-classes is performed by the analysis of multi-temporal optical satellite image series, selected in order to maximize the phenological differences among these classes.

As shown in Figure 2, the classification scheme is based on three acquisition windows from autumn to early spring, and classifies crop macro-classes according to presence/absence of seasonal vegetation cover. In more detail, satellite images need to be acquired in specific time windows, which follow the phenological stages. For iCOLT study area, the window scheme is:

1. Late October to mid-November: absence of vegetation in winter and summer crop fields, presence of vegetation in multi-annual crop fields;
2. Late January to end of February: absence of vegetation in summer crop fields, presence of vegetation in winter and multi-annual crop fields;
3. Late of March to mid-April: absence of vegetation in summer crop fields, presence of vegetation in winter and multi-annual crop fields.

For the purpose of iCOLT, the most feasible satellite constellation is the one managed by Disaster Monitoring Constellation for International Imaging (www.dmcii.com), mainly because it guarantees a short revisiting time and wide swath width covering the whole region in almost 1 of 2 acquisition frames. In case of cloud cover, additional constellation data can be used to fill the covered areas, as Landsat 8 (www.usgs.gov) or Sentinel-2 (www.copernicus.eu).

Due to the highly fragmented land cover, the best classification results are achieved with 22 m pixel size of DEIMOS-1 and UK-DMC2 from DMCii satellites, therefore in case of different ground resolution, pixels are upscaled to 22 m.

The pixels are classified by a static decision tree model; this means that it is totally not dependent on ground truths. The tree has three condition levels, so each node provides a new condition, dividing pixels of the input class into two new different classes. Even if the algorithm produces eight different final classes, they are incorporated into the three crop classes with similar phenological stages.

The algorithm’s classification results are compared to the ground truths and this allows to estimate the precision of the resulting map. On average, the accuracy is around 95%, but there are slight differences between the classes year by year. The classification algorithm is run on agricultural plain areas, where fields are mostly irrigated in the summer period and devoted to intensive agriculture. In order to reduce misclassifications, the aggregation of groups of pixels into units of a minimum 1 ha size is applied and, as a consequence, isolated pixels are set to the macroclass of the neighbouring pixels. This represents the optimum resolution at which it is possible to identify isolated and misclassified pixels, so as to improve the final quality of the product. In order to distinguish agricultural pixels from other land-use classes, a mask has been created and regularly updated. This mask includes stable features, like viability network, hydrographic network and lakes, and more variable features, like urban sprawl, yearly updated using the latest SNPA (Environmental Protection National Net of Italy) map.

Early crop map is completed by adding orchards and vineyard classes, considered as stable land cover and identified by means of local reference data and used for masking the map. In Emilia-Romagna, these data are managed by the Regional Agency that collects farmers’ annual crops declarations for the European Agricultural Fund for Rural Development payments. The crop classification final raster is vectorized to create the input for the soil water balance model.

### 2.4 Probabilistic seasonal predictions

The probabilistic seasonal predictions used as input of the iCOLT system are obtained by calibrating to local climate the operational multi-model seasonal predictions of the European System for Seasonal to Interannual Prediction (EUROSIP) run at the European Center for Medium Range Weather Forecasts (ECMWF, https://www.ecmwf.int/en/forecasts/documentation-and-support/long-range/seasonal-forecast-documentation/eurosip-user-guide/eurosip-data-products). This data set changed over the years, and in order to produce the complete dataset of calibrated reforecasts, it was decided to use only the output of the ECMWF system 5 and of the MeteoFrance system 5, using hindcasts from 1991 to 2010 (2011–2019) for calibration (prediction) purposes. Only predictions obtained with initialization time on 1 May were used. This dataset is preferred here to the Copernicus dataset, currently used for operational purposes, because it ensures a continuous coverage of forecasts over the forecast period, and a longer extension of the calibration period. These characteristics of the EUROSIP dataset make it more suitable for the current validation exercise.

The calibration is produced by applying the Model Output Statistics (MOS) scheme described in Pavan and Doblas-Reyes (2013) to operational EUROSIP data, at seasonal time scale, so as to produce calibrated
probabilistic seasonal predictions for a set of six climate indices: total precipitation (PREC), frequency of wet days (WDFQ), frequency of a wet day after a wet day (WWFQ), mean seasonal minimum (TMIN) and maximum temperature (TMAX) and mean value of the difference of maximum temperature between dry and wet days (DTDW). The observational values of these indices, needed for calibration purposes, are obtained from the Crea daily analysis, consisting of an optimal interpolation gridded dataset of observational daily precipitation and minimum and maximum temperature data at national level (Girolamo & Libertià, 1990) and covering the whole calibration period.

Validation of the probabilistic calibrated multi-model seasonal forecasts is performed over the prediction period comparing predicted and observed local anomalies. The observational validation dataset used is the ERG5 observational operational analysis produced by ARPAE-SIMC. This dataset is obtained by applying the same interpolation methods used to compute the daily regional climatological analysis described in Antolini et al. (2016) to all available hourly total precipitation and mean hourly temperature data from the automated meteo-climatological monitoring network. The analysis covers the whole regional administrative territory at hourly time scale from 1991 to present at the horizontal resolution of about 5 km resolution. The input data density of this product varies over the years, but always remains high over the plain area, so that here its characteristics are compatible with climatological applications. The high density of input data makes this product more suitable for local validation purposes than the climatological long-term analysis used to evaluate climate trends over the region (Antolini et al., 2016).

Finally, validation of probabilistic seasonal predictions is performed by computing statistical indices of probabilistic predictions anomalies against observations anomalies over the period 2011–2019. All anomalies are computed with respect to the calibration period 1991–2010. For this reason, observational bias indicates the presence of a long-term variability in local climate, which is the result of a combination of decadal and multi-decadal natural climate variability and of the impact of anthropogenic climate change on local climate.

### 2.5 Crop development and water balance model

The seasonal forecast of crop water needs is performed by CRITERIA-1D model, in its geographical version, freely available at the following link: https://github.com/ARPA-SIMC/CRITERIA1D.

The CRITERIA-1D (Consoli et al., 2016) model computes the crop development and the dynamics of soil water fluxes in agricultural soils, the model is driven by daily weather data, namely minimum and maximum temperature, precipitation and, if available, hypodermic water table depth.

CRITERIA-1D assumes a multi-layered soil and computes daily actual evaporation and transpiration, water flows among soil layers, deep drainage, surface and subsurface flows. The soil water retention and hydraulic conductivity are described by a modified version of van Genuchten–Mualem model (Chitu et al., 2020).

Crop development and the dynamics of the related processes, such as the leaf area index (LAI, m² m⁻²) and the rooting depth (m), are simulated in Criteria by means of empirical equations (Marletto et al., 2007) based on degree days (°C) sums.

Potential evapotranspiration is computed using the equation of Hargreaves and Samani (1985). The partitioning of the evapotranspiration in potential evaporation and transpiration is driven by LAI. Potential evaporation is assigned to the surface layer (if it is wet) and to the first soil layers, up to 20 cm depth, while potential transpiration is assigned to the rooting system, partitioned according to the root density. The actual evaporation and transpiration can be lower than the potential, depending on the actual soil water content and on the crop physiological parameters.

Every crop in the model has its own sensitivity to water stress, defined by the fraction of readily available water (fRAW) for the rooting system. The model estimates the suggested irrigation volume and timing according to several triggers: the current soil moisture in the rooting system, the current fRAW, the minimum period of irrigation shift and the maximum volume for a single irrigation. In addition, a threshold of tolerated water stress can be defined (Villani et al., 2011).

The CRITERIA-1D model can be used in geographical mode (CRITERIA GEO), by defining a computational unit map, where one computational unit is a polygon having the same weather, soil and crop data. For the iColt climate service, the input data for CRITERIA GEO are as follows:

- Weather daily data: ERG5 analysis 5 x 5 km-grid. The same grid is used for the downscaling of probabilistic seasonal forecast, as explained earlier in Section 2.4;
- Soil data: the pedological map of 1:250,000 resolution of Emilia-Romagna region;
- Crop data: the early crop map of Emilia-Romagna plain obtained by remote sensing data analysis as...
explained in Section 2.3. Every macroclass is defined by one reference crop, according to the features of study areas (i.e., summer crops refer to maize in CBB and CBR).

2.6 | Hypodermic water table assessment

Hypodermic groundwater is an essential water source for crops. CRITERIA-1D allows to assess hypodermic water table depth using an empirical equation, which requires as input only meteorological daily data (Tomei et al., 2010). The equation has been calibrated on the monitoring network of piezometer data of Emilia-Romagna region.

The model assumes that in a plain area the outflows from the system are balanced by the inflows so that the water table depth is related only to the sum of CWB on a recharge period. The CWB is defined as the difference between cumulative precipitation and potential evapotranspiration. This can be estimated by means of the approach described in the study by Hargreaves and Samani (1985), requiring only daily values of minimum and maximum temperature.

Therefore water table depth \( H \) can be defined as follows:

\[
H = H_0 + \alpha \sum_{i=0}^{n} w_i (P_i - PET_i),
\]

where \( n \) is the number of days of the recharge period, \( P \) (mm) is the daily total precipitation, \( PET \) (mm) is the daily potential evapotranspiration, \( \alpha \) (m mm\(^{-1}\)) is a regression parameter and \( H_0 \) (m) is a local reference depth, resulting when the CWB is equal to zero, so that the precipitation and evapotranspiration are in equilibrium. Finally, \( w \) is a weight that linearly increases over time between a minimum of 0 (\( n \) days before the estimate) and a maximum of 1 (on the day of the estimate):

\[
w_i = 1 - \frac{i}{n}.
\]

The parameters of the equations can be obtained with a linear regression between the observed water table depth and the estimation of cumulative CWB: \( n \) is the number of days that maximize the correlation coefficient, \( \alpha \) is the slope of the linear regression and \( H_0 \) is the y-intercept.

Once all parameters values have been determined, the equation can be fed using observed and forecast weather data in order to obtain a continuous series of water table depth estimates and forecasts.

In the two study areas, the water table depth presents slightly different values, as shown in Figure 3 where the climatological values at 1 June are plotted for CBR and CBB; in CBB, the water table is more shallow than CBR with only 15 cm of difference for the median value.

2.7 | iCOLT computational scheme

The scheme of computational components of iColt (Figure 4) starts with multi-model seasonal predictions for the climate indices, obtained by applying the statistical scheme described above. The climate indices of probabilistic seasonal predictions of the six input variables, listed in Section 2.4, are used as input of a weather generator (WG), based on Richardson scheme (Richardson & Wright, 1984) and modified by Stockle and Campbell (Stockle et al., 1997) in order to generate daily weather data.

The WG produces an ensemble of synthetic series of daily minimum temperature, maximum temperature and precipitation, corresponding to the number of members of multi-model seasonal predictions. Each synthetic series is used as weather input to generate the corresponding series of water table depth.

The time series of daily data are obtained by adding 3 months of synthetic daily data, produced by the WG, to
the observed weather daily data of the previous 9 months. For each ensemble member of the seasonal forecast, several time series of summer weather generated daily data are produced. The number of WG runs changes depending on the year considered so as to keep the total final number of ensemble members almost constant: before 2015 it was 90, afterwards it has been set to 102. The weather time series and the early crop map are used as input of the CRITERIA-1D model, so as to obtain the probabilistic seasonal forecasts of irrigation.

The final operational product of iCOLT is a bulletin where seasonal irrigation forecasts are represented as box plots of anomalies of irrigation June–July–August with respect to climate between 1991 and 2010. These climatological values are obtained for each forecast year from the irrigation estimates for the years 1991–2010 by imposing the same crop map as for the forecasted year. As a consequence, the climatological irrigation value changes from year to year as a function of the field crop distribution. The irrigation seasonal forecast bulletin is then available on iCOLT web page (https://sites.google.com/drive.arpae.it/servizio-climatico-icolt).

2.8 Summer irrigation forecasts

For the purposes of this study, the computational scheme described in the previous section was applied in three different ways:

I. iCOLT operational scheme fed by the probabilistic seasonal predictions;
II. iCOLT scheme forced with climate data;
III. iCOLT scheme excluding water table input from soil water balance modelling, in order to assess the impact of this process within the computation.

In the second scheme, WG is fed by climatological summer values of the six indices used in input so as to generate 99 synthetic series of both weather and water table data, describing the statistical properties of climate. These indices are computed from the observed weather data over the period 1991–2010.

In the third scheme, the boundary condition at the bottom of the soil depth is free drainage when the water content is greater than field capacity. This boundary condition is similar to a water table depth ranging from 2 to 3 m below the lowest soil layer, according to the soil hydraulic properties.

These three schemes are compared in order to assess the skills of the forecasts and to evaluate the weight of the seasonal probabilistic forecasts and the initial conditions on the irrigation predictions.

The analysis was performed over the summer seasons of the period 2011–2019 for the CBB and CBR study areas, using as climate the period 1991–2010 and as reference values the irrigation assessments obtained by forcing the soil water balance with observed weather daily data, as shown in Figure 5.

The general unavailability of observed irrigation data on wide areas and for long time series makes it necessary to use the irrigation assessment produced by the model forced with observed weather data as a proxy of irrigation observational data. These model estimates are often used as observational proxy of observed irrigation data for forecast of irrigation water needs. For instance, in the study by Ravindranath et al. (2018), a model index computed starting from the data of precipitation is used as proxy of potato irrigation and as predictand to evaluate the reliability of forecasts.

However, for an irrigation district of CBR (Prada irrigation district, total area of 1271 ha), a subset of observed data of irrigation recorded by water counters...
from 2014 to 2019 is available. These observed data have been compared with the irrigation estimated by the model forced by observed weather data, with the aim to evaluate the skill of the model in the assessment of actual crop water needs.

This analysis, with a coefficient of determination $R^2$ equal to 0.81, shows that the model irrigation is in good agreement with observed data both in quantity and variability, as presented in the time chart in Figure 6. The series is limited in time and refers to a small area of CBR; nevertheless, it shows the ability of the model to simulate irrigation water needs, and, as a consequence, to use them as reference value.

### 2.9 Statistical indices

All forecasts in the present work are expressed in terms of probability of occurrence of positive anomalies of the considered indices with respect to their climatological values over the reference period 1991–2010. As a consequence, each forecast is expressed in terms of probability of occurrence of a positive anomaly of the considered index. The assessment of the performance of the final forecast products is performed by means of several standard probabilistic scores and skill scores: the Brier Score (BS), the Brier Skill Score (BSS), the mean bias (BIAS), the coefficient of determination ($R^2$) and the Nash–Sutcliffe Efficiency Index (NSE).

The BS can be considered as the mean square error in probability space and is defined as

$$BS = \frac{1}{N} \sum_{i=1}^{N} (f_i - a_i)^2,$$

where $N$ is the total number of available probabilistic forecasts (in our case, one for each year of the validation period), $f_i$ is the predicted probability of occurrence of the event and $a_i$ is the observed probability of occurrence of the same for each of the $n$th forecast (0 is the event does not occur, 1 if it does) (Wilks, 2006). For seasonal predictions the reference forecast is climatology (50% probability of a positive anomaly event). In case of dichotomous events (positive/negative anomalies) the Reference Brier Score ($BS_{\text{ref}}$) is then 0.25 and the BSS is defined as...
The BIAS is defined as the mean difference between observed and the ensemble mean forecast data and is the systematic error of the forecast.

The $R^2$ (Wilks, 2006) is defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\text{Sim}_i - \text{Mean}_{\text{obs}})^2}{\sum_{i=1}^{n} (\text{Obs}_i - \text{Mean}_{\text{obs}})^2},$$

where $\text{Sim}_i$ is the $i$th forecasted value, while $\text{Obs}_i$ is the $i$th observed value and $\text{Mean}_{\text{obs}}$ is the mean value of observations.

The sets of results about the seasonal irrigation forecasts were analysed also through the NSE (Nash & Sutcliffe, 1970) as follow

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (\text{Obs}_i - \text{Sim}_i)^2}{\sum_{i=1}^{n} (\text{Obs}_i - \text{Mean}_{\text{obs}})^2},$$

where $n$ represents the number of data pairs, $i$ is the pair index and $\text{Mean}_{\text{obs}}$ is the average of the observed data. NSE ranges between $-\infty$ and 1.0 (1 inclusive), where NSE = 1 indicates a perfect fit, NSE = 0 means that average observed values have the same performance of model predictions and a negative value indicates a poor model performance.

### 3 | RESULTS

#### 3.1 | Probabilistic climate predictions

Validation of the probabilistic calibrated multi-model climate predictions is performed for each of the six climate indices, mentioned in Section 2.4.

For each index probabilistic climate predictions over the period 2011–2019 are evaluated using the BIAS, the BS, the BSS using as reference the climatological prediction and the $R^2$. Validation is presented for CBR and CBB in Tables 1 and 2, respectively.

As for precipitation, in both areas the negative BIAS of forecasts with respect to observations is due to the fact that, in the nine forecast years, observed cumulated summer precipitation has been, on average, less than in the previous 20 years. This feature is consistent with the observed reduction in summer total precipitation over Northern Italy (Pavan et al., 2019), but it has not been captured by the forecasts that produce, at both locations, a distribution of forecasted anomalies values centred close to 0 mm. In the absence of such bias, the forecast would have reached a BS of 0.21 or 0.25 and a BSS of 0.17 or 0.0004, respectively, in the two areas. From this analysis, it seems that while the system has some limitations in capturing the long-term variability, it has a better skill at predicting year-to-year variations of total precipitation.

Temperature parameters also present a mean increase in values during the forecast period with respect to the calibration period. This increase is consistent with the observed temperature long-term significant trends over the region for these parameters (Antolini et al., 2016; Tomozeiu et al., 2006), but it does not necessarily translate into a forecast ability of the system. In particular, for minimum mean summer temperature, the direction of the trend is captured, although underestimated, and the prediction is characterized by greater predictive ability than the simple climatological predictions at both

| TABLE 1 | Values of bias, Brier Score, Brier Skill Score and correlation for each of the six climate indices in CBR |
|---|---|---|---|---|
| BIAS | BS | BSS | $R^2$ |
| PREC | 44.7 | 0.31 | −0.23 | 0.02 |
| WDFQ | 0.02 | 0.28 | −0.13 | 0.71 |
| WWFQ | 0.002 | 0.20 | 0.20 | 0.68 |
| TMIN | −0.96 | 0.19 | 0.25 | −0.25 |
| TMAX | −0.64 | 0.22 | 0.10 | 0.47 |
| DTDW | 0.76 | 0.23 | 0.08 | 0.50 |

Abbreviations: BIAS, mean bias; BS, Brier Score; BSS, Brier Skill Score; DTDW, mean value of the difference of maximum temperature between dry and wet days; NSE, Nash–Sutcliffe Efficiency Index; PREC, total precipitation; TMAX, mean seasonal maximum temperature; TMIN, mean seasonal minimum temperature; WDFQ, frequency of wet days; WWFQ, frequency of a wet day after a wet day.

| TABLE 2 | The same as Table 1, but for CBB |
|---|---|---|---|---|
| BIAS | BS | BSS | $R^2$ |
| PREC | 43.9 | 0.35 | −0.40 | 0.15 |
| WDFQ | 0.001 | 0.22 | 0.13 | 0.63 |
| WWFQ | −0.003 | 0.23 | 0.08 | 0.20 |
| TMIN | −0.035 | 0.21 | 0.17 | −0.51 |
| TMAX | −1.58 | 0.29 | −0.16 | 0.30 |
| DTDW | 1.33 | 0.23 | 0.08 | 0.45 |

Abbreviations: BIAS, mean bias; BS, Brier Score; BSS, Brier Skill Score; DTDW, mean value of the difference of maximum temperature between dry and wet days; NSE, Nash–Sutcliffe Efficiency Index; PREC, total precipitation; TMAX, mean seasonal maximum temperature; TMIN, mean seasonal minimum temperature; WDFQ, frequency of wet days; WWFQ, frequency of a wet day after a wet day.
locations. For mean summer maximum temperature, the direction of the trend is not captured, all the same at the location where the mean bias is less intense (CBR study area) the predictive ability of the system is still better than climatology. In the other study area, debiasing would lead to predictions better than climatology.

As for the other indices, the DTDW is well predicted at both locations, and so is its long-term variability, and the same holds for the WWFQ. As for WDFQ, the predictions are better than climatology only where the long-term trend is captured, but debiasing would not lead to better prediction anyway. All the same, the $R^2$ indicates the presence of correlations between observed anomalies and the forecast median.

### 3.2 Probabilistic irrigation predictions

Probabilistic irrigation predictions between 2011 and 2019 for the CBB and CBR consist of three sets of predictions obtained by means of the three schemes described in Section 2.8.

Figures 7 and 8 show the results of the iCOLT operational scheme for CBR and CBB represented by box plots where the anomalies with respect to the period 1991–2010 are plotted. These anomalies are compared with the reference irrigation. Data are expressed as anomalies of irrigation volume (unit: m$^3$/ha). The average of the climatological irrigation volumes is about 1150 m$^3$/ha for both CBR and CBB, with an annual variability of maximum 6% due to the variability of early crop map, as every year the climate simulation is recomputed according to the current early crop map.

In the analysed time series, two extremely dry years (2012, 2017) occurred with different magnitude in the two Irrigation Boards and 1 year (2014) with low irrigation needs for both CBB and CBR. Seasonal forecasts in CBR correctly identify the strong anomaly of 2012, whereas for 2014 and 2017 they present the correct sign but a less correct magnitude.

In CBB, seasonal forecasts correctly identify the three extremes (2012, 2014, 2017) but it slightly underestimates 2012 and tend to overestimate the negative anomalies in years with irrigation needs on average, especially 2013.

Figures 9 and 10 show the results of iCOLT summer irrigation forecast computed excluding water table input.

The seasonal forecasts obtained by means of the exclusion of water table present correct signs but they
FIGURE 8  The same as Figure 7 but for CBB

FIGURE 9  The same as Figure 7 for the iCOLT scheme excluding water table input for CBR
lead to an almost complete loss of variability. This result is in line with the expectation, because the water table depth is the essential component of initial conditions of the system as it contains information about occurred precipitation and water storage in soil in the previous months.

To assess the robustness of these three sets of results, the BS, the BSS, the NSE and the $R^2$ are computed for positive anomaly events, using the irrigation needs mean values over the period 1991–2010 as reference. Validation is presented for CBB and CBR areas in Tables 3 and 4, respectively.
In both CBR and CBB, the summer irrigation forecasts obtained by iCOLT operational scheme show the best performances for all the statistical tests (Tables 3 and 4). In more detail, the skill of iCOLT operational scheme forecasts and iCOLT forced by climate show small differences, whereas the forecast excluding water table shows good performances in terms of BS and BSS but bad performances in term of NSE and $R^2$.

### 4 | DISCUSSION

In general terms, the iColt system has been shown to have skill in predicting the irrigation water need anomalies for the next summer, starting from satellite data of winter and spring, from observed weather data and from summer calibrated ensemble seasonal predictions. The comparison of the results obtained over the two study areas with or without the presence of a diagnostic scheme used to estimate the surface water table level clearly suggests that simulating water storage and capillary rise from water table significantly improves the predictions in term of amplitude of the forecasted anomalies, especially when an intense anomaly of crop water needs is observed. This is due to the characteristic inertia of the soil conditions, which is linked to the precipitation of the previous months. If the water table depth and the soil water content are not correctly initialized and represented in the model, the overall forecast ability of the system is significantly reduced. At the same time, the calibrated ensemble seasonal predictions positively contribute to the final skill of the system albeit presenting a reduced amplitude in the year-to-year variability, typical of all statistically downscaled products (Wilks, 2006). In particular, the skills of the forecasts obtained by forcing the system with climate data are always somewhat lower than those obtained using the calibrated operational seasonal forecasts.

It is worth mentioning that the skill of the irrigation forecast is higher than the skill of probabilistic climate predictions, because the climatic predictions are only one of the components of the computational chain where the other key component is the initial condition of soil water content, that the model estimates by means of observed weather and water table data (with almost 1 year of previous data).

It is also important to mention that the system can capture the spatial variability of the amplitude of irrigation in different regional areas, due possibly to the use of detailed early crop maps, which include the spatial distribution of irrigated/not irrigated crops and of perennial/annual crops. In the absence of this information or in the presence of less precise information, it is expected that the spatial variability of the predictions would be captured to a much lesser degree.

Regarding optical remote sensing data, the main constraint are the weather conditions during the acquisition windows. It is mandatory to choose sensors with wide swath and high revisiting periods to prevent difference in crop development stage and to increase chances of acquiring a good image. A way to solve the cloudy acquisition problems could be to add to the classification procedure a fourth window at the beginning of the summer period, which could confirm the classification results and correct mis-classification. Currently, this new procedure step is still under development.

Finally the present validation exercise would benefit from the use of observed irrigation water use data. For this reason, a data collection campaign was launched, so as to collect data describing the year-to-year variability of the irrigation water used at Land Reclamation and Irrigation Board level.

### 5 | CONCLUSIONS

The iCOLT climate service is able to predict agricultural water demand for summer irrigation in Emilia-Romagna. It is a “low cost” project with high added value because its products can be helpful in a wide range of disciplines: agriculture, water management and Land Reclamation and Irrigation Boards administration or planning of new irrigation systems.

The presented system has been used operationally since summer 2011 in order to produce forecasts of crop irrigation water needs for the summer season, and it currently uses as input the Copernicus seasonal predictions dataset. This scheme allows to assess crop water needs for the whole irrigation season at the regional and Irrigation Board scales.

Since summer 2018, a quasi real time in season service (https://servizigis.arpae.it/moses/home/index.html) has been added to the seasonal forecast service so as to compute daily agrometeorological variables (potential evapotranspiration and crop water needs) based on short range weather forecasts as part of the outcomes of the H2020 European Project MOSES (https://cordis.europa.eu/project/id/642258/it) and H2020 European Project CLARA (https://www.clara-project.eu/).

These two different tools (seasonal and short range forecasts of irrigation) could offer to the Irrigation Boards two different visions of the water management: a global evaluation of the probable irrigation season needs is offered by the seasonal forecast, a more detailed weekly estimation of the water balance is offered by the 7-day forecasts.
These two approaches allow a rational planning of the water resource in order to reduce or better manage the use of water for irrigation and the related energy consumption of the pumping plants. To this extent, the quantification of these volumes should represent an economic and environmental assessment tool coupled to iCOLT and used by the Irrigation Boards, which could provide a perspective towards climate change adaptation and mitigation.

ACKNOWLEDGEMENTS

The research leading to these results has received funding from the European Union, Horizon 2020 Research and Innovation Action Programme under the project CLARA, Grant Agreement No. 730482, and Horizon 2020 Innovation Action Programme under the project MOSES, Grant Agreement No. 642258. Part of the work was also funded by the HIGHLANDER project, co-financed by the Connecting European Facility Programme of the European Union under Grant agreement No. INEA/CEF/ICT/A2018/1815462. We thank Consorzio di Bonifica della Romagna (Alessandro Fabbri and Enrico Montanari) for providing observed data of irrigation volumes for the Prada irrigation district. We thank Dr. Andrea Montani and to anonymous reviewers for useful discussion.

AUTHOR CONTRIBUTIONS

Giulia Villani: Conceptualization (equal); investigation (lead); methodology (equal); writing – original draft (lead); writing – review and editing (equal). Fausto Tomesi: Conceptualization (equal); investigation (equal); methodology (equal); software (lead); writing – original draft (equal); writing – review and editing (equal). Valentina Pavan: Conceptualization (equal); investigation (equal); methodology (equal); writing – original draft (equal); writing – review and editing (equal). Alessandro Pirola: Methodology (equal); writing – original draft (equal); writing – review and editing (equal). Andrea Spisni: Methodology (equal). Vittorio Marletto: Methodology (equal).

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How to cite this article: Villani, G., Tomei, F., Pavan, V., Pirola, A., Spisni, A., & Marletto, V. (2021). The iCOLT climate service: Seasonal predictions of irrigation for Emilia-Romagna, Italy. Meteorological Applications, 28(4), e2007. https://doi.org/10.1002/met.2007